How Does Peer-to-Business Lending Affect Financial Policy of SMEs?[*]

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Abstract

We study how alternative sources of financing, Peer to Business (P2B) platforms, affect the financial policy of small and medium-sized enterprises (SMEs). We find that firms obtaining P2B loans are higher quality firms as they are large, more profitable, with higher sales growth, higher bank debt, and lower default rates. We conclude that P2B platforms are serving the same type of firms than traditional banks. While P2B loans do not seem to affect investment policy and performance, it does affect financial policy. Firms use the availability of P2B to reduce long-term bank debt, while they increase short-term bank debt following P2B lending. In addition, SMEs increase the number of lending relationships and reduce their dependence on a single bank, in particular those with less stable funding and lower liquidity. Our findings suggest that FinTech lending complements the debt financing choices of SMEs and allows them to diversify away from traditional banks.

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1. Introduction

Credit allocation has gone through a revolution with the rise of web-based platforms. While banks traditionally fulfilled the financing needs of small and medium-size enterprises (SME), individual investors are increasingly providing credit to firms through peer-to-business (P2B) platforms. As technology changes the competitive landscape for financial intermediation, it raises several important questions: Does financial innovation (FinTech) improve firm welfare? Are firms better off when they engage in long-lasting and largely exclusive relationships with banks? Will FinTech substitute bank lending and make banking relationships obsolete or will be a complement?

The Boot and Thakor (2000) model predicts that increased capital market competition should reduce bank (relationship) lending and rents. More capital market based competition would make the overall financial system more competitive with fewer banks. For borrower welfare, this paper highlights that there is an important difference between transactional borrowers, who would be better off, and relationship borrowers would be worse off. If FinTech operates as a capital market alternative to banks and provides transactional capital market based debt, then it could help firms obtain a credible outside option to improve its bargaining power with respect to its lenders (Ioannidou and Ongena (2010)), and reduce the hold-up problem (Rajan (1992),Sharpe (1990)). On the other hand, it could undermine the effectiveness of relationship banking, which is crucial to mitigate information asymmetries (Boot and Thakor (1994), Thadden (1995), Boot (2000)). Welfare improvement, thus, depends on where FinTech is located in the continuum of bank loans and public debt, as well as on the consequences for the borrowers' relationship with banks and the borrowers' credit quality.

Alternatively, the rise of peer-to-business (P2B) platforms could allow SMEs to access capital market for the first time, as SMEs are traditionally constrained in its access to public debt. In this case, FinTech lending would expand the credit market by catering to a different type of firms, a riskier unexplored market segment (de Roure, Pelizzon, and Tasca (2016), Hau, Huang, Shan, and Sheng (2019), Maggio and Yao (2020), Buchak, Matvos, Piskorski, and Seru (2018),

Fuster, Plosser, Schnabl, and Vickery (2018), Erel and Liebersohn (2020), Balyuk, Berger, and Hackney (2020)), thereby extending the credit supply.

Overall, it is not clear whether FinTech directly competes with banks, and what is the consequence of the presence of this new source of debt financing on bank-firm relationships. Similarly, the impact of the rise of peer-to-business (P2B) platforms on firm outcomes is ex-ante uncertain. The aim of this paper is to shed light on these issues. We study how alternative sources of debt financing through P2B platforms, financed by retail investors, can influence the capital structure choices and banking relationship of firms.

To this end we use two unique datasets. First, we use proprietary data from a leading independent Portuguese P2B platform that directly links retail investors to SME borrowers. We merge these data to detailed financial statements and credit registry data of the Bank of Portugal to obtain credit information on FinTech borrowers. Having access to granular firm-level data and firm-bank relationships provides us with the opportunity to provide new insights about the interaction between FinTech and the banking sector, such as whether traditional and FinTech credit markets are substitutes or complements in serving the financial needs of SMEs.

Studying how P2B lending influences the capital structure choices and banking relationships of SMEs is empirically challenging, as unobservable borrower characteristics may affect both the likelihood of obtaining P2B lending and firm outcomes. To mitigate this endogeneity 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 chose to do it through a P2B platform with an otherwise similar group of firms who is raising 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 include in our specifications different sets of high-dimensional fixed effects, such as industry-time fixed effects. Such an inclusion makes sure that different industry-level dynamics between firms relying on traditional financial intermediaries and firms obtaining P2B lending cannot explain our results. Finally, we adopt a propensity score matching approach.

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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.

We find that 654 small and medium enterprises raise debt capital via P2B platform over the period 2016-2018. We first investigate which firms use FinTech as a source of debt financing as compared to firms that decide to borrow from traditional financial intermediaries. We find that firms that borrow through the P2B platform are larger, more profitable, and have higher sales growth as compared to those who borrow from traditional financial intermediaries. Importantly, we find that firms accessing the P2B platform have higher levels of pre-existing bank debt and lower default rates. These results suggest that firms obtaining P2B lending are higher quality firms, thus the new P2B platforms are complements to traditional banks and they are not serving different segments of firms.

Next, we explore how firms use the P2B loans. We do not observe significant real effects following P2B loans as there are no significant changes in firm assets, nor in firm profitability. However, we find signficant effects on financial policy. Firms borrowing through the FinTech platform change significantly their debt structure. Firms significantly change the way they manage their capital structure and exposure to the banking sector. We find that firms use the availability of P2B loans to reduce their long-term exposures to the banking sector, while simultaneously increase short-term bank debt. At the same time, accessing the P2B platform allows SMEs to increase the number of banking relationships, as well as reducing their dependence on a single bank. We also find that, net of the costs of the FinTech loan, firms manage to reduce their borrowing costs, as the interest rate on bank loans for these firms becomes 2 to 4 basis points lower, on average. Therefore, our results indicate that FinTech empowers SMEs to reduce bank dependence and to take more ownership of their capital structure choices. Firms' benefits coming from their efforts to diversify their pool of lenders and the use of alternative financing allows to reduce funding costs.

To improve our understanding of the reasons behind the choice to switch to FinTech credit,

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and what role banking relationships have in such a choice, we explore cross-sectional differences in firms' bank dependence. Specifically, we study the characteristics of the banks with a lending relationship with the SMEs in our sample. We find that SMEs are more likely to switch to P2B lending if they have relationships with banks that have low profitability, rely less on deposits, and have more liquidity constraints. This indicates that firms prefer to reduce their exposure to banks with less stable financing sources and lower liquidity. These results highlight the importance of the quality of the banks themselves in the choice to access the new P2B platforms, and they constitute a contribution to the literature that emphasizes the firm-level determinants of banking relationships (Farinha and Santos (2002), Bonfim, Dai, and Franco (2018)).

Our findings contribute to the literature in several ways. First, we show that P2B provides loans to credit-worthy firms, thus targeting banks' clients. In contrast, the traditional financial intermediation literature (Sharpe (1990)) indicates that competition should lead newcomers to allocate capital toward lower quality and younger firms. In addition, the empirical findings on peer-to-peer (P2P) platforms conclude that FinTech serves a riskier unexplored market segment in consumer loans (de Roure, Pelizzon, and Tasca (2016), Hau, Huang, Shan, and Sheng (2019), Maggio and Yao (2020), mortgage origination (Buchak, Matvos, Piskorski, and Seru (2018), and business loans (Fuster, Plosser, Schnabl, and Vickery (2018), Balyuk, Berger, and Hackney (2020)). Our paper provides evidence of a complementarity between FinTech and bank lending in line with the arguments for capital market funding (Diamond (1991), Hoshi, Kashyap, and Scharfstein (1993) and Song and Thakor (2010).

Second, in a recent paper, Havrylchyk and Ardekani (2020) explore the characteristics of 187 SMEs in France which raise capital from a lending-based crowdfunding platform. The authors find that these 187 SMEs have lower leverage, less cash, higher funding costs and less tangible assets that could be pledged as a collateral as compared to remaining French SMEs. Our paper differs by showing that firms that borrow from the P2B platforms do not appear to be credit constrained, as that they have relations with multiple banks, and higher bank debt outstanding. SMEs that are funded through the P2B platform change their debt maturity

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structure by borrowing long term with the platform, which they then supplement with new short-term bank loans. The possibility to raise new short-term debt from traditional financial intermediaries after the FinTech loan is consistent with the notions that the firms accessing P2B loans are not credit constrained. In short, we find that P2B lending is a complement for bank lending in terms of serving the bank borrowers yet substitutes bank lending with respect to long-term loans.

Finally, we emphasize an important demand-level explanation for the rise in FinTech credit. Using aggregate debt offering at the regional or country level, several papers suggest FinTech took over traditional financial intermediary market share when it comes to business lending (See Gopal and Schnabl (2020), Balyuk, Berger, and Hackney (2020), and Cortés, Demyanyk, Li, Loutskina, and Strahan (2020). Large banks reduced the lending to small businesses as they faced strong regulatory burdens and losses, leaving room for FinTech lenders. We find that firms themselves prefer FinTech as it allows them to diversify their pool of lenders. SMEs are willing to pay a premium to the P2B platform to raise new long-term debt as compared to bank debt, especially those SMEs who are borrowing from weaker banks. FinTech lending enables firms subsequently to improve its bargaining power with respect to its lenders and to refinance at more favorable terms by reducing their debt maturity and hedge the refinancing risk that normally short-term debt entails. In short, FinTech helps to mitigate the hold up problem of SMEs (Ioannidou and Ongena (2010); Rajan (1992); Sharpe (1990)).

Our results have important policy implications for the architecture of the financial system to favor the development of market-based platforms (P2B). The existence of market-based systems for SMEs enhances welfare as it allows SMEs to diversify their lending relations. While FinTech for now does not seem to alleviate capital constraints of SMEs, as it targets firms who already have access to credit through traditional financial intermediaries, it increases their bargaining power with banks and reduces their funding cost. This is especially relevant in Europe where most firms mostly rely on banks for external funding. In particular, SMEs are heavily reliant on (short-term) bank credit and debt capital markets are exclusively available for the largest often

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public firms.

The rest of the paper proceeds as follows. Section 2. summarizes the extant literature on FinTech lending. Section 3. describes the data. Section 4. presents our results. Section 5. concludes.

2.   Literature Review

How different are nontraditional lenders such as FinTech platforms from banks? Does FinTech substitute or complement traditional financial intermediaries? Do they cater to the same or different (riskier) clientele? So far the literature provides mixed evidence on these questions.

The role of FinTech in providing financial services to individuals has been relatively more explored in the context of mortgage loan originations (Buchak, Matvos, Piskorski, and Seru (2018), Fuster, Plosser, Schnabl, and Vickery (2018)) and unsecured consumer credit (see, among others, Danisewicz and Elard (2018), de Roure, Pelizzon, and Thakor (2019), Balyuk (2019)).

Regarding consumer loans the literature suggests that FinTech differs from banks in that it caters to less creditworthy individuals thereby extending credit to those excluded from bank credit. For example, Maggio and Yao (2020) study the differences between traditional banks and FinTech lenders using unique consumer loan data from a large credit bureau. They find that FinTech lenders tend to originate loans to less creditworthy individuals, which are more likely to default, and thereby gather data to improve their credit models, and subsequently increase their market share by extending credit to higher-quality borrowers. This is consistent with model predictions of Hau, Huang, Shan, and Sheng (2019) who conjecture that FinTech credit is relatively more attractive for individual borrowers with low credit scores who are often excluded from bank credit. Several other papers explore the relation between the availability of local bank credit and the propensity of consumers to borrow from peer-to-peer (P2P) networks and vice-versa to study the differences in the adoption of FinTech credit across regions. Tang (2019) exploits a regulatory change that caused banks to tighten their lending criteria to study whether banks and P2P lenders are substitutes or complements. Using the data available by the

Lending Club, Tang (2019) finds that P2P lending is a substitute for bank lending by serving infra-marginal bank borrowers but complements bank lending with respect to small loans.

In the context of residential mortgage loans, Buchak, Matvos, Piskorski, and Seru (2018) find that FinTech lenders are less likely to serve less creditworthy FHA borrowers and higher unemployment regions. Erel and Liebersohn (2020) shows that in lower-income areas and in areas with fewer banks, more borrowers turned to online and nonbank loans for their Paycheck Protection Program (PPP) loan during the COVID-19 recession period. Internationally, de Roure, Pelizzon, and Thakor (2019) examine German peer-to-peer lending (Auxmoney) and conclude that such platforms serve a market neglected by German commercial banks. Thakor (2020) argues P2P lenders will not replace banks anytime soon, but will rather take some market share away from banks when banks are capital-constrained, and for borrowers who do not have collateral to offer secured loans.

When it comes to small business lending, it is even less clear as to whether FinTech platforms act as substitutes or complements to banks credit supply. Chen, Hanson, and Stein (2017) argue that after the 2007-2009 financial crisis, large banks reduced the lending to small business as they faced strong regulatory burdens and losses, leaving room for non-bank lenders. Chernenko, Erel, and Prilmeier (2019) is one of the first study to analyze the terms of direct loans by non-bank lenders to publicly-traded medium sized firms during the 2010-2015 period. They show that non-bank lenders, defined as finance companies (FCOs), firms whose primary business is to lend to consumers and businesses but do not issue deposits, provide relatively more credit to unprofitable businesses, catering to a riskier market segment than traditional bank offering. Cortés, Demyanyk, Li, Loutskina, and Strahan (2020) argue that regulatory burden and stress tests lead large bank to move away from risky small business lending. They find that banks exit markets where they do not have a local presence, and simply raise interest rates where they have a local branch. Banks capitalize on their local presence and relationship with firms and can afford to raise interest rates on these firms as it is costly for them to switch. They also find that aggregate lending to SMEs does not decrease, as there is a substitution effect from large banks

to small banks and thus leaves room for non-bank lenders. Cornelli, Frost, Gambacorta, Rau, Wardrop, and Ziegler (2019) analyze cross-country differences and argue FinTech credit seems to complement other forms of credit, rather than substitute them.

The results of Gopal and Schnabl (2020) support a substitution effect due to the reduction in the supply of credit by banks. They find increased lending by non-bank lenders, especially independent finance companies, which almost perfectly offsets the reduction in bank lending in the aftermath of 2007-2009 financial crises.

Balyuk, Berger, and Hackney (2020) argues that FinTech's competitive advantage lies in more efficient processing of hard information and loses out when firms have a strong lending relation with a bank. At the county level, they observe more FinTech loans at the expense of loans by large/out-of-market banks more than small/in-market banks. This is consistent with FinTech being more efficient in processing hard information, which is the source of information used by large/out-of-market banks, rather than hardening of soft information in which small relationship banks prevail. This paper highlights the cross-sectional differences across banks and similarly it is important to document differences across the firms as recipients of the credit, the demand side and that is where our paper comes in.

3. Data

3.1 FinTech P2B Platform

The data come from an independent Portuguese P2B platform ("Raize") that finances Portuguese SMEs. We have access to all the loans extended from the outset of the platform in December 2016 through September 2019.

The median loan extended by the FinTech platform is €20,000 euro, with a 7% rate and maturity of 36 months. The smallest loan is €4,000, while the maximum amount is €315,000. The minimum interest rate is 3% and the highest rate is 10.29%. The activity of this FinTech platforms seems to be concentrated in financing small firms and start ups. They offer loans for

young companies, less than 2 years old but already in operation, with financial capacity and potential for growth. In the case of SMEs, the FinTech promises approval within 48 hours and financing within 5 days for loans with terms between 1 to 60 months (less than 5% of banks give SMEs credit with maturity above 1 year). The FinTech platform offers savings of up to 80% of banking commissions and no prepayment penalties.

Investors in the FinTech platform receive a fixed rate and pay no commissions. The platform counts more than 53,919 investors who made an average gross return of 6.38% over the sample period. The platform follows a pure matching model, investors directly select prospective loans based on a range of credit information, such as general 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 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.

3.2   Firm-Level Data

We collect accounting firm-level information from the Central Balance Sheet data (henceforth CB), managed by the Bank of Portugal. It consists of a repository of yearly financial statements on the universe of non-financial corporations operating in Portugal from 2010 to 2019. The data include information on balance sheet statement, profit and loss statement, and cash flow statement.

We focus on SMEs over the period 2010-2019 and we apply the following filters to the sample. First, we exclude large firms, i.e, companies with more than 250 employees. This is because our focus is on SMEs, and besides, none of the large firms received FinTech financing. Second, we limit our sample to firms that are organized as public or private limited liability companies, as these are the only legal forms that characterize firms that use FinTech financing. Third, we compile the list of industry affiliations of firms that received Raize financing. Then, if a firm in the CB database does not operate in one of such industries, we drop the firm from our sample.

Fourth, we exclude firms operating in districts where none of the firms in our FinTech sample is headquartered. Finally we limit our sample to firms that increase their external debt funding. This choice is driven by the desire to increase homogeneity between the firms that receive FinTech funding and the comparison firms, as both groups of firms are demanding additional external funds. After applying these filters, we are left with $413,636$ firms, corresponding to $2,419,675$ firm-year observations.

3.3   Bank-Firm Matched Data

In some of our tests, we employ variables that use information from the Central Credit Registry (CRC) of the Bank of Portugal combined with the banks' balance sheet and income statement as well as the firms' financial statements. The CRC contains loan-level information, such as the identity of the lender, the borrower, and the loan quantity. Due to the sensitive nature of this data, we do not have direct access to CRC information, but we are able to obtain aggregated values. The data is aggregated at the firm level, thus the bank variables used in the tests 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.   Results

In this section, we examine whether bank financing and debt crowd-funding are complements or substitutes when SMEs raise new debt. To that end, we first examine the characteristics of firms who received FinTech financing versus those who raise debt from traditional banks. We then explore how the firms use of this new capital and whether is affects firm investment and financial policy.

4.1 Which Firms Obtain FinTech Loans?

First, we study the characteristics of firms that access P2B lending relative to other firms in our sample.

Table 1 shows a univariate analysis that compares accounting-level variables (Panel A) between the sample of firms obtaining a P2B loan and otherwise similar firms that raise debt from traditional financial intermediaries. The table shows that firms obtaining a P2B loan are larger in number of employees and total assets. Firms who borrow from P2B platforms are also more profitable as proxied by return on assets (ROA). The P2B firms have a lower current ratio and hold less cash but have a higher interest coverage ratio and sales growth rate. P2B firms use significantly more leverage, but at the same time display a lower level of overdue credit. In Panel B, we compare the differences across bank-related variables aggregated at the firm-level using value-weighted averages across the banks with a lending relationship with the firm where the weights are given by the outstanding amount of debt. Firms who raise capital from the FinTech platform tend to have debt with banks with less deposits and liquidity.

In sum, these univariate results suggest that firms using the P2B platform are higher-quality firms: larger firms, firms with more tangible assets to pledge as collateral, firms with access to bank debt, firms with lower overdue credit, and firms with higher growth and profitability. These results are in contrast with previous studies predicting that FinTech should be mostly finance firms with no collateral (see e.g., Thakor (2020)). Panel B suggests that firms accessing P2B loans aim to diversify their lending relations to depend less on banks with less stable funds and illiquid banks.

Next, we examine whether these results are robust to a multivariate setting. Specifically, we run the following firm-level regression:

$$RaizeFinancing_{i,t} = \alpha_{j,t} + \beta_1 Employees_{i,t} + \beta_2 ROA_{i,t} + \beta_3 CurrentRatio_{i,t} + \beta_4 EBITDA \backslash Interests_{i,t}$$
$$+ \beta_5 Tangibles_{i,t} + \beta_6 Cash_{i,t} + \beta_7 Leverage_{i,t} + \beta_7 OverdueDebt_{i,t} + \beta_8 SaleGrowth_{i,t} + \epsilon_{i,t} \quad (1)$$

where $P2BFinancing_{i,t}$ is a dummy variable that takes value of one the year in which a firm receives a loan from Raize, and 0 otherwise. Since we aim to study the determinants of obtaining P2B financing, the sample excludes firms after they receives its last P2B loan. We report results of a model with no fixed effects (columns (1) and (4)), with year fixed effects (columns (2) and (5)), or industry-time fixed effects (columns (3) and (6)), which absorb time-varying unobserved heterogeneity across industries.[1]

The estimates in Table 2 confirm the univariate test results. Firms receiving P2B financing seem to be higher quality firms. They are larger and have higher profitability (ROA) and interest coverage ratio. They are characterized by a greater use of external funding (i.e., less cash and higher leverage), but at the same time they have less overdue debt. Columns (4)-(6) include sale growth as explanatory variable, which due to our limited sample period reduces the number of observations. Consistent with the finding that firms obtaining P2B loans are higher quality firms, we find that the coefficient on sale growth is positive and significant, which indicates that firms with more investment opportunities are more likely to have access to P2B lending.

Overall, our results cast doubts on the view that banks and FinTech platforms serve two different segments of the population of firms. In our sample, firms accessing the FinTech platform are more profitable and collateral assets, which are arguably firms that can also potentially obtain bank debt. Interestingly, this is confirmed by the evidence that firms obtaining a P2B loan are firms with higher access to the banking system, as testified by the significantly larger pre-existing level of bank debt.

4.2 How Do Firms Use FinTech Loans?

In this section, we study how firms use P2B funding. We explore several potential uses using the following specification:

$$Y_{i,t} = \alpha_i + \alpha_{ct} + \beta_1 Raize \times PostFinancing + X_{i,t-1}\gamma + \epsilon_{i,t} \tag{2}$$

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[1]In unreported tests we find that our results are robust to the use of a logit model.

where $Y_{i,t}$ is an outcome for firm i at time t. In performing this analysis, we restrict the sample to firms that increase their external funding in a given year. Specifically, every year we construct a cohort of firms selecting those companies obtaining a P2B loan, as well as any firm increasing the level of debt relative to the previous year. Every cohort of firms enters our analysis for the years 2010-2018, and we include in all our regressions cohort-year fixed effects (α_{ct}) to ensure that our coefficients are estimated out of variation occurring within cohort. Moreover, we include firm fixed effects (α_i), which intend to absorb time-invariant differences between firms that obtain P2B funding and firms who do not. $X_{i,t-1}$ is a matrix of firm-level covariates, which includes all the variables used in equation (1).

In addition to our baseline equation (2), we adopt two alternative empirical settings to further address concerns that firms accessing the P2B platform are different in some unobserved, time-varying dimension, compared to other firms. The concern is that these firms would have displayed a different behavior even absent the availability of FinTech funding. First, we augment specification (2) with an additional set of high-dimensional fixed effect: industry-time fixed effects, which makes sure industry-level shocks do not drive our results, even if these drivers are unobservable and time-varying. Second, we adopt a propensity-score matching approach. We compute the propensity score using equation (1), then we construct the matched sample selecting for each firm that obtain a P2B loan the ten closest matches.[2]

Table 3 shows that firms obtaining FinTech funding grow more as compared to other firms in terms of number of employees (Columns (1) and (2)), sales (Columns (3) and (4)), and total assets (Columns (5) and (6)). These results are robust when we include inclusion of high-dimensional fixed effects (Panel B) or we adopt a propensity-score matching approach (Panel C).

Table 4 takes a closer look at assets by decomposing them into fixed assets, inventories, accounts receivables, and cash. In the baseline specification there is a positive significant increase in inventories (column (3)) after obtaining P2B financing. However, this result is not robust to the inclusion of industry-time fixed effects, nor to the propensity score matching approach. Using the propensity score matched approach, we find that firms increase their fixed assets by 1.9% of

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[2]Our results are robust to restricting the number of matches to five.

their total assets and reduce their cash balance by 1.3% of total assets after getting financing via the lending platform.

Subsequently, we explore the performance of these P2B funded firms studying firms' return on sales (ROS), return on assets (ROA), and return on equity (ROE). If these firms were credit constrained before borrowing from the FinTech platform, we expect to find an improvement in all these performance measures. We do not observe a consistent and significant improvement in profitability after obtaining the P2B financing, which suggests that these firms were not credit constrained.

While there is limited evidence for the usage of the FinTech credit for investment opportunities or working capital needs, we explore how obtaining FinTech credit influences the lending relationships and cost of funding of SMEs. We start by exploring the liability side of firms in Table 6. We observe that the availability of a P2B loan leads to a significant increase in total debt. When we account for size and industry fixed effects in Panel B, or use the matched sample in Panel C, we find an increase in long-term debt for firms accessing the P2B platform. In all three panels, we find a significant increase in short-term debt.

Table 7 perform the same analysis in Table 6 but excluding the amount of P2B loans obtained by firms from their outstanding 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.[3] In other words, the long-term debt increase observed in Table 6 appears to be solely due to the debt raised through the P2B platform. At the same time, SMEs use the P2B debt to reduce their long-term exposures to traditional financial intermediaries. As indicated by column (2) in the three panels of Table 7, 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

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[3]Note that the vast majority (94.6%) of loans extended by the P2B platform have a duration greater than one year.

term exposure to the banking system, and instead supplement the FinTech loan with additional short-term bank debt.

4.3   The Impact on Lending Relationships and Funding Costs

In the previous section we find that firms use FinTech funding to manage their exposures to the banking sector by switching from long-term bank debt to short-term bank debt. In this section, we further explore the relationships between firms accessing the FinTech platform and the banking sector.

In the first two columns of Table 8, we use as dependent variable the number of lending relationships a firm has (including P2B lending). After obtaining P2B financing, SMEs increase the number of lending relationships. As the coefficient is significantly different from 1 (p-value < 0.001), 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 their dependence on a single lender. In columns (3) and (4) of Table 8, we analyze the ratio of total debt accounted by its largest lender. We find that this ratio decreases by 8.3% for firms accessing the P2B platform, as compared to the other firms in the sample raising external capital. Thus, P2B lending seems to allow firms to rely less on their main bank, and reduce debt concentration.

In the last four columns of Table 8 we study firms' funding costs. Columns (5) and (6) use as dependent variable the total funding costs including P2B loans. We find that funding costs increase for firms obtaining a Raize loan. Columns (7) and (8) use as dependent variable the funding costs excluding P2B loans (i.e., the cost of bank loans). We find that the cost of bank funding significantly decrease after a firm has access to P2B lending. We conclude that P2B loans are more expensive than bank loan on average, but firms accessing the P2B platform benefit from a reduction in the costs of bank funding due to probably to a more diversified their pool of lenders.

We also explore the cross-sectional dependence on banks in more detail by studying the char-

acteristics of the relationship banks of SMEs that access FinTech debt. An important question is what type of comparative advantage the FinTech platform has over banks. This is relevant given the documented impact on firms' lending relationships and funding costs. [4]

Table 9 show the differences in the characteristics of banks financing firms that access the FinTech platform, as compared to those funding other firms in our sample. We analyze a set of banks' variables including: bank ROA, bank deposits, bank loans, the sum of bank cash and short-term investments, and bank equity (all variables scaled by bank total assets). The estimates in Table 9 show a consistent pattern. Firms are less likely to use FinTech platform to raise debt when they have lending relationships with more profitable banks, banks with a larger ratio of deposits to assets and more liquid banks. At the same time, firms that have relationships with banks with a higher loans to total assets ratio are more likely to resort to P2B platforms to raise external capital. Overall, our findings suggest that the characteristics of banks matter for the choice of accessing FinTech platform. Firms served by less profitable banks, banks with less stable funding, and banks with a higher transformation ratio are more likely to rely on P2B funding.

5. Conclusion

Using a proprietary data set from a leading independent Peer-to-Business (P2B) platform combined with detailed administrative data on firms, we study the impact of P2B platforms on SMEs financing choices and lending relationships. We compare the characteristics of firms that access P2B lending. We find that firms that borrow through FinTech platforms are larger, more profitable, have strong sales growth and higher bank debt as compared to those who borrow from traditional financial intermediaries. We conclude that FinTech substitutes for bank credit by targeting high-quality SMEs that already have access to the banking system.

When it comes to the usage of the new debt capital, firms seems to increase their investment

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[4]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 a firm i, where the weights are given by the outstanding amount of debt extended by bank j to firm i at time t.

in fixed assets and reduce cash holdings. However, there is no significant effect on profitability after a firm gains access to FinTech capital. In terms of financial policy, we find that firms use the availability of P2B loans to reduce long-term bank debt, while they increase short-term bank debt following P2B lending.

Our results indicate that FinTech empowers SMEs to become less financially dependent on traditional banks and to take ownership of their capital structure choices. After obtaining P2B financing, SMEs increase the number of lending relationships, reduce their dependence on the largest lender, and reduce borrowing cost net of the premium paid to the P2B platform. Firms thus benefit from their efforts to diversify their pool of lenders and include less traditional forms of debt financing.

We also study the characteristics of the banks with whom the SMEs that raise FinTech debt have relationships. We find that SMEs are more likely to use the P2B platform if they have lending relationships with less profitable banks, banks with less stable funding, and banks with more liquidity constraints. We conclude that firms want to reduce their exposure to poor banks and diversify their lending relationships to include FinTech as a supplier of capital. The existence of market-based systems that SMEs can access appears to be welfare enhancing as it allows SMEs to diversify their lending relationships and reduce the overall cost of funding.

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Table 1: Summary Statistics

This table reports univariate comparisons between firms that receive P2B financing and firms that do not receive P2B financing. The sample period is 2010-2018. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we limit our sample to firms that increase their external funding. Panel A reports statistics for firm-level accounting variables. Panel B shows statistics for bank-related variables aggregated at the firm-level. 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.

Panel A: Firm Variables

	P2B Firms	Other Firms	Difference	
Employees (log)	1.611	1.391	0.219***	(0.000)
Total Assets (log)	12.180	12.075	0.105***	(0.000)
ROA	0.037	-0.067	0.104***	(0.000)
Current Ratio	2.487	3.318	-0.831***	(0.000)
EBITDA / Interests	0.147	0.047	0.100***	(0.000)
Tangibles	0.283	0.261	0.023***	(0.000)
Cash	0.119	0.150	-0.030***	(0.000)
Sale Growth	0.165	0.020	0.144***	(0.000)
Leverage	0.317	0.281	0.036***	(0.000)
Overdue Debt	0.005	0.011	-0.006***	(0.000)
Observations	2,973	1,239,499	1,242,472	

Panel B: Bank Variables

	P2B Firms	Other Firms	Difference	
Bank ROA	0.029	0.029	-0.000	(0.805)
Bank Deposit	0.504	0.520	-0.016***	(0.000)
Bank Loan	0.656	0.654	0.002	(0.229)
Bank Liquidity	0.185	0.191	-0.007***	(0.000)
Bank Equity	0.075	0.073	0.001	(0.224)
Observations	2,196	630,578	632,774	

Table 2: What Type of Firms Obtain FinTech Funding?

This table studies the characteristics of firms that obtain access to the P2B platform. The dependent variable is an indicator variable for firms that receive P2B financing. Industry-year fixed effects are defined using the Portuguese classification of economic activities (CAE3). The sample period is 2010-2018. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we limit our sample to firms that increase their external funding. 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.

| | P2B Financing Dummy | | | | | |
	(1)	(2)	(3)	(4)	(5)	(6)
Employees (log)	0.014***	0.014***	0.012***	0.001	-0.003	-0.008
	(5.54)	(5.55)	(4.06)	(0.26)	(-0.66)	(-1.37)
ROA	0.021***	0.023***	0.023***	0.034***	0.036***	0.032***
	(13.79)	(14.56)	(12.80)	(10.94)	(11.29)	(8.24)
Current Ratio	-0.001***	-0.001***	-0.001***	-0.001	-0.001*	-0.001
	(-3.67)	(-5.41)	(-4.27)	(-0.94)	(-1.91)	(-1.11)
EBITDA / Interests	0.066***	0.067***	0.068***	0.095***	0.099***	0.100***
	(8.14)	(8.29)	(8.40)	(6.10)	(6.37)	(6.45)
Tangibles	-0.001	-0.008	-0.007	-0.011	-0.019	0.007
	(-0.08)	(-0.82)	(-0.70)	(-0.62)	(-1.01)	(0.35)
Cash	-0.040***	-0.053***	-0.068***	-0.098***	-0.113***	-0.118***
	(-4.08)	(-5.33)	(-6.40)	(-4.39)	(-5.04)	(-4.92)
Leverage	-0.012***	0.017***	0.015***	0.001	0.027***	0.020**
	(-2.58)	(3.55)	(3.14)	(0.07)	(2.99)	(2.21)
Overdue Debt	-0.107***	-0.143***	-0.128***	-0.164***	-0.195***	-0.174***
	(-5.91)	(-7.65)	(-6.78)	(-6.81)	(-7.68)	(-6.42)
Sale Growth				0.059***	0.037***	0.039***
				(7.01)	(4.57)	(4.78)
Year FE		X			X	
Industry-Year FE			X			X
Observations	960,144	960,144	960,141	378,761	378,761	378,751
Adjusted R^2	0.002	0.002	0.012	0.002	0.002	0.015

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Table 3: The Use of FinTech Funding - Firm Size

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are the logarithm of the firm number of employees, the log of firm sales, and the log of firm total assets. We regress these variables on *After Financing*, an indicator variable that takes value one for firms that receive P2B funding in the years after the deal. Industry-year fixed effects are defined using the Portuguese classification of economic activities (CAE3). The sample period is 2010-2018. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we limit our sample to firms that increase their external funding. 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.

Panel A: Baseline Specification

	Employees		Sales		Tot. Assets	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	0.218***	0.090***	0.283***	0.168***	0.375***	0.264***
	(11.06)	(7.30)	(9.86)	(7.07)	(13.39)	(11.22)
Controls		X		X		X
Cohort-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,083,412	2,083,412	2,335,453	2,335,453
Adjusted R^2	0.90	0.93	0.89	0.90	0.92	0.93

Panel B: Industry Fixed Effects

	Employees		Sales		Tot. Assets	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	0.143***	0.065***	0.154***	0.102***	0.015***	0.010**
	(8.46)	(5.26)	(7.68)	(5.45)	(3.13)	(2.11)
Controls		X		X		X
Cohort-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,083,412	2,083,412	2,335,453	2,335,453
Adjusted R^2	0.90	0.93	0.89	0.90	0.99	0.99

Panel C: Propensity-Score Matching

	Employees		Sales		Tot. Assets	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	0.211***	0.155***	0.394***	0.309***	0.386***	0.327***
	(12.24)	(10.53)	(13.57)	(11.48)	(15.18)	(13.66)
Controls		X		X		X
PS Group-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Observations	156,393	156,393	153,191	153,191	156,393	156,393
Adjusted R^2	0.96	0.96	0.94	0.95	0.97	0.97

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Table 4: The Use of FinTech Funding - Assets

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are variables describing the asset side of firms' balance sheet, including: fixed assets, inventories, trade receivables, cash and bank deposits, all normalized by total assets. We regress these variables on *After Financing*, an indicator variable that takes value 1 for firms that receive P2B funding in the years after the deal. Industry-year fixed effects are defined using the Portuguese classification of economic activities (CAE3). The sample period is 2010-2018. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we limit our sample to firms that increase their external funding. *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.

Panel A: Baseline Specification

	Fixed Assets		Inventories		Receivables		Cash	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After Financing	0.010	0.004	0.010**	0.007	-0.000	-0.000	-0.017***	-0.012**
	(1.24)	(0.56)	(2.01)	(1.38)	(-0.08)	(-0.05)	(-3.25)	(-2.39)
Controls		X		X		X		X
Cohort-Year FE	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.73	0.73	0.88	0.88	0.81	0.81	0.68	0.69

Panel B: Industry Fixed Effects

	Fixed Assets		Inventories		Receivables		Cash	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After Financing	0.005	0.003	-0.005	-0.005	-0.001	-0.001	-0.004	-0.002
	(0.67)	(0.41)	(-0.95)	(-0.99)	(-0.19)	(-0.17)	(-0.72)	(-0.41)
Controls		X		X		X		X
Cohort-Year FE	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.74	0.74	0.88	0.88	0.81	0.81	0.74	0.75

Panel C: Propensity-Score Matching

	Fixed Assets		Inventories		Receivables		Cash	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After Financing	0.022***	0.019***	0.008	0.005	0.007	0.008	-0.017***	-0.013**
	(3.09)	(2.68)	(1.55)	(1.05)	(1.21)	(1.33)	(-2.84)	(-2.20)
Controls		X		X		X		X
PS Group-Year FE	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X
Observations	156,393	156,393	156,393	156,393	156,393	156,393	156,393	156,393
Adjusted R^2	0.89	0.89	0.94	0.94	0.90	0.90	0.84	0.84

Table 5: The Use of FinTech Funding - Profitability

This table investigates how firms use the funds obtained through the P2B fintech platform. The dependent variables are variables describing a firm profitability, including: return on sales, return on assets, and return on equity. We regress these variables on *After Financing*, an indicator variable that takes value 1 for firms that receive P2B funding in the years after the deal. Industry-year fixed effects are defined using the Portuguese classification of economic activities (CAE3). The sample period is 2010-2018. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we limit our sample to firms that increase their external funding. *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.

Panel A: Baseline Specification

	ROA		EBIT/AT		ROE	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	-0.007	-0.011	-0.006	-0.009	-0.034	-0.029
	(-0.63)	(-1.13)	(-0.58)	(-0.84)	(-0.99)	(-0.84)
Controls		X		X		X
Cohort-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.53	0.53	0.52	0.52	0.20	0.20

Panel B: Industry Fixed Effects

	ROA		EBIT/AT		ROE	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	-0.059***	-0.038***	-0.061***	-0.037***	-0.043	-0.038
	(-5.89)	(-3.60)	(-6.07)	(-3.52)	(-1.19)	(-1.08)
Controls		X		X		X
Cohort-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.58	0.59	0.58	0.59	0.22	0.22

Panel C: Propensity-Score Matching

	ROA		EBIT/AT		ROE	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	0.000	0.010	0.002	0.015	-0.029	-0.024
	(0.02)	(0.57)	(0.13)	(0.84)	(-0.66)	(-0.54)
Controls		X		X		X
PS Group-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Observations	156,393	156,393	156,393	156,393	156,393	156,393
Adjusted R^2	0.67	0.68	0.66	0.67	0.47	0.47

Table 6: The Use of FinTech Funding - Liabilities

This table investigates how firms use the funds obtained through the P2B fintech platform. The dependent variables are variables describing the liability side of firms' balance sheet, including: long-term debt, short-term debt, and total debt, all normalized by total assets. We regress these variables on *After Financing*, an indicator variable that takes value 1 for firms that receive P2B funding in the years after the deal. Industry-year fixed effects are defined using the Portuguese classification of economic activities (CAE3). The sample period is 2010-2018. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we limit our sample to firms that increase their external funding. *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.

Panel A: Baseline Specification

	Long-Term Debt		Short-Term Debt		Total Debt	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	-0.022***	-0.018**	0.044***	0.037***	0.141***	0.120***
	(-2.63)	(-2.15)	(5.76)	(4.95)	(13.15)	(12.32)
Controls		X		X		X
Cohort-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.67	0.68	0.55	0.56	0.56	0.58

Panel B: Industry Fixed Effects

	Long-Term Debt		Short-Term Debt		Total Debt	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	0.038***	0.030***	0.050***	0.041***	0.130***	0.113***
	(4.18)	(3.39)	(6.65)	(5.57)	(12.54)	(11.73)
Controls		X		X		X
Cohort-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.70	0.70	0.60	0.61	0.60	0.62

Panel C: Propensity-Score Matching

	Long-Term Debt		Short-Term Debt		Total Debt	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	0.027**	0.021*	0.060***	0.058***	0.163***	0.164***
	(2.39)	(1.90)	(7.54)	(7.34)	(15.11)	(14.54)
Controls		X		X		X
PS Group-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Observations	156,393	156,393	156,393	156,393	156,393	156,393
Adjusted R^2	0.82	0.83	0.75	0.75	0.77	0.77

Table 7: The Use of FinTech Funding - Liabilities Net of P2B Funding

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, including: long-term debt, short-term debt, and total debt, all normalized by total assets. In this table 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 *After Financing*, an indicator variable that takes value 1 for firms that receive P2B funding in the years after the deal. Industry-year fixed effects are defined using the Portuguese classification of economic activities (CAE3). The sample period is 2010-2018. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we limit our sample to firms that increase their external funding. *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.

Panel A: Baseline Specification

	Long-Term Debt		Short-Term Debt		Total Debt	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	-0.089***	-0.084***	0.043***	0.036***	0.072***	0.050***
	(-11.11)	(-10.87)	(5.60)	(4.79)	(7.19)	(5.64)
Controls		X		X		X
Cohort-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.67	0.68	0.55	0.56	0.56	0.58

Panel B: Industry Fixed Effects

	Long-Term Debt		Short-Term Debt		Total Debt	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	-0.032***	-0.040***	0.048***	0.039***	0.056***	0.039***
	(-3.98)	(-5.10)	(6.48)	(5.40)	(5.88)	(4.45)
Controls		X		X		X
Cohort-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X
Observations	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.70	0.70	0.60	0.61	0.60	0.62

Panel C: Propensity-Score Matching

	Long-Term Debt		Short-Term Debt		Total Debt	
	(1)	(2)	(3)	(4)	(5)	(6)
After Financing	-0.042***	-0.048***	0.058***	0.057***	0.090***	0.091***
	(-3.76)	(-4.33)	(7.39)	(7.19)	(8.55)	(8.27)
Controls		X		X		X
PS Group-Year FE	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Observations	156,393	156,393	156,393	156,393	156,393	156,393
Adjusted R^2	0.82	0.83	0.75	0.75	0.77	0.77

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Table 8: The Use of FinTech Funding - Funding Relationships and Funding Costs

This table investigates how firms use the funds obtained through the P2B platform. The dependent variables are variables describing the relationships between the firms and financing entities as well as firm funding costs. These include: number of relationships, the fraction of a firm debt accounted for by the largest relationship, 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 *After Financing*, an indicator variable that takes value 1 for firms that receive P2B funding in the years after the deal. Industry-year fixed effects are defined using the Portuguese classification of economic activities (CAE3). The sample period is 2010-2018. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we limit our sample to firms that increase their external funding. *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.

Panel A: Baseline Specification

	Rel. N.		Rel. Max		Funding Costs		Funding Costs NR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After Financing	1.213***	1.098***	-0.083***	-0.070***	0.010***	0.009***	-0.002**	-0.004***
	(16.87)	(15.89)	(-10.24)	(-8.75)	(7.94)	(6.99)	(-2.14)	(-3.22)
Long-Term Debt %					0.025***	0.024***	0.025***	0.024***
					(188.38)	(184.08)	(188.36)	(184.05)
Controls		X		X		X		X
Cohort-Year FE	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X
Observations	1,797,385	1,797,385	1,797,385	1,797,385	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.82	0.83	0.72	0.73	0.53	0.53	0.53	0.53

Panel B: Industry Fixed Effects

	Rel. N.		Rel. Max		Funding Costs		Funding Costs NR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After Financing	1.123***	1.069***	-0.074***	-0.067***	0.009***	0.009***	-0.004***	-0.005***
	(18.20)	(17.66)	(-9.81)	(-8.97)	(7.85)	(7.24)	(-3.69)	(-4.42)
Long-Term Debt %					0.026***	0.026***	0.026***	0.026***
					(235.27)	(232.33)	(235.25)	(232.31)
Controls		X		X		X		X
Cohort-Year FE	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X	X	X
Observations	1,797,385	1,797,385	1,797,385	1,797,385	2,335,453	2,335,453	2,335,453	2,335,453
Adjusted R^2	0.84	0.85	0.74	0.75	0.55	0.55	0.55	0.55

Panel C: Propensity-Score Matching

	Rel. N.		Rel. Max		Funding Costs		Funding Costs NR	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After Financing	1.209***	1.139***	-0.083***	-0.074***	0.009***	0.008***	-0.003***	-0.004***
	(23.09)	(22.18)	(-11.17)	(-10.03)	(7.44)	(6.49)	(-2.64)	(-3.71)
Long-Term Debt %					0.028***	0.028***	0.028***	0.028***
					(75.77)	(75.35)	(75.71)	(75.29)
Controls		X		X		X		X
PS Group-Year FE	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X
Observations	148,615	148,615	148,615	148,615	156,393	156,393	156,393	156,393
Adjusted R^2	0.94	0.94	0.89	0.89	0.73	0.73	0.73	0.73

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Table 9: Determinants of P2B Financing - Bank Variables

This table studies the characteristics of the banks that provide funding to firms that have access to the P2B platform. The dependent variable is an indicator variable for firms that receive P2B financing. Industry-year fixed effects are defined using the Portuguese classification of economic activities (CAE3). The sample period is 2010-2018. We exclude financial firms and utilities, as well as firms with more than 250 employees. Moreover, we limit our sample to firms that increase their external funding. 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.

| | P2B Financing Dummy | | | | | |
	(1)	(2)	(3)	(4)	(5)	(6)
Bank ROA	-0.133*					-0.575***
	(-1.72)					(-2.80)
Bank Deposit		-0.084***				-0.089***
		(-3.70)				(-3.78)
Bank Loan			0.109***			0.081**
			(3.26)			(2.14)
Bank Liquidity				-0.136***		0.012
				(-3.49)		(0.27)
Bank Equity					0.034	-0.011
					(0.59)	(-0.20)
Controls	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X
Observations	631,212	631,212	631,212	631,212	631,212	631,212
Adjusted R^2	0.01	0.01	0.01	0.01	0.01	0.01

Appendix

Table A1: Variable Description

Variable	Definition
Firm-Level Independent Variables	
Employees (log)	Natural logarithm of the number of paid and unpaid employees of the company. Source: Central Balance Sheet Database.
Total Assets (log)	Natural logarithm of the firm total assets. Source: Central Balance Sheet Database.
ROA	Return on assets, defined as EBITDA over total assets. Source: Central Balance Sheet Database.
Current Ratio	Defined as current assets over short-term debt. Source: Central Balance Sheet Database.
EBITDA / Interests	The ratio of a firm EBITDA over interest expenses. Source: Central Balance Sheet Database.
Tangibles	The ratio of tangible fixed assets over total assets. Source: Central Balance Sheet Database.
Cash	The ratio of cash and bank deposits over total assets. Source: Central Balance Sheet Database.
Sale Growth	Natural logarithm of the ratio of firm sales in year t over firm sales in year $t-1$. Source: Central Balance Sheet Database.
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.
Firm-Level Dependent Variables	
Employees (log)	Natural logarithm of the number of paid and unpaid employees of the company. Source: Central Balance Sheet Database.
Total Assets (log)	Natural logarithm of the firm total assets. Source: Central Balance Sheet Database.
Sales	Natural logarithm of the firm sales. Source: Central Balance Sheet Database.
Fixed Assets	The ratio of tangible plus intangible assets over total assets. Source: Central Balance Sheet Database.
Inventories	The ratio of inventories and consumable biological assets over total assets. Source: Central Balance Sheet Database.
Receivables	The ratio of trade receivables over total assets. Source: Central Balance Sheet Database.
Cash	The ratio of cash and bank deposits over total assets. Source: Central Balance Sheet Database.
Long-Term Debt (Table 6)	The ratio of non-current debt (maturity > 1 year) over total assets. Source: Central Balance Sheet Database.
Short-Term Debt (Table 6)	The ratio of current debt (maturity ≤ 1 year) over total assets. Source: Central Balance Sheet Database.
Total Debt (Table 6)	The ratio of current and non-current debt over total assets. Source: Central Balance Sheet Database.
Long-Term Debt (Table 7)	The ratio of non-current debt (maturity > 1 year) minus non-current Raize debt over total assets. Source: Central Balance Sheet Database.
Short-Term Debt (Table 7)	The ratio of current debt (maturity ≤ 1 year) minus current Raize debt over total assets. Source: Central Balance Sheet Database.
Total Debt (Table 7)	The ratio of current and non-current debt minus Raize debt over total assets. Source: Central Balance Sheet Database.
Relationships Number	The number of active financing relationships of a firm. Source: Central Credit Responsibility.
Relationships Max.	The largest financing relationship (in percentage term) of a firm. Source: Central Credit Responsibility.
Firm-Bank Variables	
Bank ROA	Firm-level average of the ratio of bank ROA 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 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.
Bank Equity	Firm-level average of the ration of bank equity 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.