The Role of FinTech in Small Business Lending*

Paul Beaumont† **Huan Tang**‡ **Eric Vansteenberghe**§

Abstract

This paper studies FinTech platforms' role in SMEs' access to financing using French administrative data. We show that firms served by FinTech platforms have less tangible assets than bank borrowers. Relative to observably similar firms that take out bank loans or were denied FinTech credit, FinTech borrowers experience a long-term 20% increase in bank credit after the loan origination. The credit increase only occurs when FinTech borrowers invest in new assets, and they are subsequently more likely to pledge collateral to banks. We conclude that FinTech lenders, by providing unsecured lending, improve firms' credit access by alleviating collateral constraints.

*We thank Manuel Adelino, Francesco D'Acunto, Matteo Benetton, Hans Degryse, Bruno Biais, Sebastian Doerr, Matthias Efing, Laurent Frésard, Johan Hombert, Ulrich Hege, Yi Huang, Dirk Jenter, Evren Ors, Boris Vallée, Kumar Rishabh, and participants in the ACPR research seminar, the HEC Brownbag Seminar, the LSE Brownbag Seminar, the Junior Entrepreneurial Finance and Innovation Workshop, the WFA Early Career Women Conference, the CESM 2021, the 9th European Banking Authority Research Workshop, the 4th Annual IMF Macro-Finance Research Conference, the 5th Shanghai-Edinburgh-London Fintech Conference, the FINEST Autumn Workshop, and University of Lugano for their valuable comments. We thank Fabien Michel for providing access to the PretUp data. We thank Anne Sophie Lawniczak for contributing to an early version of the paper.

†Desautels Faculty of Management, McGill University: paul.beaumont@mcgill.ca

‡London School of Economics & CEPR: h.tang13@lse.ac.uk

§Paris School of Economics - EHESS; Banque de France: eric.vansteenberghe@acpr.banque-france.fr

1 Introduction

Access to finance is crucial for small business growth, yet small and medium-sized enterprises (SMEs) routinely report difficulty accessing credit. Since the 2008 financial crisis, the increased regulatory burden and stricter scrutiny of bank lending have further exacerbated the credit constraints of small businesses (Cortés et al., 2020; Fraisse, Lé and Thesmar, 2020) and hindered firm growth (Bord, Ivashina and Taliaferro, 2015; Chen, Hanson and Stein, 2017; Doerr, 2021). In contrast, FinTech lending platforms have been growing rapidly, thereby partially filling the gap left by banks (Gopal and Schnabl, forthcoming).[1] The development of FinTech platforms, therefore, has generally been encouraged by policymakers, with various regulatory measures being taken to scale up this market for its potential positive impact on SMEs and job creation.[2] However, despite the expansion of FinTech small business lending and regulatory efforts to foster its development, little is known about the role FinTech lenders play in the access of SMEs to financing. FinTech platforms rely on different technologies, follow a different business model, and are subject to different regulations than banks, suggesting that they could offer a different service to SMEs. Are FinTech platforms merely substituting for banks, or do they complement the existing range of financing services offered to SMEs? Answering this question would help us better understand the interplay between FinTech lenders and banks and, therefore, how FinTech platforms fit into the SME lending market.

In this paper, we use granular data on the near universe of FinTech and bank loans in France to analyze the role of FinTech lenders in SMEs' access to finance. Two key facts emerge from the data. First, compared to bank borrowers, FinTech borrowers are more levered and have less tangible assets, suggesting that they are more likely to face difficulties obtaining additional funding from banks. Second, FinTech loans are more costly, with a 5.5-percentage-point (p.p.) interest rate gap that persists even when controlling for observable firm characteristics (e.g., credit risk) and loan characteristics (e.g., maturity, size).

These findings suggest that FinTech lenders do not simply substitute for banks but instead

[1] According to the US Federal Reserve's Small Business Credit Survey (2019), 32% of small businesses that sought financing applied with a FinTech or online lender, up from 19% in 2016. In comparison, 44% applied with small banks and 49% with large banks.

[2] For instance, Regulation (EU) 2020/1503 harmonized FinTech regulations across EU members to create a unique European market for FinTech lending. The EU commission's action plan on FinTech explicitly mentions job creation as a motive for fostering the growth of FinTech lenders (source). More generally, over 50 countries have introduced regulatory sandboxes to foster the growth of the FinTech market (Cornelli et al., 2021). During the recent COVID-19 pandemic, the US, UK, and French governments provided unprecedented guarantees for new loans originated by FinTech platforms to facilitate SMEs' access to financing.

play a distinct role in the financing of SMEs. This could arise from various features of their business model. First, since they do not take deposits, FinTech lenders are subject to less stringent regulations than banks, which could allow them to offer different lending products to SMEs. Indeed, under the Basel III framework, a bank has to set aside twice as much capital for an unsecured loan to an SME as for a secured loan, while the cost is the same for a FinTech lender.[3] Accordingly, FinTech loans to SMEs are typically unsecured, whereas access to collateral is considered key to obtaining bank financing (Berger and Udell, 1995; Schmalz, Sraer and Thesmar, 2017).[4] Firms may turn to FinTech platforms if they lack assets to pledge, or if they want to preserve their future borrowing capacity (*collateral*). Second, FinTech lenders often leverage new technologies (e.g., machine learning, big data) to better screen firms and lend to profitable businesses overlooked by banks. Firms that face high information asymmetries with banks may be better served by FinTech platforms (*information*). Third, FinTech platforms have adopted streamlined and semiautomated screening processes, allowing them to make quicker decisions. Liquidity-constrained firms may accept paying a higher rate to FinTech platforms in exchange for timelier funding (*speed*). According to the US Federal Reserve's Small Business Credit Survey (2019), SMEs are indeed aware of the advantages of FinTech lending and cite the absence of required collateral, the different screening criteria, and the fast decision process as the three most important factors influencing their decisions to apply for a FinTech loan.

To formally study the role of FinTech lending in SMEs' access to financing, we exploit the fact that these different hypotheses yield distinct testable predictions on banks' reaction to the origination of a new FinTech loan. We find strong evidence for the collateral hypothesis. Compared to observably similar non-FinTech borrowers that were either denied FinTech credit or took a bank loan, FinTech borrowers experience a 20% increase in bank credit in the two years following the FinTech loan origination. The increase in bank credit is only observed for loan categories that are more likely to require collateral (e.g., long-term loans) and when FinTech loans are used to finance the acquisition of new assets. This is in line with the idea that compared to bank loans, unsecured

[3] Under the foundation approach, the loss-given-default (LGD) for a senior unsecured loan to a nonfinancial firm is 40%. It is 17.8% for a loan fully secured on physical assets other than real estate and 14.3% for a loan secured on real estate. Since the LGD enters linearly in the computation of capital requirements, an unsecured loan is approximately two times more costly in terms of regulatory capital. See this link for the computation of capital requirements and this link for the computation of LGD.

[4] OECD (2015) or World Economic Forum (2015) describe FinTech lending to SMEs as being mostly unsecured. In the Small Business Credit Survey (2019), 45% of the firms that applied for a FinTech loan mentioned the absence of collateral as a factor influencing their decision to turn to a FinTech platform. Currently, among the 9 FinTech lenders having issued more than $50Mns in loans to SMEs in the US (source), 8 platforms report unsecured financing solutions on their website.

FinTech loans are less likely to encumber assets, and therefore enhance firms' asset pledgeability and borrowing capacity (Donaldson, Gromb and Piacentino, 2020).

Our dataset is uniquely suited to study the role of FinTech lending in three ways. First, we observe the near universe of loans originated by French FinTech platforms between 2014 and 2019. The 10 FinTech platforms in our sample facilitated 2,013 loans, representing 82% of the FinTech lending volume in France.[5] France is the second largest market for FinTech lending to SMEs and the largest market for bank lending in the European Union (Ziegler et al., 2021), making it an ideal laboratory to investigate the interactions between FinTech lenders and banks. Second, using administrative data from the Bank of France, we can combine our dataset with granular information on bank loans, firm characteristics, and trade credit defaults. The quasi-exhaustive nature of the data allows us to investigate which types of firms borrow from FinTech platforms and why. Third, we observe all *rejected* applicants on one major lending platform in the sample, which allows us to construct a benchmark group for FinTech borrowers.

We exploit the richness of our data to study firms' credit dynamics following the origination of a FinTech loan. Focusing on FinTech borrowers only, we find they experience a 20% long-run increase in bank credit following the new loan. The gap appears gradually over the first six months following the origination of the new loan and persists in the subsequent 18 months. These patterns suggest that FinTech credit does not substitute for bank credit. However, one cannot, at this point, conclude that this result is specific to FinTech borrowers. An alternative explanation is that firms that face profitable investment opportunities (e.g., have high credit demand) simultaneously apply to multiple lenders, including FinTech platforms and banks, and obtain the FinTech loan before the bank loan. In this case, the increase in bank credit reflects firms' unobserved credit demand rather than banks' reaction to the FinTech loan origination.

To rule out the alternative explanation, we construct two groups of benchmark firms. The first group is composed of firms that obtained a new bank loan during the sample period ("bank borrowers"). Since FinTech borrowers are by construction first-time borrowers on FinTech platforms, we impose that benchmark firms also take a loan from a new bank lender to control for factors associated with the creation of a new lending relationship (Degryse, Ioannidou and von Schedvin, 2016). We refer to the new bank and FinTech loans taken as "outside loans" throughout.[6] The

[5]The market share is based on our own calculation using the FinTech loan sample and a portal website on FinTech loans *TousNosProjets*, provided by BPI (*Banque publique d'investissement*, the French Public Investment Bank).

[6]We exclude outside loans from the computation of total bank credit. See Degryse, Ioannidou and von Schedvin (2016) for a similar setting.

second group is composed of firms that applied for a FinTech loan but were rejected ("rejected borrowers"). We ensure that FinTech and benchmark borrowers are observably similar before the outside loan using a propensity score matching procedure. Specifically, we match FinTech borrowers and benchmark borrowers based on recent credit dynamics, the size and origination year of the outside loan, and a rich array of firm characteristics (e.g., rating, industry, size, and tangible assets).

Our identifying assumption is that observably similar FinTech and benchmark borrowers have similar credit demand. Comparing FinTech borrowers to bank borrowers allows us to test whether bank credit increases systematically after firms obtain an outside loan or whether the increase only occurs following the origination of FinTech loans. Comparing FinTech borrowers and rejected applicants, in contrast, allows us to control for the factors that would simultaneously drive firms' decision to specifically borrow from FinTech platforms and firms' subsequent access to bank credit. Using both benchmark groups, we document that FinTech borrowers experience a larger increase in bank credit than benchmark borrowers, the magnitude being very close to the 20% increase observed for FinTech borrowers only. This suggests that most, if not all, of the increase in bank credit observed for FinTech borrowers is associated with the origination of the FinTech loan.

Next, we shed light on why FinTech borrowers obtain more bank credit after receiving a FinTech loan. The increase in bank credit can be explained either by the information or the collateral advantage of FinTech lenders, but the underlying mechanism would be different. Under the *collateral* hypothesis, unsecured FinTech loans could allow firms to invest in new assets without posting collateral or personal guarantees, thereby expanding firms' borrowing capacity. Under the *information* hypothesis, a successful FinTech loan application could serve as a positive signal about firm quality, prompting banks to lend more to FinTech borrowers.[7]

We first examine which types of *bank loans* grow in reaction to the approval of the FinTech loan. We find that the increase is almost exclusively driven by long-term credit. There is a mild increase in used lines of credit and no effect on other loans. This is consistent with the collateral hypothesis, as long-term loans are more likely to require collateral than other types of loans and, therefore, to be sensitive to the amount of pledgeable assets of the firm.[8] Moreover, following loan origination, FinTech borrowers are more likely to pledge collateral to obtain credit from banks than

[7] Under the *speed* hypothesis, an increase in bank lending could happen if firms first apply for a FinTech loan to meet urgent liquidity needs, which they then refinance at a lower rate using a bank loan obtained with a lag. However, we find that only 3% FinTech borrowers repay within the first six months of the loan, during which the increase in bank credit takes place. Removing these firms from the analysis does not change the results.

[8] For instance, see Benmelech, Kumar and Rajan (2020). We document similar patterns in our data.

benchmark borrowers, a direct prediction of the collateral hypothesis.

We then examine which types of *FinTech loans* are more likely to be followed by an increase in bank credit. Our dataset allows us to observe the purpose of bank and FinTech loans, that is, whether they are used to finance the acquisition of new assets.[9] Under the collateral hypothesis, we expect the relative increase in bank loans to be more pronounced when new loans are used to finance new assets. This is because acquiring new assets through unsecured FinTech loans should expand firms' subsequent borrowing capacity more than acquiring them through secured bank loans. Our results are in line with this hypothesis, with a positive and significant increase in bank loans when FinTech loans are used to finance new assets. In contrast, we do not find any significant change in bank credit when the new loans are used for other purposes (e.g., commercial growth).

Next, we identify which types of *firm-bank relationships* are driving the increase in bank credit. The information hypothesis would predict a more pronounced effect when the information asymmetry between firms and banks is more severe. We proxy for the degree of information asymmetry using the length of the lending relationship, the distance between firms and banks, and whether the firm has a thin credit file (i.e., the presence of a credit rating). We find that the increase in bank credit is not driven by lenders who recently started interacting with the firm, remote lenders, or unrated (e.g., opaque) firms. Hence, we conclude that the information advantage cannot explain the increase in credit experienced by FinTech borrowers.

Last, we present evidence that FinTech platforms originate loans more quickly. Specifically, we test whether firms are more likely to borrow from a FinTech platform rather than a bank right after a negative liquidity shock. We use trade credit defaults by customers as a plausible source of negative liquidity shocks on suppliers (Boissay and Gropp, 2013). We find that firms are 2-percentage-point more likely to borrow from a FinTech platform than a bank during a quarter in which they experience at least one customer default. In contrast, customer defaults do not predict the take-up of new bank loans. Moreover, the positive effect of customer defaults on FinTech borrowing is only observed for recent defaults, not for customer defaults that occurred more than three months prior.

Our results suggest that FinTech lending allows SMEs to borrow more in total (€15,000 on average compared to bank borrowers) and to obtain funding in a timelier manner. But do FinTech borrowers perform better after receiving a FinTech loan? On the liability side, we find that com-

[9] The purpose of FinTech loans available in our sample is based on the loan purpose description posted on the platforms' website. The purposes of bank loans are also available in the administrative data. We classify bank loans as being "for investment" if they are reported as equipment loans, and "not for investment" otherwise.

pared to both types of benchmark firms, FinTech borrowers rely less on trade credit (e.g., accounts payable) after the loan origination. This suggests that obtaining a FinTech loan allows firms to substitute away from expensive sources of short-term financing.[10] Regarding firm performance, we find heterogenous results. Comparing FinTech borrowers to observably similar rejected borrowers, we find that FinTech borrowers grow faster, invest more in tangible assets, and default less after the outside loan, supporting the idea that borrowers that are granted FinTech credit fare better than firms that are denied funding. Relative to bank borrowers, we find that FinTech borrowers grow and invest at a similar rate. Moreover, despite a larger repayment burden associated with the higher cost of FinTech loans, there is no difference in default rates between FinTech and bank borrowers with low ex-ante credit risk (e.g., interest rate below median). In contrast, firms with high ex-ante credit risk default more following a FinTech loan origination. Taken together, these findings support the view that FinTech lending facilitates the access of SMEs to unsecured funding, which can have heterogeneous effects on performance depending on their ex-ante credit risk.

To what extent is the model of FinTech platforms sustainable? We find that after excluding platforms' fees and accounting for firms' repayment profile, investors earn a 4.9% internal rate of return on average when lending on FinTech platforms. This suggests that providing unsecured lending to SMEs can be profitable for lenders while also facilitating the access to credit of low-collateral firms. Overall, our findings suggest the lower regulation costs faced by FinTech lenders gives them an advantage over banks in the unsecured small business lending market. Fostering the growth of Fintech lenders, therefore, may not only allow to fill the void left by increasingly regulated banks, but also improve SMEs' access to bank credit.

Literature This paper contributes to a growing literature on the determinants of the growth of FinTech lending and its implications for credit markets (Thakor, 2020; Berg, Fuster and Puri, 2021).

Our paper first adds to a strand of research exploring the role of bank regulation in the growth of FinTech lending. In the context of consumer lending, Buchak et al. (2018) and De Roure, Pelizzon and Thakor (2022) show that the growth of FinTech platforms is more pronounced when traditional banks face more regulatory constraints. In contrast, Begley and Srinivasan (forthcoming) show that small banks, which were less affected by new bank regulations, played a larger role than FinTech

[10] Previous work has estimated trade credit to be more costly than FinTech loans, with an annual cost of trade credit ranging between 25% and 50% (Ng, Smith and Smith, 1999; Giannetti, Burkart and Ellingsen, 2011; Klapper, Laeven and Rajan, 2012).

lenders in filling the void left by big banks. In the context of small business lending, Gopal and Schnabl (forthcoming) find that nonbank and FinTech lenders substitute for banks to supply secured loans as a result of the tightening of banking regulations following the Great Recession. Unlike Gopal and Schnabl (forthcoming) who focus on the supply of secured loans, the FinTech platforms in our data exclusively offer unsecured loans. Analyzing the supply of unsecured loans by FinTech lenders is important, as firms report the absence of required collateral as being one of the main reasons to apply for a FinTech loan (Small Business Credit Survey, 2019). Moreover, we observe both unsecured and secured bank loans as well as the purpose of the loans, which allows us to fully uncover the interactions between bank and FinTech lending. In contrast with previous studies, we show that the regulatory advantage of FinTech companies can lead to a *complementarity* between nonbank and bank credit.

Second, this paper contributes to a stream of work that focuses on information production by FinTech lenders and investors. In the context of consumer credit markets, there is evidence that FinTech lenders improve capital allocation efficiency by exploiting and producing more information than traditional lenders (Balyuk, forthcoming; Balyuk, Berger and Hackney, 2020; Berg et al., 2020; Di Maggio and Yao, 2021). Chava et al. (2021), in contrast, do not find that FinTech lenders enjoy an informational advantage in screening borrowers. In the context of small business lending, Ghosh, Vallee and Zeng (2021) provide evidence of informational synergies between cashless payments and lending activities, as FinTech platforms can use the information embedded in transaction data to infer firms' quality. Our paper adds to this body of research by showing that banks do not treat the origination of a FinTech loan as a valuable signal of firm quality.

Our study also relates to papers on the quality of the services offered by FinTech platforms (e.g., speed and flexibility). Using survey data, Barkley and Schweitzer (2021) find that FinTech borrowers are less satisfied than businesses that borrow from banks but more satisfied than businesses that were denied credit. Fuster et al. (2019) show that FinTech mortgage lenders process mortgage applications 20% faster than other lenders and that FinTech borrowers do not feature higher ex-post default rates. While we find evidence that FinTech lenders are more responsive than banks in meeting borrowers' liquidity needs, our results indicate that obtaining a FinTech loan facilitates SMEs' access to credit primarily through the relaxation of collateral constraints.

Last, our paper also speaks to the literature on the interplay between FinTech and bank lenders. Tang (2019) and Di Maggio and Yao (2021) investigate whether FinTech platforms and banks serve different borrowers in the US consumer credit market. Ben-David, Johnson and Stulz (2021) and

Erel and Liebersohn (2020) focus on the supply of FinTech credit in the US during the COVID-19 pandemic. Erel and Liebersohn (2020), in particular, find that FinTech lenders provided more PPP loans to SMEs in areas where banks were less present, suggesting that FinTech lenders complemented banks in supplying PPP loans. Eça et al. (2021) show that, in the Portuguese corporate lending market, FinTech borrowers tend to be higher quality firms than regular bank borrowers and that they use FinTech lenders as a way to reduce their dependence on banks. Using a similar dataset to ours, Havrylchyk and Ardekani (2020) also find that FinTech borrower have lower borrowing capacity than bank borrowers. We add to this strand of research by providing firm-level evidence that FinTech platforms improve the access to credit of small firms typically underserved by banks, and by showing that the presence of collateral constraints plays a key role in the complementarity between FinTech and bank credit.

The remainder of the paper is organized as follows. Section 2 provides institutional details on the FinTech SME loan market in France. Section 3 describes our data sources and provides a detailed description of FinTech loan and borrower characteristics. In Section 4, we compare the credit dynamics of FinTech and benchmark borrowers. Section 5 presents the different tests of the economic mechanisms leading to the increase in bank credit. In Section 6, we present evidence on the speed advantage of FinTech lenders and results on firm performance. We also discuss the external validity of our results. Section 7 concludes.

2 FinTech SME loan market in France

Since 1945, lending activities in France have been regulated under a "banking monopoly" (*monopole bancaire*) regime, which prohibits nonbank entities from carrying out lending activities. This regulation was relaxed in 2014 to introduce a new lender category – crowdfunding intermediaries (hereafter "FinTech platforms"). Such platforms are subject to neither capital nor liquidity requirements, as they are not classified as banks. However, they are only allowed to intermediate corporate loans of less than one million euro, with a €2,000 limit on the amount invested per individual investor. Effectively, this loan size cap restricts the borrower pool, which motivates our focus on SMEs. We estimate that between 2016 and 2019, there were 14 active FinTech platforms that collectively issued €530 million in loans.

The application process is exclusively online. Borrowers have to meet some minimum requirements to apply. For example, on Lendix, one of the major French FinTech platforms, firms have to be more than three years old or have more than €250,000 in sales. To qualify for a loan, firms submit a loan request specifying the project they seek funding for and the amount of funding. Upon receiving the application, platforms collect information on applicants and make a decision, typically within 48 hours. Platforms in our sample have access to applicants' accounting data and credit history from the Banque de France. On average, platforms report on their website that they approve 2% of submitted applications.

Most FinTech platforms guarantee full funding of the project conditional on passing the screening stage. The platforms complement the funds advanced by individual lenders either by advancing their own funds or funds from institutional investors partnering with the platform. This guarantee of total funding makes FinTech financing more attractive to borrowers. From the borrower's perspective, the screening is therefore carried out by the platform, not by individual lenders.

Once accepted by the platform, the borrowers' project is displayed online to lenders. Both individual and institutional investors can invest in FinTech platforms. Lenders have access to a brief description of the project along with loan characteristics (e.g., loan amount, interest rate, and maturity) and information on the firm (e.g., the credit score assigned by the platform and some basic accounting information).

The borrowing costs typically have three components. The first part is a fixed application fee that is incurred upon submitting the application. The second part is an upfront origination fee proportional to the loan amount and ranges from 3% to 5% across platforms. This fee is paid only if the project is fully funded by the investors. Finally, similar to a traditional loan, borrowers pay interest to investors. FinTech platforms set the interest rate based on their internal credit scoring algorithm in most cases.[11] FinTech platforms can charge additional fees to borrowers in the case of late or early repayment. Importantly, no collateral or personal guarantee is required on these loans.

3 Data and Descriptive Statistics

In this section, we describe our data. These datasets provide detailed information on FinTech loans, bank loans, firm credit history and financials, and firm bankruptcy status. We combine the various databases using a unique firm identifier ("SIREN").

[11] A few platforms use an auction mechanism to match investors and borrowers.

3.1 Data sources

FinTech loans. Our data on FinTech loans come from two sources. First, we collect information on FinTech loans by scraping Crowdlending.fr, a French website founded in late 2014 that aggregates information on FinTech loans for individual investors. Since 2016, the website has been collecting information from platforms' websites on individual loans for the universe of French FinTech lenders, including those originated before 2016. We exclude platforms that provide equity or convertible bond financing to have credit instruments comparable to bank loans.[12] We also remove one platform (Agrilend) that exclusively finances agricultural firms. We observe the main characteristics of the loan (e.g., interest rate, maturity, face value), as well as information on repayment status, such as whether the loan is still being repaid, repaid in full, or has been defaulted upon.

We complete this dataset with additional data collected by the Banque de France (the French central bank). Since 2016, the Banque de France has collected monthly data on loans intermediated by FinTech lending platforms. FinTech lending platforms report the information voluntarily in exchange for access to the credit score created by the Banque de France. In total, this database covers 10 platforms.[13] The Banque de France dataset completes the information from Crowdlending.fr in three ways: (i) the Banque de France dataset covers outstanding loan balances at a monthly frequency, which allows us to observe the actual fraction of payment made by firms and early repayments; (ii) information on interest rates and maturities is not always reported on Crowdlending.fr, so we use the information provided by the Banque de France whenever it is available; and (iii) the Banque de France dataset reports the purpose of the loan.

We combine information from these two datasets to obtain our main sample, which contains 2,013 loan applications. These loans represent over 80% of FinTech loans to SMEs in France as of 2020. We focus on loans originated before July 1st, 2019, to have a sufficient number of observations for each firm after the origination of a FinTech loan. In doing so, we also exclude any loan originated during the COVID-19 pandemic period. For firms borrowing multiple times from FinTech platforms, we retain only the first FinTech loan.

Rejected FinTech applicants. Our data also allows us to observe rejected FinTech applicants. One of the 10 lenders in our sample (PretUp) shared with us the list of firms that did not pass the platform's initial screening process and the date of the rejection decision. For each borrower,

[12] This leads us to exclude Enerfip, Investbook, Lendosphere, and MyOptions.

[13] Lendix changed its name to October during our sample period.

we only consider the first rejected application. In total, there are 30,539 rejected firms between January 2014 and July 2019.

In Figure A.1, we show the market share, average loan amount, interest rates and maturity for the 10 platforms. Based on these statistics, loans originated by Pretup are similar to those issued by most FinTech platforms. The only exception is loan size: two platforms, Lendix and Lookanfin, originate loans two times larger than those on other platforms. In our empirical analysis, we check the robustness of our results to the exclusion of these two platforms.

Credit registry. We obtain data on firm credit using the French credit registry. It contains monthly information on the near universe of bank-firm lending relationships. Specifically, the dataset covers any firm with a credit exposure exceeding €25,000 to at least one bank. We observe both credit effectively extended to the firm and banks' credit commitments. Loan balance is reported by category, such as long-term loans and lines of credit. In addition, we observe some firm characteristics, including industry, location, and the internal firm size category defined by the Banque de France. Firms are classified as microenterprises, very small, small, medium-sized enterprises, or large enterprises based on their number of employees, revenues and total assets. We provide the definition of the size categories in Appendix Table B.3. We use the internal firm size category to identify SMEs. We compute the total credit exposure across all banks by credit category at the monthly frequency for each firm in the sample and only retain observations in the 2013-2020 period.

Details of individual bank loans: M-Contran. The M-Contran survey provides details on individual bank loans. All main credit institutions report exhaustive information for all individual loans originated in the first month of each quarter by the reporting bank branches.[14] On average, there are approximately 100,000 new loans in each reporting period. We observe a wide range of characteristics for each loan, including the loan amount, the loan type (e.g., revolving, overdraft), the loan purpose (e.g., investment), maturity, and whether it is secured. As with FinTech loans, we only retain loans originated before July 2019.

Firm characteristics: FIBEN and Orbis. FIBEN reports the credit score, accounting, and financial information for all companies with an annual turnover of over €750,000 for the period 2014-2020. The Banque de France constructs the credit score to reflect a firm's ability to meet

[14]The list of reporting branches is stable over the sample period and is given at here.

its financial commitments in a three-year horizon. This score incorporates information on firms' balance sheets, trade bill payment incidents, the micro- and macroeconomic environment, and the quality of business partners and managers. Firms that are below the turnover threshold do not receive a credit score. Table B.3 presents a description of each credit score category and the associated expected default probabilities.

The FIBEN dataset covers a smaller set of firms than the credit registry because of the reporting turnover threshold. We therefore complement FIBEN with the Bureau Van Dijk ORBIS database, which reports balance sheets and financial statements for a wider set of French firms.

Trade credit default: CIPE. The CIPE dataset ("Fichier Central Des Incidents de Payment sur Effets") reports all firms' payment defaults related to trade bills. Defaults are recorded on a daily basis and are defined as any trade bill between two firms not paid in full and/or on time. For each payment default record, the following information is reported: the SIREN number of the defaulter, the due date of the payment, the default amount, the name of the firm that has been defaulted upon, and the reason for the default. Defaults are sorted into four categories: disagreement, omission, illiquidity, or insolvency.[15]

A key challenge of using the CIPE dataset is that we only observe the firm's name that has been defaulted upon and not its SIREN number. We retrieve the SIREN number based on firm name using an online search engine ("SIRENE API") made available by the French Statistical Institute (Insee). For each name in the database, the API gives a list of companies and a score measuring the similarity between the original name and the potential match's name. When there is more than one potential match, we retain the best-ranked match. We discard matches for which the runner-up score is too close to the best-ranked match (i.e., the distance between the two is less than 0.01). This allows us to identify 4,862 payment incidents in which P2P borrowing firms are the party being defaulted upon (359 firms). We aggregate the daily payment incident records at a quarterly frequency.

Bankruptcy status: BODACC. BODACC ("Bulletin officiel des annonces civiles et commerciales") provides information on firm bankruptcy status based on commercial and civil court legal

[15] Disagreement refers to cases in which the customer rejects the claim because it disagrees on the terms of the trade bill or because it is not satisfied with the goods or services provided by the supplier; omission is when the customer omits to pay, i.e., it neither endorses nor repudiates the bill; illiquidity happens when the customer does not have sufficient funds in its bank account to pay the bill on time and in total; and last, insolvency occurs when the customer has filed for bankruptcy or is being liquidated.

announcements. This dataset records the firm's name, the date of the announcement, and the type of legal procedure (e.g., bankruptcy or liquidation).

Construction of the datasets. We construct our main sample as follows. First, we remove firms in the following industries: agriculture, finance, public administration, mining, and utilities. Second, we restrict our sample to firms that are present for at least three consecutive months in the credit registry before applying to obtain an *outside loan*. An outside loan is a loan originated by a lender with which the firm was not previously in a lending relationship. A firm is a *FinTech borrower* if the outside loan is a FinTech loan and the loan application is accepted, a *rejected applicant* if the outside loan is a FinTech loan and the loan application is rejected, or a *bank borrower* if the firm borrows from a new bank. New bank loans are observed in the M-Contran dataset.[16] We focus only on fixed-term bank loans (e.g., we exclude revolving credit lines or overdrafts). We also exclude working capital loans and leasing loans because FinTech loans are, in practice, not backed by specific assets such as accounts receivable or assets on lease. 97% of bank borrowers only obtain one outside loan during the sample period, and when they receive multiple outside loans, we randomly keep one outside loan per firm. We then complete this dataset with information from CIPE, Orbis/FIBEN, and BODACC.

3.2 Descriptive statistics

FinTech loans. We first provide summary statistics on FinTech loans and the credit dynamics of FinTech borrowers. Table 1 Panel A presents descriptive statistics on the 2,013 FinTech loans for which we have detailed information from the Banque de France. The average loan size is approximately €150,000, and the median amount is €50,000. The average interest rate including fees is 7.8%, but there is substantial variation: the maximum interest rate is 16.8%. Loan maturity ranges between 3 and 84 months, with an average of 38 months.

On the investor side, a project is financed by 501 individual investors on average. Individual investors provide 87% of total financing, with the remaining 13% being supplied by institutional investors (nonbank legal entities, such as the platforms themselves, or banks). Panel a of Figure 1 shows the number and amount of loans by loan purpose. A majority of the loans are used to finance investment (47.7%) and commercial growth (27.2%), based on the number of loans in each category. The purpose distribution is similar when we consider the breakdown by loan volume.

[16] We exclude renegotiated loans and loans originated by public or quasi-public banks or banks with stakes in FinTech platforms.

Next, we document how FinTech loans differ from traditional bank loans and how FinTech firms compare to peer firms borrowing only from banks.

Loan characteristics. In Table 2, we compare FinTech loans to fixed-term bank loans originated in the same year. In columns 2, 4, and 7, we add rating, location, industry, and size fixed effects to control for observable differences in the pool of borrowers. FinTech loans are smaller, with a difference of 140,000 euros on average compared to bank loans. The maturity of FinTech loans is two years shorter than bank loans on average, and the difference is significant regardless of whether we control for observable characteristics (columns 3-4). Finally, the results in columns 5-7 show that compared to similar bank loans issued to similar borrowers, FinTech loans are much more expensive. On average, after controlling for loan size and maturity and borrowers' characteristics, the interest rate of FinTech loans is 5.5 p.p. higher (by comparison, the baseline bank interest rate is equal to 1.8%). Note that both FinTech and bank interest rates are inclusive of fees.

The presence of a premium for FinTech loans is consistent with previous evidence on mortgage loans (Buchak et al., 2018) and suggests that FinTech lenders play a different role than banks in the financing of SMEs. This could arise from the different specificities of FinTech lenders' business models. First, since FinTech lenders are less regulated than banks, FinTech lenders are able to offer unsecured loans, while banks usually require SMEs to pledge collateral. Firms may apply for a FinTech loan if they lack assets to pledge or to preserve collateral to maintain future access to bank financing. Second, FinTech lenders may be better able to screen firms and hence be willing to offer credit to firms overlooked by banks. FinTech borrowers may turn to FinTech lenders if they anticipate facing difficulties obtaining bank credit. Third, borrowers could be willing to pay for the speed and convenience of the FinTech loan origination process. It typically takes the platforms less than a week, sometimes less than a day, to approve a FinTech loan application, while the processing time is more than one month with banks.

Firm characteristics. Panels b and c of Figure 1 show the distribution of FinTech and bank borrowers across industries and credit ratings. Most firms in the sample are not rated by the Bank of France: firms without credit ratings represent 61.4% and 75.8% of FinTech and bank borrowers, respectively. If anything, therefore, FinTech borrowers are less opaque than bank borrowers. Among rated firms, the modal credit rating is 4 or 5+, that is, firms for which the probability of default in a three-year horizon is estimated to be between 1.5 and 3.5%. This corresponds to ratings between the investment and speculative (or "junk") categories (Baa3/Ba2) in the US rating system. FinTech borrowers tend to be underrepresented in the construction and real estate industries (10.8% versus 30.5% for bank borrowers). In contrast, they are overrepresented in the wholesale and retail trade, accommodation and food, and scientific and technical activities industries.

We present descriptive statistics on FinTech and bank borrowers in Panel a of Table B.1. We select several variables commonly used in the literature as proxies for access to financing. Specifically, we compare firms in terms of size (as measured by total assets or employment), age, leverage (total liabilities over total assets), asset tangibility (tangible assets over total assets), or credit rating (e.g., see Fazzari et al., 1988; Almeida, Campello and Weisbach, 2004; Hadlock and Pierce, 2010). We also examine to what extent bank and FinTech borrowers are able to generate liquidity internally (as measured by EBIT or net working capital), have access to short-term financing solutions (presence of a bank line of credit), and face similar investment opportunities (investment ratio) or labor market conditions (as measured by the size of the workforce). Except for total assets, employment, age, and rating, all variables in the table are normalized by total assets.

The average bank borrower in our sample is 14 years old, has approximately 1 million euros in total assets, and employs 14 workers, which is consistent with the fact that FinTech platforms cater mostly to SMEs. The average leverage ratio is 67% and the average asset tangibility ratio is 29%, in line with the capital structure of the average French firm in Rajan and Zingales (1995)[17]. FinTech borrowers are of the same size (either in terms of total assets or employment) as bank borrowers. They also feature similar EBIT, working capital, employment, and investment ratios. However, they are younger, more levered, and have less tangible assets, suggesting they may face more difficulty obtaining additional bank financing. We then compare accepted and rejected FinTech applicants. Panel b of Table B.1 shows that successful FinTech applicants have more assets, generate more liquidity, are older, are more profitable, and are less levered. Figure A.2 shows that rejected borrowers are less likely to be rated and, when they are, have worse ratings than FinTech borrowers.

The comparison across FinTech, bank, and rejected FinTech borrowers suggests that these three groups enjoy different conditions for access to financing. We use a propensity score matching procedure to compare similar firms in terms of observable variables when studying firms' credit dynamics after obtaining an outside loan or after applying for a FinTech loan. We describe our

[17]We define total liabilities following Rajan and Zingales (1995), that is, as the sum of current and long-term liabilities.

matching procedure in detail in Section 4.

4 Credit dynamics

In this section, we present our main findings on firms' credit dynamics around FinTech loan origination. We start with FinTech borrowers only, which we then compare to two benchmark groups of firms to examine whether FinTech borrowers and non-FinTech borrowers exhibit distinct credit dynamics.

4.1 Credit dynamics of FinTech borrowers

We first investigate how firms' bank credit evolves after they receive a FinTech loan. It is ex ante unclear whether bank credit should increase or decrease after loan origination. On the one hand, firms may value the fast and streamlined lending services offered by FinTech platforms and switch from traditional lenders to FinTech lenders. We should observe in this case that firms borrow less from banks after obtaining a FinTech loan. On the other hand, obtaining unsecured FinTech loans may allow firms to acquire assets that they could subsequently pledge as collateral to obtain more bank credit. Moreover, a successful FinTech application could serve as a positive signal of firm quality, potentially mitigating information asymmetry between banks and firms. In that case, we could also observe an increase in bank credit after the origination of the FinTech loan.

We focus on FinTech borrowers present in the dataset detailed in Section 3. We require firms to be present in at least three consecutive months in the credit registry before taking out a FinTech loan. When a firm borrows multiple times from FinTech platforms, we retain only the first FinTech loan. We will now refer to this dataset as the ”unmatched sample”.

We study firms' credit dynamics around FinTech loan origination using the regression specification in Equation (1). The dependent variable is the logarithm of one plus the total bank credit $y_{i,t}$ firm i has in month t relative to the FinTech loan origination at $t = 0$.[18] For each firm, we retain 36 monthly observations, starting 12 months before the loan origination and ending 24 months thereafter. D_t are a series of indicators for the relative time between the calendar month and the month of the FinTech loan origination. The coefficient of interest is β_t, which captures the amount of bank loans a firm obtains relative to the reference level at $t = 0$. Standard errors are clustered

[18] The total credit amount is strictly positive for 99% of the observations, hence replacing $log(1+y)$ by $log(y)$ does not change our findings on total bank credit. We use $log(1 + y)$ so as to keep the same sample when splitting total credit amount by loan categories (e.g., long-term loans, lines of credit).

at the firm level.

$$log(1 + y_{i,t}) = \sum_{t \in [-12,24]} \beta_t \times D_t + \gamma_{i,year} + \varepsilon_{i,t}. \quad (1)$$

Figure 2 plots the evolution of the amount of bank credit around the FinTech loan origination. Bank credit remains constant in the 12-month period preceding the FinTech loan. In the first six months after loan origination, firms experience a significant 20% increase in bank credit, and this effect persists two years after origination.

These patterns suggest that FinTech credit does not substitute for bank credit. Instead, firms obtain more credit from banks immediately after FinTech loan origination. This does not necessarily mean, however, that firms' access to credit improved following the origination of the FinTech loan. An alternative explanation is that firms that face profitable investment opportunities simultaneously apply to multiple lenders, including FinTech platforms and banks, and obtain the FinTech loan before the bank loan. In this case, the increase in bank lending reflects firms' unobserved credit demand rather than an improvement in firms' access to bank credit after FinTech loan origination.

To distinguish between these different explanations, we rely on the richness of our data and compare FinTech borrowers to observably similar non-FinTech borrowers. We construct two benchmark groups: 1) firms that obtain a bank loan the same year as FinTech borrowers ("bank borrowers") and 2) FinTech applicants that were rejected the same year as FinTech borrowers ("rejected borrowers").

When comparing FinTech borrowers to bank borrowers, the underlying assumption is that observably similar firms face similar investment opportunities. Hence, they are likely to apply for a similar amount of credit. Therefore, the comparison should inform us whether the increase in bank credit follows the origination of the FinTech loan *instead of any outside loan.* The comparison between FinTech borrowers and rejected applicants, in contrast, allows us to control for the factors that simultaneously drive firms' decision to specifically borrow from FinTech platforms and firms' subsequent access to bank credit.

4.2 Matching procedure

FinTech borrower vs. Bank borrower We start by constructing a benchmark group of similar bank borrowers. This matched sample serves three goals. First, we can tightly control for credit demand by firms, as we require the benchmark firms to have applied for and received an outside loan of similar size the same year as FinTech borrowers. Therefore, the difference in the long-term credit balance of the two groups is unlikely to be driven by differential investment opportunities. Second, requiring the benchmark firms to obtain a loan from a *new* bank lender allows us to control for the effects of a new lending relationship on subsequent credit supply (Degryse, Ioannidou and von Schedvin, 2016). Last, firms that resort to new lenders might already have exhausted their borrowing capacity with their existing banks. Hence, by imposing that benchmark bank borrowers also resort to new lenders, we control for factors driving this decision.

The matching procedure is as follows. We start with all bank borrowers that received a new bank loan during the sample period 2014-2019. For each FinTech borrower, we identify bank borrowers in the same two-digit industry and size category. To control for observable differences between FinTech and bank borrowers, we apply a propensity score matching algorithm (five nearest neighbors with replacement) on multiple covariates within each industry $\times$ size cell. We use three sets of covariates in the estimation of the propensity score. The first set captures the monthly credit dynamics of firms: the logarithm of the total amount of bank loans in the six months preceding the outside loan. Second, we match on the log amount of the outside loan, the year of the outside loan, and whether the firm has a line of credit with any bank at the time of the outside loan origination. For FinTech borrowers, the outside loan is the FinTech loan, and for bank borrowers, the loan is obtained from a new bank lender. The last set of covariates consists of firm characteristics. Those variables are firms' age, credit rating, total liabilities, tangible assets, and EBIT, all taken at the last year-end before the outside loan is originated. We divide the last three variables by total assets. Because not all SMEs are covered by FIBEN or Orbis, we further include three indicator variables for when each of these three variables is missing.

The final matched sample includes 218,484 firm-month observations during the 36-month window around the origination of the outside loan. Because we allow for replacement in the matching, a bank borrower may be matched to several FinTech borrowers. We check the robustness of our results to running the regressions on the unmatched sample and to using alternative matching procedures in the next section.

FinTech borrower vs. Rejected borrowers The second benchmark group of firms we consider are those that applied for FinTech credit but were rejected by the platform. To select rejected borrowers, we apply a similar matching algorithm with the following two modifications. First, we additionally include the logarithm of total assets in the estimation of the propensity score, as there is a larger gap in total assets between the two groups of firms. Second, we remove the size of the outside loan from the matching process because it is not defined for the rejected borrowers. The matched sample includes 237,684 firm-month observations during the 36-month window around the origination of the outside loan.

Figure 5 presents the covariate balance checks for the two samples before and after the propensity score matching. All variables are normalized to have a mean of zero and a standard deviation of one. In Appendix Table Table B.2, we report the t test results on the original variables. In both matched samples, the benchmark firms and FinTech borrowers do not exhibit significant differences in most dimensions. FinTech borrowers have a slightly lower working-capital-to-asset ratio and a higher leverage ratio than matched rejected borrowers. However, the economic magnitudes of these differences are rather small (-0.016 p.p and 0.018 p.p., respectively). Moreover, all else being equal, a higher leverage ratio and a lower EBIT should make it more difficult for FinTech borrowers to obtain bank credit. If anything, these remaining small differences should lead us to underestimate the subsequent increase in bank credit.

Figure 4 plots the evolution of the log amount of bank loans for firms in the two matched samples. This allows us to visually inspect the parallel trends assumption. Panel a (resp., Panel b) shows the average amount of bank loans (in logarithm) in the period starting 12 months before and ending 24 months after the origination of the new loan (t=0) for FinTech borrowers and bank borrowers (resp., rejected borrowers). In both panels, before time 0, the two groups of firms exhibit parallel credit dynamics. After the outside loan origination, relative to the benchmark group, FinTech borrowers experience faster growth in bank credit in the first six months, which results in a persistent difference in the total amount of bank credit between the two groups of firms.

Overall, these results suggest that our matching procedure effectively controls for differences in a rich set of observables between the FinTech borrowers and benchmark firms before the outside loan. In the next section, we rely on this procedure to study firms' credit dynamics after receiving (or applying for) an outside loan.

4.3 Comparing credit dynamics of FinTech, bank, and rejected borrowers

Based on the matched samples, we now investigate how firms' access to bank credit evolves around the outside loan origination. $FinTech_i$ is a variable that takes a value of one if firm i is a FinTech borrower and zero if it belongs to the benchmark group (i.e., either a bank borrower or a rejected borrower).

We estimate Equation (2), where we interact the $FinTech$ indicator with a set of indicator variables for the month relative to the time of origination:

$$log(1 + y_{i,t}) = \sum_{t\in[-12,24]} \beta_t FinTech_i \times D_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t}, \quad (2)$$

where the outcome variable is the logarithm of one plus the amount of outstanding bank credit firm i has in relative month t. We include firm×year fixed effects $\gamma_{i,year}$ to control for time-varying firm characteristics and unobservable factors that vary at the firm-year level. We also add year-month fixed effects ρ_{month} to control for macroeconomic shocks that are common to FinTech borrowers and firms from the benchmark groups. Standard errors are clustered at the firm level.

This specification allows us to visualize the relative change in firms' credit dynamics around outside loan origination and more rigorously inspect the pretrends. Our coefficients of interest β_t are plotted in Figure 5. Panel a is based on the sample of matched FinTech and bank borrowers, whereas Panel b shows the regression coefficients based on the sample of matched FinTech and rejected borrowers.

The two panels show consistent results. First, we find no significant difference in the credit dynamics between FinTech and benchmark borrowers in the 12 months before the origination of the outside loan. This lends credence to our assumption that FinTech borrowers face growth opportunities similar to those of benchmark firms. Second, after the outside loan, relative to both bank borrowers and rejected borrowers, FinTech borrowers experience a 20% increase in the total amount of bank credit. The gap between bank and FinTech borrowers appears immediately after the outside loan and takes approximately six months to reach its long-term level. Since the two benchmark groups are composed of very different firms, it is reassuring to find similar results both in terms of patterns and economic magnitudes. This suggests that unobservable firm characteristics are unlikely to be the main driver of the increase in bank credit.

Figure 5 and Figure 2 show that the credit dynamics of FinTech firms are quantitatively and qualitatively similar before and after the inclusion of benchmark groups. Hence, the increase in bank credit observed for FinTech borrowers is unlikely to be driven by unobservable factors related to their credit demand.

In the remainder of this section, we assess the robustness of our results by estimating Equation (3) using the unmatched sample and samples obtained with different matching procedures:

$$log(1 + y_{i,t}) = \beta FinTech_i \times Post_t + \delta Post_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t}, \quad (3)$$

where we interact the $FinTech_i$ dummy with $Post_t$. Our coefficient of interest β is reported in Table B.4. In column 1, we report the regression coefficients based on the unmatched sample. In columns 2-3, we employ one-nearest neighbour propensity score matching without replacement and with replacement, respectively. Column 4 shows our main specification described above. In columns 5 and 6, we replace firm×year fixed effects with firm fixed effects and industry-, location-, rating×year fixed effects, respectively. Finally, in column 7, we exclude FinTech loans from two platforms, Lendix and Lookandfin, and redo the matching. As mentioned in Section 3, the FinTech loans origination by the 10 platforms are rather homogenous, except for the average loan size. In particular, Lendix and Lookandfin originate loans two times larger than loans on other platforms. We also check the robustness of our results to the exclusion of these two platforms.

Our preferred specification (in column 4) generates a DiD estimator of 8% (7%) when the benchmark group is bank borrowers (rejected borrowers). This is smaller than the 20% long-term credit growth shown in Figure 5 because of the gradual increase in bank credit in the first six months.

Although the set of firms varies across samples, we find quantitatively similar results: FinTech borrowers experience a 6%-12% increase in their bank debt relative to the two benchmark groups following loan origination. When we replace firm × year fixed effects with firm fixed effects and industry-, location-, rating × year fixed effects, the DiD estimator becomes larger, ranging from 13% to 16% (based on columns 5-6 of Panels a and b).

Thus far, we have shown that the FinTech loan origination is followed by an expansion in bank credit, and this result holds when we compare FinTech borrowers to either similar bank borrowers or rejected FinTech applicants. This finding implies that firms experience an improvement in credit access following FinTech loan origination. In the next section, we explore the economic mechanisms that could explain this finding.

5 Why does bank credit increase following a FinTech loan?

Our results show that FinTech borrowers are able to borrow more from banks relative to similar benchmark firms following the origination of the outside loan. Two hypotheses can explain this result. The first explanation relates to the fact that FinTech loans are unsecured. Obtaining an unsecured FinTech loan allows firms to invest in new assets without posting collateral. As a result, the newly acquired assets can be pledged to banks, expanding firms' borrowing capacity.

Bank borrowers, in contrast, typically have to pledge collateral to obtain a loan (Berger and Udell, 1995; Davydenko and Franks, 2008; Schmalz, Sraer and Thesmar, 2017). Obtaining a FinTech loan instead of a bank loan would therefore alleviate collateral constraints. We refer to this mechanism as the *collateral channel*. Second, as FinTech platforms often leverage new technologies to better screen firms and lend to profitable businesses neglected by banks, a successful FinTech loan application may signal good firm quality. Banks may be willing to extend more credit upon observing this signal. Indeed, FinTech loan originations are recorded in firms' credit reports, which are available to bank loan officers. We refer to this as the *information channel*.

These two channels would apply heterogeneously to different types of firms, FinTech loans and bank credit. In the following subsections, we test the collateral and information hypotheses by performing cross-sectional tests to determine under which conditions the increase in bank credit is more pronounced.

5.1 Collateral hypothesis

Under the collateral channel hypothesis, we expect the increase in bank credit to be more pronounced in the long-term loan category, for which collateral requirements are common.[19] Moreover, we expect this effect to be concentrated among firms that use FinTech loans to finance the acquisition of new assets. In contrast, the effect should disappear when firms do not use the loan to finance new assets (i.e., to finance commercial growth or shot-term financing – see Figure 1 for the list of loan purposes). Last, if the FinTech credit indeed allows firms to relax collateral constraints by borrowing later against the newly acquired assets, we should expect a higher propensity of FinTech borrowers to pledge collateral in subsequent bank loans. In the following, we present evidence consistent with each of these three predictions.

We first study the patterns of various types of bank credit following the origination of the outside loan. We replace the outcome variable in Equation (3) with the log amount of long-term loans, used lines of credit, and other loans and report the results in columns 1-3 of Table 3, respectively. In Panel (a), the benchmark group is bank borrowers, and in Panel (b), it is rejected FinTech applicants. As predicted, we observe strong growth in long-term credit for FinTech borrowers relative to both benchmark groups. Specifically, compared to similar bank borrowers (resp., rejected

[19] M-Contran provides information on whether a loan is secured. Consistent with Benmelech, Kumar and Rajan (2020), we show in Table B.5 that long-term loans are more likely to be secured by assets than lines of credit and other types of loans. The fraction of secured loans for these three categories is 40.65%, 27.88% and 28.2%, respectively. The fraction of secured loans in total is consistent with what Ivashina, Laeven and Moral-Benito (2022) document from Spanish data.

FinTech applicants), FinTech borrowers experience a 25% (resp., 16%) increase in long-term credit. In contrast, we only find a marginally significant increase in credit lines when we use bank borrowers as the benchmark group and no effect on other credit types.

To further understand the timing of the increase in long-term loans, we plot the monthly change in long-term loans using the specification in Equation (2) in Figure 6. The left and right parts of Figure 6 show the results when the benchmark group is bank borrowers and rejected borrowers, respectively. In both figures, we observe that FinTech borrowers exhibit a sharp increase in long-term credit relative to the benchmark groups immediately after FinTech loan origination. The loan amount gradually increases for 3-6 months and then remains constant. Importantly, we do not observe differential trends between the FinTech borrowers and benchmark firms before outside loan origination.

In addition, we report the dynamics of used lines of credit and other types of credit in Panels (b) and (c) of Figure 6. In line with the regression results in Table 3, FinTech borrowers experience mild yet insignificant growth in these two credit categories. Note that the construction of our dataset leads to a mechanical reduction in FinTech borrowers' used lines of credit use after loan origination. This is because we exclude the outside loan and, more generally, any loans associated with the new lender in the computation of total bank credit. When a firm receives a new loan (either from a FinTech or a new bank lender), it will deposit the amount received in its current account. This mechanically reduces the amount drawn on overdrafts, a component of used credit lines. For FinTech borrowers, the reduction in the used lines of credit appears in the data, since the new lender is the FinTech platform. For bank borrowers, the reduction in the used credit lines does not appear in the data, since the new loan will be deposited in the current account at the new bank, which we exclude from the computation of bank credit.[20] The same argument applies to the comparison between FinTech borrowers and rejected borrowers, as the latter do not receive any outside loans.[21]

Next, we exploit the heterogenous effects across loan purposes and examine whether the growth in bank credit is stronger when the FinTech loan is used to finance the acquisition of new assets. To do so, we split the unmatched sample depending on whether the outside loan is used to finance investment in new assets and perform the same propensity score matching procedure on the sub-

[20]Because of the mechanical decrease in used lines of credit, we may be underestimating the short-run effect of obtaining a FinTech loan on total bank credit.

[21]In untabulated tests, we find that the lines of credit of *bank* borrowers are not impacted by the origination of the new bank loan. Hence, the reduction at $t = 1$ is purely driven by the mechanical increase (decrease) in FinTech borrowers' current account (used credit lines).

samples. Hence, FinTech borrowers that use the loan to acquire assets are matched only to bank borrowers that do the same.[22] The results are reported in columns 4-5 of the two panels of Table 3. In line with the predictions of the collateral channel, we find a significant effect only when the FinTech loan is used to finance the acquisition of new assets. Long-term loans grow by 12% and 8% relative to bank borrowers and rejected borrowers, respectively. Firms do not enjoy improved access to bank credit when the outside loan is used for other purposes. We also plot the evolution of bank credit for these two subsamples in Figure 7. As expected, there is no difference between FinTech borrowers and benchmark firms before $t = 0$. Consistent with our previous results, FinTech borrowers experience a relative increase in total bank credit immediately after outside loan origination.

Last, we test whether firms are more likely to pledge collateral after the origination of the FinTech loan. Since the credit registry only reports the outstanding loan balance but not loan-specific characteristics, we test this prediction using the detailed loan-level data from M-Contran (see Section 3). We proceed as follows. First, for each firm in our sample, we identify all loans issued to the firm in the M-Contran database and their collateralization status. Second, we estimate

$$\mathbb{1}(Secured)_{i,t} = \beta FinTech_i \times Post_t + \delta Post_t + \alpha_i + \mu_{s,year} + \varepsilon_{i,t}. \tag{4}$$

where γ_i is a firm fixed effect, $\mu_{s,\ year}$ is an industry-year fixed effect, and $\mathbb{1}(Secured)_{i,t}$ is an indicator variable equal to one if the firm obtains at least one secured bank loan in a given quarter and zero if the firm obtains unsecured loans or no loan in that quarter. The inclusion of firm fixed effects allows us to tease out differences across firms in the probability of being included in M-Contran and to focus instead on within-firm differences over time in the probability of observing a secured loan in M-Contran.[23] Matching our baseline dataset to M-Contran, however, leads us to lose a fraction of our sample of borrowers.[24] For this reason, we also report the results based on the sample obtained by matching the universe of FinTech and benchmark firms (that is, before the propensity score procedure) and M-Contran ("unmatched sample").

[22] Note that we can only split FinTech and bank borrowers based on loan purposes but not rejected borrowers. For rejected borrowers, the procedure only ensures that when splitting the sample based on the loan purpose of the FinTech borrowers, we also keep the corresponding subset of matched rejected borrowers.

[23] Reporting bank branches have to declare all new loans issued to firms in a given quarter (the list of reporting bank branches is stable over time). Hence, we cannot interpret the coefficients as changes in the probability of having a secured loan but rather as changes in the probability of obtaining a secured loan from a reporting bank branch.

[24] While all benchmark bank borrowers, by construction, take up at least one bank loan that is included in M-Contran, this is not the case for FinTech and rejected borrowers. Hence, the number of firms and observations in the regression sample is significantly lower when the benckmark group is rejected borrowers.

Table 4 shows the results. The first two columns (resp., last two columns) show the results based on the comparison of FinTech borrowers and bank borrowers (resp., rejected FinTech applicants). The estimated coefficients for the interaction term are positive and significant in the first two columns. Moreover, the magnitudes are similar across the unmatched and matched samples. This suggests that relative to bank borrowers, FinTech borrowers are more likely to pledge collateral to obtain bank financing after FinTech loan origination. Comparing FinTech borrowers to rejected applicants, we find qualitatively similar results: the point estimates are positive, although only significant for the unmatched sample. Note that the coefficient on *Post* is negative, suggesting that the ability of bank borrowers to pledge collateral decreases after obtaining a new bank loan. One interpretation is that firms progressively exhaust the set of assets they can pledge, leading them to resort less and less to secured loans (Donaldson, Gromb and Piacentino, 2020).

Another implication of the collateral channel is that larger FinTech loans should be followed by larger subsequent increases in bank credit. As firms obtain more unsecured funding from FinTech lenders, they should acquire more assets, which can be pledged to obtain larger bank loans. Figure 8 maps the size of the outside loan to the subsequent change in bank credit for FinTech and bank borrowers. We calculate the change in bank credit in the six months following the outside loan, that is, when the credit expansion can be observed in the data (see Figure 5). The estimated slopes of the linear fitted lines are reported together with the significance levels. Two observations emerge from Figure 8. First, the fitted line is upward-sloping for both groups of firms. This implies that on average, firms subsequently obtain more bank credit as the size of the outside loan increases. Second, and more important, the slope for FinTech borrowers is 0.25, which is significantly higher than that of bank borrowers (0.15). This difference in slope means that for each additional €10,000 in the outside loan, FinTech borrowers subsequently obtain €1,000 (=10,000*(0.25-0.15)) more in bank credit than bank borrowers.

In summary, our findings thus far are in line with the collateral hypothesis, regardless of whether we exploit the heterogeneity across bank credit or FinTech loan categories.

5.2 Information hypothesis

In this section, we show that the increase in bank credit is not explained by banks reacting to the information on firm quality contained in a successful FinTech loan application.[25]

[25] Note that this does not necessarily imply that FinTech lenders do not produce valuable information on firm quality.

Under the information channel, we expect the increase in bank credit to be more pronounced when the degree of information asymmetry between firms and banks is large. Following the convention in the literature, we measure the severity of information asymmetry in three ways: the length of the lending relationship, the distance between borrowers and bank branches, and the degree of opaqueness of the firm (as measured by whether it has received a credit rating).[26] The implicit assumptions are that banks with a short lending relationship with the firm and banks located far from the firm observe less information about the firm than relationship lenders and local lenders. As a result, the latter lenders are less likely to react to an external signal of firm quality. We first measure the opaqueness of the firm by whether the firm has received a credit rating from the Banque de France. A feature of the French credit market is that Banque de France is the single provider of credit ratings to firms, which implies that a firm that is unrated by the Banque de France will be considered opaque by all lenders. Over half of the small firms do not receive a credit rating from the Banque de France due to a lack of credit history (see Figure 1 and Figure A.2). If the increase in bank credit for FinTech borrowers is mainly driven by a reduction in information asymmetry, we should observe that the new bank loans are mostly extended to firms that were previously opaque for banks.

Second, exploiting comprehensive information on firm-bank lending relationships in the credit registry, we distinguish existing lenders from new lenders who recently started lending to the firm and close lenders from distant lenders. We define existing lenders as banks with a lending relationship longer than five years (sample median of the length of lending relationships) with the firm as of the origination of the FinTech/bank loan and new lenders otherwise. Last, we consider a lender to be local if it is located in the same county ("département") and remote otherwise. On average, 59% of firm-level credit is from existing lenders, and 72% is from local lenders.

Table 5 presents the results for the two matched samples. We find that FinTech borrowers receive more credit from existing lenders relative to both benchmark groups, and they also receive more credit from new lenders relative to rejected borrowers. For example, based on the first two columns of Panel a, existing lenders increase lending by 10% (t-stat.= 2.5), while new lenders increase lending by only 2% (t-stat.= 0.3). It is unlikely that the reduced information asymmetry between those banks and firms drives the overall credit expansion experienced by FinTech borrowers.

[26]For instance, see Berger and Udell (1995) for the role of the length of lending relationships, Degryse and Ongena (2005) on geographical distance, and Sufi (2009) on credit ratings.

In columns 3-4 of the two panels, we split banks into local and distant banks and find that the increase in bank credit is driven by local lenders. FinTech borrowers obtain 25% (resp., 13%) more credit from local lenders than bank borrowers (resp., rejected FinTech applicants), and there is no significant change in the amount of credit from distant lenders. Again, these results do not support the information hypothesis.

Finally, we exploit the heterogeneity in firms' rating status and implement propensity matching in the two subsamples of rated and unrated firms. In this way, we only compare unrated (rated) FinTech firms to unrated (rated) benchmark borrowers. Columns 5-6 of both panels show that both rated and unrated FinTech borrowers experience a credit expansion, and the magnitudes are similar. The presence of an increase in bank credit for rated firms in both panels is difficult to reconcile with the information hypothesis, as the degree of information asymmetry should presumably be limited for those firms. In contrast, the collateral hypothesis could be at play for both rated and unrated firms.

Taking stock of all the cross-sectional tests, we do not find the information channel to be a plausible explanation for the credit expansion.

6 Additional results and discussion

In this section, we present three sets of additional results. First, we show that firms are more likely to turn to FinTech platforms than banks when facing urgent liquidity needs, suggesting that FinTech platforms are faster in processing loan applications. Second, we document the difference in the performance of FinTech and benchmark borrowers, following loan origination. Third, we examine the profitability of the FinTech loans. We discuss the external validity of our results at the end of the section.

6.1 Speed channel

FinTech lenders may have a competitive edge in meeting firms' urgent liquidity needs because of their faster online application and funding process. In this subsection, we examine whether, compared to similar firms that take a new bank loan, FinTech borrowers are systematically more likely to have recently experienced a negative liquidity shock. If FinTech lenders are indeed faster at meeting firms' liquidity needs, we should observe that liquidity shocks are more likely to be followed by the origination of FinTech loans than bank loans.

We use the information on defaults on trade credit from the CIPE dataset to identify negative liquidity shocks. Using the same dataset, Boissay and Gropp (2013) show that firms that experience a default from their customers are more likely to default on their suppliers or even to go bankrupt, suggesting that trade credit defaults constitute an economically meaningful liquidity shock.

Specifically, we define a dummy $Customer\ default_{i,q}$ equal to one if at least one customer of firm i defaulted on trade credit in quarter q. We define variables at the quarter level instead of the month level because we only observe the origination of individual bank loans at the quarter level, as described in Section 3. Since we are interested in what motivates firms to choose between FinTech lenders and banks, we do not apply the propensity matching procedure and perform this test on the unmatched sample that includes bank and FinTech borrowers in the same two-digit industry and size category (see Section 4 for the sample construction). We estimate the following equation:

$$\mathbb{1}(Outside\ loan)_{i,q} = \beta Customer\ default_{i,q} + \delta FinTech_i \times Customer\ default_{i,q} + \alpha_i + \mu_{s,q} + \varepsilon_{i,q}, \quad (5)$$

where $\mathbb{1}(Outside\ loan)_{i,q}$ is a dummy equal to one if firm i takes an outside loan at time q, $FinTech_i$ is equal to one if the firm borrows from a FinTech platform, α_i is a firm fixed effect, and $\mu_{s,q}$ is an industry $\times$ quarter fixed effect.

The coefficient β measures how the probability of a firm taking up a new loan from a bank is associated with the firm's probability of facing a customer default in the same quarter. The coefficient δ measures whether, on average, firms are more or less likely to turn to FinTech platforms than banks immediately after experiencing a negative liquidity shock. The firm fixed effect ensures that β and δ are identified using the time-series variation in the correlation between trade credit defaults and credit demand for a given firm. Last, industry $\times$ quarter fixed effects control for sectoral shocks that could lead to systematic relationships between customer defaults and credit demand.

The results of this specification are presented in column 1 of Table 6. The coefficient of $Customer\ default_{i,q}$ is both economically and statistically insignificant, suggesting that customer defaults do not predict the timing of the take-up of new bank loans. In contrast, we find that firms are two percentage points more likely to borrow from a FinTech platform during the quarter in which they experience at least one customer default. The magnitude of the coefficient (2 p.p.) is substantial, the unconditional average of the probability of taking a new loan being equal to 4.5%. We find a similar relationship between the probability of taking up a new loan in quarter q and the probability of having experienced a customer default in quarter $q-1$ (column 2).

If firms indeed turn to FinTech platforms because of their quick application process, we should observe that customer defaults only predict the probability of taking a new loan in the short run. In column 3, we replace $Customer\ default_{i,q}$ with $Customer\ default_{i,Before\ q-2}$, a dummy variable that equals one if at least one of the customers of firm i defaults on a trade bill between times $q-4$ and $q-2$ but not at $q-1$ or q. As expected, the results show that having experienced customer defaults more than two quarters ago does not predict a higher propensity of taking a FinTech loan.

One potential issue with trade credit defaults as sources of liquidity shocks is that other factors may simultaneously affect customer defaults and firms' demand for credit. For instance, young firms may be more prone to take up new loans and less likely to deliver goods or services of the promised quality, leading their customers to refuse the payment of trade bills. Following Boissay and Gropp (2013), we exploit the granularity of our dataset to limit the role of omitted variables. The CIPE database classifies payment incidents into four main types: disagreement between customer and supplier, illiquidity, omission, and insolvency. Customer defaults due to illiquidity are more likely to be exogenous to the supplier's financial conditions, causing unexpected urgent liquidity needs for the supplier. In contrast, customer defaults caused by disagreement are more likely to be anticipated and hence less exogenous to the timing of the loan application.

Based on this rationale, we split the sample based on whether the payment incidents are caused by customer illiquidity or not in columns 4 and 5. We find that the positive correlation between customer defaults and FinTech loan take-up is driven by illiquidity defaults. There is no correlation between customer defaults due to disagreement and the origination of FinTech loans. This supports our interpretation of customer defaults as exogenous liquidity shocks driving the probability of taking a new FinTech loan.

Our results show that liquidity shocks and the origination of new loans tend to be more synchronized for FinTech borrowers. We interpret this finding as evidence that FinTech platforms are faster at originating loans and therefore better equipped to meet firms' liquidity needs.

Can the speed advantage of FinTech lenders also explain the increase in bank credit for FinTech borrowers? This could be the case if firms use FinTech loans as a form of bridge financing and refinance FinTech loans with less expensive bank loans. To examine this possibility, we study whether the increase in bank credit is driven by FinTech borrowers who repay their loans before maturity. Figure 9 plots the distribution of FinTech borrowers based on the timing of repayment of the FinTech loan, that is, the ratio of the time (in months) it takes for a firm to fully repay its

FinTech loan over the maturity of the FinTech loan. The evidence suggests that the vast majority of FinTech borrowers repay their loan around the maturity date. For 82% of FinTech borrowers, the loan is repaid after a period corresponding to more than 80% of the loan's maturity. This suggests that the increase in bank credit in the first 6 months following the new loan observed in Figure 6 is unlikely to be driven by FinTech firms refinancing their loans.[27] Overall, our results lead us to conclude that while FinTech platforms may be faster than banks at processing loan applications, differences in speed are unlikely to explain the increase in bank credit experienced by FinTech borrowers.

6.2 Firm performance

Other firm outcomes We show that FinTech lending allows firms to borrow more and to obtain funds more quickly. But how do firms perform after receiving a FinTech loan? We estimate Equation 10, where the outcome variables are firm's total assets, tangible assets, employment, and working capital, all observed at a yearly frequency. We use the logarithm of these variables, except for working capital, which can be negative. Hence, we normalize the working capital with lagged total assets. The regression results are reported in Table 7.

$$y_{i,t} = \beta FinTech_i \times Post_t + \delta Post_t + \alpha_i + \mu_{s,t} + \varepsilon_{i,t} \tag{6}$$

Based on the first two columns of Panel a, we observe that both FinTech and bank borrowers experience an increase in total assets and tangible assets, consistent with firms using the outside loan to finance the acquisition of new assets. We do not observe that FinTech borrowers invest more in new assets than bank borrowers, which is expected given that FinTech and matched bank borrowers obtain similarly sized outside loans. However, this finding, combined with the fact that FinTech borrowers pledge more collateral to obtain subsequent bank loans, suggests that the assets acquired with FinTech loans are less encumbered. Hence, obtaining unsecured FinTech loans improves firms' asset pledgeability.

In addition, the fact that FinTech borrowers do not experience higher growth in total assets despite subsequently receiving more bank credit suggests that firms either consolidate debt or spend more on other factors of production. We find no differences in employment across FinTech and bank

[27] Figure A.3 plots the distribution of the realized maturity of FinTech loans, that is, the number of months for the loan to be fully repaid. Approximately 96% of the loans are fully repaid after six months. Hence, it cannot explain the gradual increase in bank credit observed in the first six months after loan origination (Figure 5). In untabulated tests, we also verify that removing firms that repay their loans fully within six months does not change our results.

borrowers, indicating that FinTech borrowers do not hire more workers (column 3). In contrast, we find that FinTech firms rely less on trade credit (e.g., accounts payable). There is no change in the other components of working capital (e.g., cash holdings, accounts payable, or inventory), as shown in columns 4-6. These results suggest that FinTech firms use the additional funding to reduce their reliance on trade credit, a costly source of unsecured short-term financing. In terms of economic magnitude, the estimated coefficient in column 5 implies that FinTech borrowers experience a 2.6-p.p.reduction in the account-payables-to-asset ratio relative to bank borrowers. This represents a €8,400 decrease in the use of account payables by the average firm, and it corresponds to over 50% of the subsequent increase in bank credit experienced by FinTech borrowers.[28]

Next, we turn to the comparison between FinTech and rejected borrowers. Compared to rejected borrowers, FinTech borrowers obtain more credit not only from banks but also from FinTech platforms. Hence, we expect the gap in firm growth to be more pronounced. Indeed, panel b of Table 7 shows that FinTech borrowers exhibit stronger growth in total assets (14.2%), tangible assets (13.7%), and employment (9.2%) than rejected firms. In addition, accounts payable decrease by 2.3% for FinTech borrowers. These results suggest that FinTech borrowers use FinTech loans to finance growth opportunities and decrease short-term financing costs.

Default probability and credit rating How does the credit expansion experienced by FinTech borrowers affect their probability of default? The previous results indicate that FinTech borrowers perform better than rejected borrowers on various dimensions after loan origination, suggesting they should default less. In contrast, it is unclear ex ante whether FinTech borrowers should default more or less than bank borrowers. While FinTech borrowers can borrow more than bank borrowers, allowing them to rely less on trade credit, they also face higher interest expenses. Whether FinTech borrowers default more following a FinTech loan, therefore, will depend on the interest payments they face (e.g., credit risk).

We measure the probability of default using both information on firm liquidation and bankruptcy and credit ratings. Information on bankruptcy and liquidation status is collected from BODACC. We first construct a dummy variable that is equal to one if a firm enters a liquidation or bankruptcy procedure in a given quarter. In addition, we use the credit rating as a proxy for the expected

[28] We calculate the level change in the amount of bank credit for FinTech borrowers using two different methods. First, we take the median amount of bank credit for FinTech borrowers (€180,000) in the month before FinTech loan origination (we choose the median and not the mean because bank credit is highly skewed). Multiplying this figure by the average percentage increase in bank credit after the outside loan origination (8%), we obtain an increase of €14,400. Alternatively, relying on Table 1 and Figure 8, we calculate that an average FinTech loan of €150,000 translates into €15,000 (=(0.25-0.15)*150,000) in additional bank credit for FinTech borrowers.

probability of default and examine both the intensive margin (the evolution of credit ratings conditional on being rated) and extensive margin (the probability of becoming rated conditional on being unrated before the outside loan). We estimate Equation 10, where t represents the quarter relative to the outside loan origination. The regressions include firm fixed effects and industry-quarter fixed effects.

Table 8 report the estimation results. Based on Panel a, we find that FinTech borrowers are 4.8 p.p. more likely to enter a liquidation or bankruptcy procedure than bank borrowers and experience a deterioration in their credit rating (a lower value means a better rating). Unrated firms are also more likely to become rated. This is consistent with the functioning of the French rating system, which covers firms either when they become sufficiently large (i.e., sales exceeding €0.75 million) or when they default.

To test whether the higher default rates are explained by higher interest expenses, we split FinTech and bank loans based on the interest rate they pay for the outside loan. The even columns of Panel a report the coefficients interacted with an indicator variable for loans with above-median rates *High rate* (the median is computed separately for bank and FinTech borrowers). By summing the coefficients of *Post* and *High rate* $\times$ *Post*, we see that bank borrowers who receive high-rate loans do not experience an increase in liquidation and bankruptcy probability compared to the preorigination period. The same result holds for FinTech borrowers who receive low-rate loans, as indicated by the sum of the coefficients of *Post* and *FinTech* $\times$ *Post*. In contrast, FinTech borrowers who receive high-rate loans are 6.6 p.p. more likely to be liquidated or enter bankruptcy, consistent with the idea that defaults are driven by the higher interest burden faced by FinTech borrowers. Columns 4 and 6 show that the deterioration of credit ratings or the higher probability of becoming rated after the outside loan is not driven by FinTech borrowers that receive a high-rate loan, suggesting that the Banque de France estimates a higher three-year probability of default for FinTech borrowers regardless of the interest expenses that they face.

Panel b shows the results for FinTech and rejected borrowers. Compared to rejected borrowers, FinTech borrowers are 6.2 p.p. less likely to default and have better credit ratings after loan origination. In contrast, we do not find any difference in the probability of receiving a rating between the two groups. Overall, these findings suggest that obtaining a FinTech loan allows firms to grow more, making them less likely to default.

Profitability of FinTech loans How profitable is it to lend to FinTech borrowers? While we do observe a higher default rate among FinTech borrowers than bank borrowers, default risk is likely to be priced into the interest rate. Among loans for which we observe the entire repayment profile, we find a default probability of 4.6% and average charged-off amount representing 21.4% of the loan principal. Taking into account defaults and early repayments, we find that the internal rate of return of FinTech loans is 5.9% for the platform and the investors combined. Assuming a 3% origination fee and a 0.04% monthly management fee, as charged by the largest platform in our sample (i.e., Lendix), we find that the internal rate of return for investors alone is 4.9%. Hence, the average investor in our dataset makes a profit when lending to FinTech borrowers.

6.3 External validity

To what extent can we generalize our results outside of the French credit market? In this section, we discuss the external validity of our results by comparing French FinTech platforms, banks, and SMEs to their foreign counterparts.

We first discuss whether our results can be generalized to other FinTech markets. The French FinTech sector is representative of the European market in general. According to Ziegler et al. (2021), France is the second-largest market in the EU in terms of volume of FinTech lending to SMEs, behind Italy. Outside Europe, the largest market for SMEs remains the United States, with $8.27 billion in issued loans. One reason for the relatively small size of the French market compared to the US or UK market is that FinTech lending platforms have only been given accreditation by the French banking authority since 2014, which is seven years after the creation of first FinTech lending platforms in the US and the UK. Another reason is the presence of institutional investors. Unlike the US and UK, platforms in continental Europe are currently dominated by individual investors. Despite the cross-country differences in market size and investor composition, the characteristics of FinTech credit are considered to be relatively homogeneous across countries. Specifically, FinTech lending to small firms is typically unsecured (OECD, 2015; World Economic Forum, 2015). In the US, SMEs cite lower collateral requirements as one of the main factors influencing their decisions to apply to a FinTech lender (Small Business Credit Survey, 2019). Moreover, among the 9 FinTech lenders having issued more than $50Mns in loans to SMEs in the US (source), 8 platforms report unsecured financing solutions on their website. Since the mechanism we describe only relies on FinTech loans being unsecured, we believe it is likely to hold outside of France, including in the US.

We also argue that the collateral constraints faced by small firms are not uniquely present in France. We find that FinTech credit improves access to credit by alleviating collateral constraints. FinTech lenders could play a similar role outside of France for three reasons. First, there has been an extensive literature showing that collateral is a key determinant of SMEs' access to credit in a wide range of countries.[29] Second, collateral requirements are largely determined by banking regulations, which are common to all European Union countries (Capital Requirements Directive - IV) and, more generally, follow the Basel III agreement adopted by the G20 countries. Finally, the French banking sector is the largest in Europe in terms of total assets, with four Global Systematically Important Banks ("G-SIBS"; e.g., see EBF (2020)). Liberti and Mian (2010) show that more developed banking systems tend to be associated with lower collateral requirements for firms. If anything, therefore, collateral constraints should be tighter in countries with less developed banking sectors.

Last, our sample of SMEs is comparable to those in other countries. Our dataset covers 80% of the French FinTech market and includes firms from various industries. Since the size distribution and the industry composition of French firms is similar to that of other OECD countries (Boissel and Matray, forthcoming), we believe that our empirical findings is not specific to firms in our sample.

7 Conclusion

The simultaneous decline in bank lending to SMEs and the emergence of FinTech lending platforms raises the question of the role played by FinTech lenders in the small business credit market. We first show that firms that borrow from FinTech platforms have less tangible assets and more debt, suggesting that they may face larger constraints obtaining additional funding from banks. To understand the impact of FinTech credit on a firm's access to financing, we construct two benchmark groups of non-FinTech borrowers that either borrow from a new bank lender or are rejected for FinTech credit. We document that FinTech borrowers experience a 20% long-run credit expansion relative to both benchmark groups.

This credit expansion is due to the unsecured nature of FinTech loans. Firms use the FinTech loan to finance investments without posting collateral, which allows them to subsequently pledge

[29] For instance, see Degryse and Van Cayseele (2000); Jimenez, Salas and Saurina (2006) for Europe, Berger and Udell (1995); Benmelech, Kumar and Rajan (2020) for the US, Hanedar, Broccardo and Bazzana (2014) for Asia, or Beck et al. (2006) for cross-country evidence.

the newly acquired assets to obtain more bank credit. Firms take advantage of the relaxation of collateral constraints by investing in tangible assets and reducing the use of trade credit, a costly source of unsecured financing.

We find, however, that the relaxation of collateral constraints has heterogeneous effects on defaults depending on firms' ex ante credit risk. FinTech borrowers that receive high interest rates (e.g., high credit risk) default more than bank borrowers, while low-risk FinTech borrowers default at the same rate, suggesting that the higher cost of FinTech loans is not sustainable for high-risk borrowers. FinTech borrowers' higher propensity to default, however, does not necessarily make lending on Fintech platforms unprofitable. Based on our calculation of the internal rate of return on FinTech loans, we conclude that unsecured lending can be profitable for lenders while also benefiting low-risk firms.

Overall, our findings suggest that in the presence of regulations preventing banks from providing secured lending to SMEs, fostering the emergence of FinTech platforms could fill in the gap in the SME credit market and benefit firms in the long run.

References

Almeida, Heitor, Murillo Campello, and Michael S Weisbach. 2004. "The cash flow sensitivity of cash." *The Journal of Finance*, 59(4): 1777–1804.

Balyuk, Tetyana. forthcoming. "Financial innovation and borrowers: Evidence from peer-to-peer lending." *Management Science*.

Balyuk, Tetyana, Allen Berger, and Johan Hackney. 2020. "What is fueling FinTech lending? The role of banking market structure." *Working Paper*.

Barkley, Brett, and Mark Schweitzer. 2021. "The rise of Fintech lending to small businesses: Businesses' perspectives on borrowing." *International Journal of Central Banking*, 17(1): 35–65.

Beck, Thorsten, Aslı Demirgüç-Kunt, Luc Laeven, and Vojislav Maksimovic. 2006. "The determinants of financing obstacles." *Journal of International Money and Finance*, 25(6): 932–952.

Begley, Taylor A, and Kandarp Srinivasan. forthcoming. "Small bank lending in the era of fintech and shadow banking: a sideshow?" *The Review of Financial Studies*.

Ben-David, Itzhak, Mark Johnson, and René M Stulz. 2021. "Why did small business Fintech lending dry up during March 2020?" *Working Paper*.

Benmelech, Efraim, Nitish Kumar, and Raghuram Rajan. 2020. "The decline of secured debt."

Berger, Allen N, and Gregory F Udell. 1995. "Relationship lending and lines of credit in small firm finance." *Journal of Business*, 351–381.

Berg, Tobias, Andreas Fuster, and Manju Puri. 2021. "FinTech lending." *Working Paper*.

Berg, Tobias, Valentin Burg, Ana Gombović, and Manju Puri. 2020. "On the rise of fintechs: Credit scoring using digital footprints." *The Review of Financial Studies*, 33(7): 2845–2897.

Boissay, Frederic, and Reint Gropp. 2013. "Payment defaults and interfirm liquidity provision." *Review of Finance*, 17(6): 1853–1894.

Boissel, Charles, and Adrien Matray. forthcoming. "Dividend taxes and the allocation of capital." *American Economic Review*.

Bord, Vitaly, Victoria Ivashina, and Ryan Taliaferro. 2015. "Large banks and the transmission of financial shocks." *Working Paper*.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2018. "Fintech, regulatory arbitrage, and the rise of shadow banks." *Journal of Financial Economics*, 130(3): 453–483.

Chava, Sudheer, Rohan Ganduri, Nikhil Paradkar, and Yafei Zhang. 2021. "Impact of marketplace lending on consumers' future borrowing capacities and borrowing outcomes." *Journal of Financial Economics*, 142(3): 1186–1208.

Chen, Brian S, Samuel G Hanson, and Jeremy C Stein. 2017. "The decline of big-bank lending to small business: Dynamic impacts on local credit and labor markets." *Working Paper*.

Cornelli, Giulio, Sebastian Doerr, Leonardo Gambacorta, and Ouarda Merrouche. 2021. "Regulatory Sandboxes and Fintech Funding: Evidence from the UK."

Cortés, Kristle R, Yuliya Demyanyk, Lei Li, Elena Loutskina, and Philip E Strahan. 2020. "Stress tests and small business lending." *Journal of Financial Economics*, 136(1): 260–279.

Davydenko, Sergei A, and Julian R Franks. 2008. "Do bankruptcy codes matter? A study of defaults in France, Germany, and the UK." *The Journal of Finance*, 63(2): 565–608.

Degryse, Hans, and Patrick Van Cayseele. 2000. "Relationship lending within a bank-based system: Evidence from European small business data." *Journal of Financial Intermediation*, 9(1): 90–109.

Degryse, Hans, and Steven Ongena. 2005. "Distance, lending relationships, and competition." *The Journal of Finance*, 60(1): 231–266.

Degryse, Hans, Vasso Ioannidou, and Erik von Schedvin. 2016. "On the nonexclusivity of loan contracts: An empirical investigation." *Management Science*, 62(12): 3510–3533.

De Roure, Calebe, Loriana Pelizzon, and Anjan Thakor. 2022. "P2P lenders versus banks: Cream skimming or bottom fishing?" *The Review of Corporate Finance Studies*, 11(2): 213–262.

Di Maggio, Marco, and Vincent Yao. 2021. "FinTech borrowers: Lax screening or cream-skimming?" *The Review of Financial Studies*, 34(10): 4565–4618.

Doerr, Sebastian. 2021. "Stress tests, entrepreneurship, and innovation." *Review of Finance*, 25(5): 1609–1637.

Donaldson, Jason Roderick, Denis Gromb, and Giorgia Piacentino. 2020. "The paradox of pledgeability." *Journal of Financial Economics*, 137(3): 591–605.

EBF. 2020. "Banking in Europe: EBF Facts and Figures 2020." *Technical Report.*

Eça, Afonso, Miguel A Ferreira, Melissa Porras Prado, and Antonino Emanuele Rizzo. 2021. "How does peer-to-business lending affect financial policy of SMEs?" *Working Paper.*

Erel, Isil, and Jack Liebersohn. 2020. "Does fintech substitute for banks? Evidence from the paycheck protection program." *Working Paper.*

Fazzari, Steven M, R Glenn Hubbard, Bruce C Petersen, Alan S Blinder, and James M Poterba. 1988. "Financing constraints and corporate investment." *Brookings Papers on Economic Activity*, 1988(1): 141–206.

Fraisse, Henri, Mathias Lé, and David Thesmar. 2020. "The real effects of bank capital requirements." *Management Science*, 66(1): 5–23.

Fuster, Andreas, Matthew Plosser, Philipp Schnabl, and James Vickery. 2019. "The role of technology in mortgage lending." *The Review of Financial Studies*, 32(5): 1854–1899.

Ghosh, Pulak, Boris Vallee, and Yao Zeng. 2021. "FinTech lending and cashless payments." *Working Paper.*

Giannetti, Mariassunta, Mike Burkart, and Tore Ellingsen. 2011. "What you sell is what you lend? Explaining trade credit contracts." *The Review of Financial Studies*, 24(4): 1261–1298.

Gopal, Manasa, and Philipp Schnabl. forthcoming. "The rise of finance companies and FinTech lenders in small business lending." *The Review of Financial Studies.*

Hadlock, Charles J, and Joshua R Pierce. 2010. "New evidence on measuring financial constraints: Moving beyond the KZ index." *The Review of Financial Studies*, 23(5): 1909–1940.

Hanedar, Elmas Yaldız, Eleonora Broccardo, and Flavio Bazzana. 2014. "Collateral requirements of SMEs: The evidence from less-developed countries." *Journal of Banking & Finance*, 38: 106–121.

Havrylchyk, Olena, and Aref Ardekani. 2020. "Real effects of lending-based crowdfunding platforms on the SMEs." *Working Paper*.

Ivashina, Victoria, Luc Laeven, and Enrique Moral-Benito. 2022. "Loan types and the bank lending channel." *Journal of Monetary Economics*, 126: 171–187.

Jimenez, Gabriel, Vicente Salas, and Jesus Saurina. 2006. "Determinants of collateral." *Journal of Financial Economics*, 81(2): 255–281.

Klapper, Leora, Luc Laeven, and Raghuram Rajan. 2012. "Trade credit contracts." *The Review of Financial Studies*, 25(3): 838–867.

Liberti, José M, and Atif R Mian. 2010. "Collateral spread and financial development." *The Journal of Finance*, 65(1): 147–177.

Ng, Chee K, Janet Kiholm Smith, and Richard L Smith. 1999. "Evidence on the determinants of credit terms used in interfirm trade." *The Journal of Finance*, 54(3): 1109–1129.

OECD. 2015. "New approaches to SME and entrepreneurship financing: Broadening the range of instruments." *Technical Report*.

Rajan, Raghuram G, and Luigi Zingales. 1995. "What do we know about capital structure? Some evidence from international data." *The Journal of Finance*, 50(5): 1421–1460.

Schmalz, Martin C, David A Sraer, and David Thesmar. 2017. "Housing collateral and entrepreneurship." *The Journal of Finance*, 72(1): 99–132.

Small Business Credit Survey. 2019. "Report on employer firms." *Technical Report*.

Sufi, Amir. 2009. "The real effects of debt certification: Evidence from the introduction of bank loan ratings." *The Review of Financial Studies*, 22(4): 1659–1691.

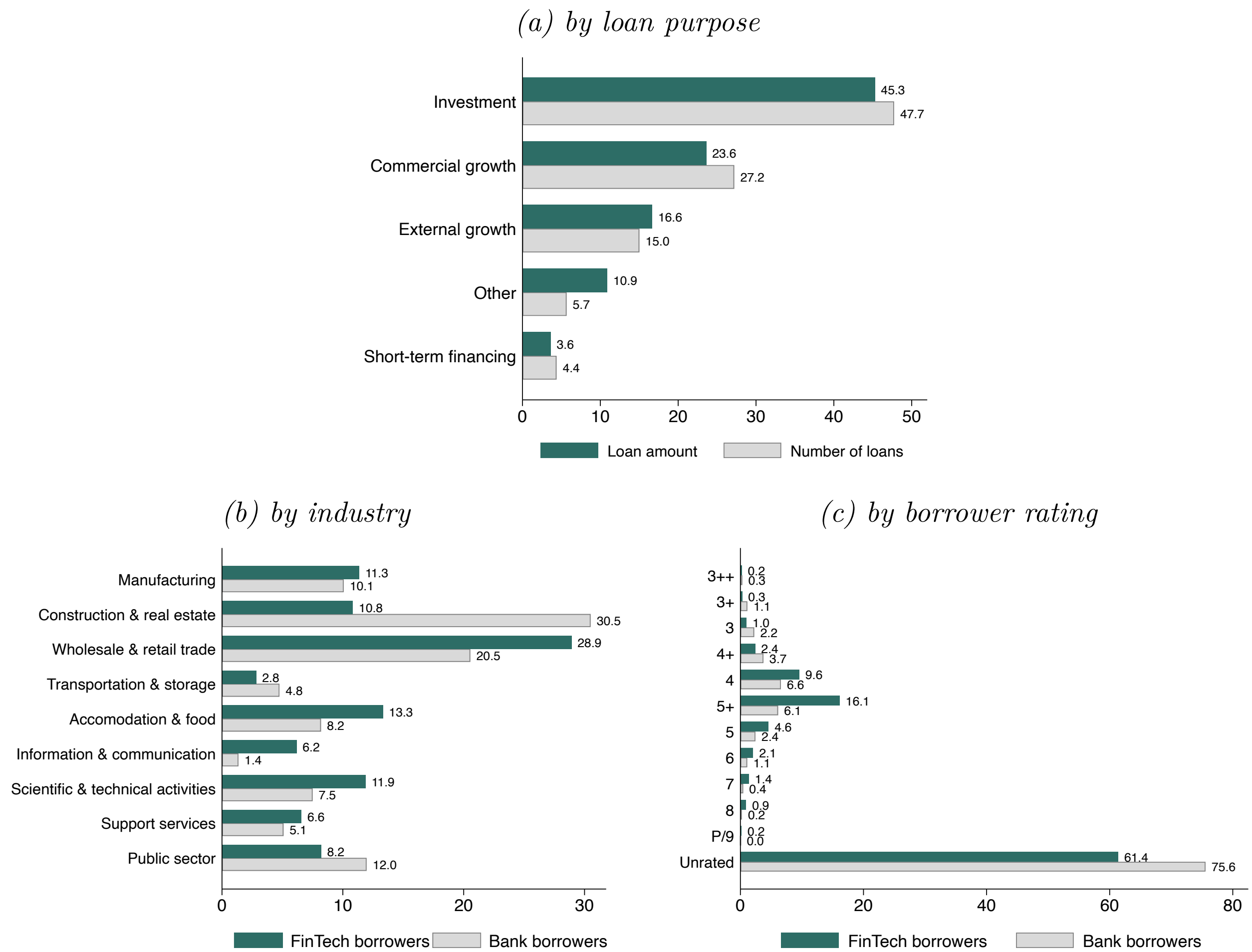
Tang, Huan. 2019. "Peer-to-peer lenders versus banks: substitutes or complements?" *The Review of Financial Studies*, 32(5): 1900–1938.

Thakor, Anjan V. 2020. "Fintech and banking: What do we know?" *Journal of Financial Intermediation*, 41: 100833.

World Economic Forum. 2015. "The Future of FinTech: A Paradigm Shift in Small Business Finance." *Technical Report.*

Ziegler, Tania, Rotem Shneor, Karsten Wenzlaff, Krishnamurthy Suresh, Felipe Ferri de Camargo Paes, Leyla Mammadova, Charles Wanga, Neha Kekre, Stanley Mutinda, Britney Wang, et al. 2021. "The 2nd Global alternative finance market benchmarking report." *Technical Report.*

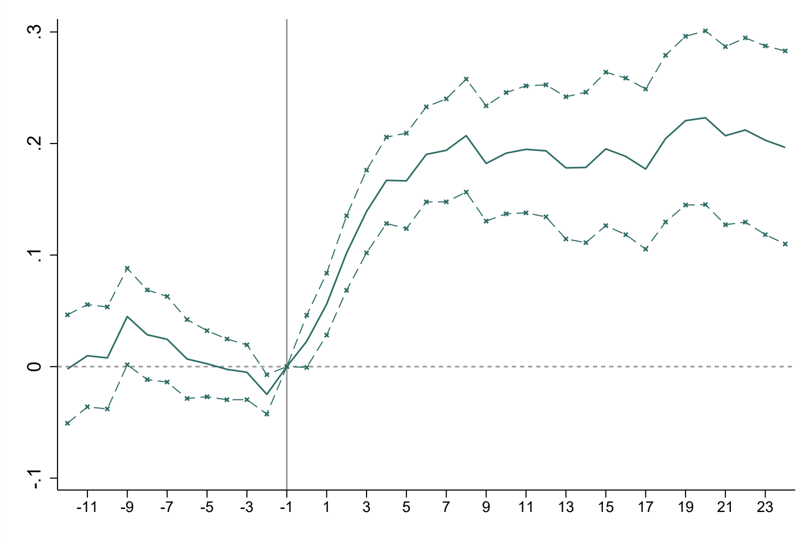
FIGURE 1
FinTech and bank borrower composition



NOTE.—This figure presents the breakdown (in %) of loans by purpose category (Panel a), firm industry (Panel b), and firm credit rating (Panel c). In Panel a, percentages are computed both in terms of the number of loans (white bars) and loan volume (green bars). In Panels b and c, green (white) bars give the breakdown of FinTech (bank) borrowers. Purpose categories are from the Banque de France FinTech dataset only. Bank loans are observed in the M-Contran database. The M-Contran dataset is a survey representative of the universe of new bank loans issued by banks to nonfinancial firms. Data on firms come from FIBEN and Orbis. We retain only FinTech and bank loans originated between January 2016 and June 2019.

FIGURE 2

Credit dynamics of FinTech borrowers



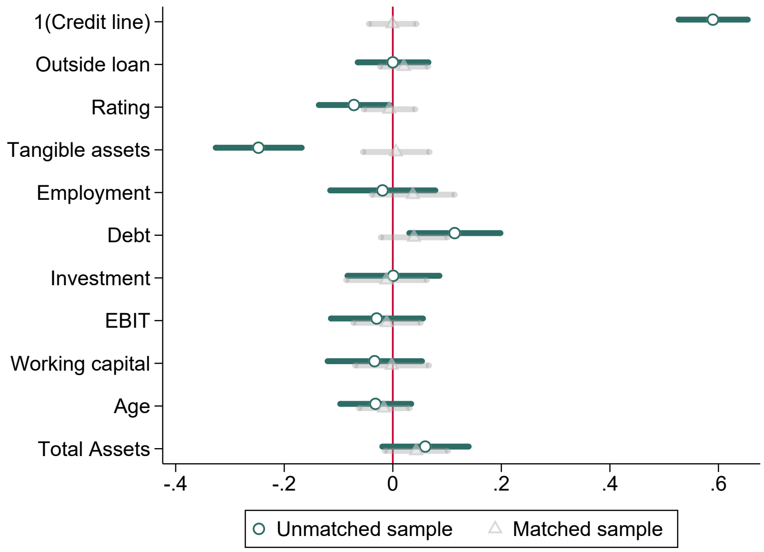
NOTE.—The figure presents the estimation results of the following equation, using the 36-month window around the origination of the outside loan at $t = 0$:

$$log(1 + y_{i,t}) = \sum_{t \in [-12,24]} \beta_t \times D_t + \gamma_{i,year} + \varepsilon_{i,t},$$

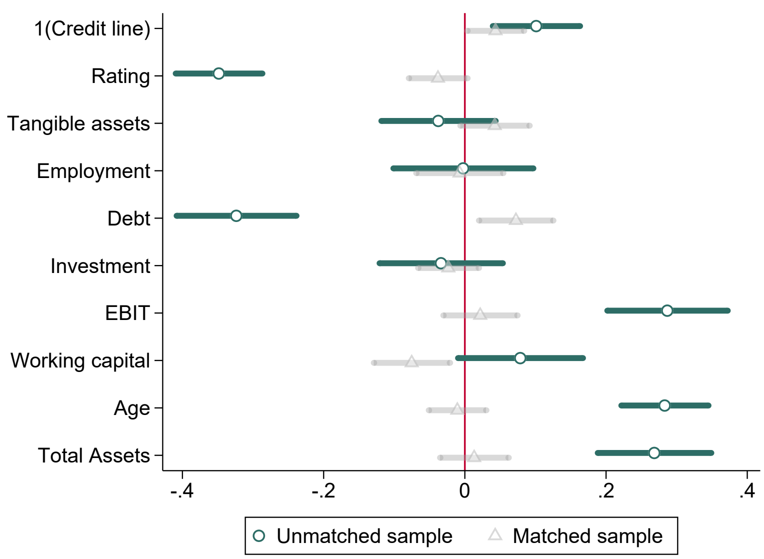
where $y_{i,t}$ is the total amount of bank credit that firm i has in month t. Only FinTech firms are included in the estimation. Coefficients are reported along with the 95% confidence intervals. Standard errors are clustered at the firm level. The base group in D_t is $t = -1$. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. We retain outside loans originated between January 2014 and June 2019.

FIGURE 3
Testing covariates balance

(a) FinTech borrowers vs. Bank borrowers



(b) FinTech borrowers vs. Rejected borrowers

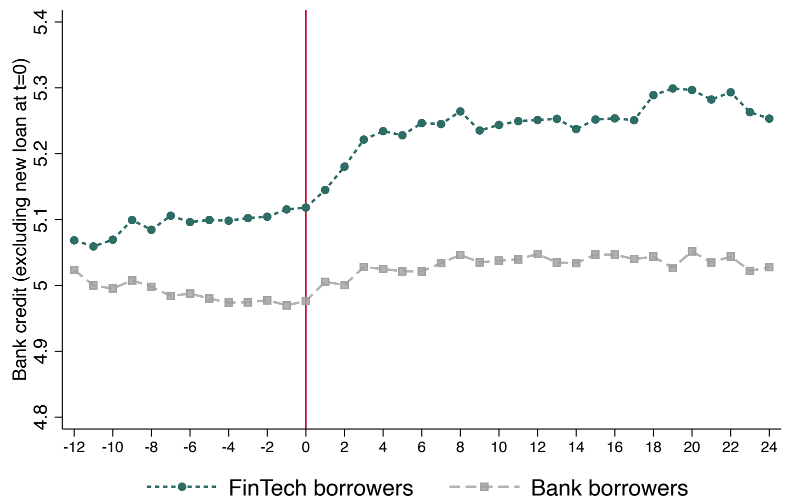


Note.—This figure shows estimates and 95% confidence intervals of the differences in various characteristics of FinTech borrowers and bank borrowers in Panel a and of FinTech borrowers and rejected borrowers in Panel b. All variables are normalized to have a mean of zero and a standard deviation of one and are taken the year before the outside loan origination. A positive coefficient means that the variable has a higher mean for FinTech borrowers. *Rating* is the numerical equivalent of the Bank of France rating (1 for the best rating, 12 for the worst rating, 13 if the firm is unrated - see Table B.3). *Total Assets* and *Employment* are measured in logarithm. *Tangible assets*, *Debt*, *EBIT*, *Investment*, *Working capital* are normalized by total assets. *Age* is measured in years. $\mathbb{1}$(*Credit line*) indicates whether the firm has a line of credit before the outside loan origination. *Outside loan* is the log amount of the outside loan. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. We retain outside loans originated between January 2014 and June 2019.

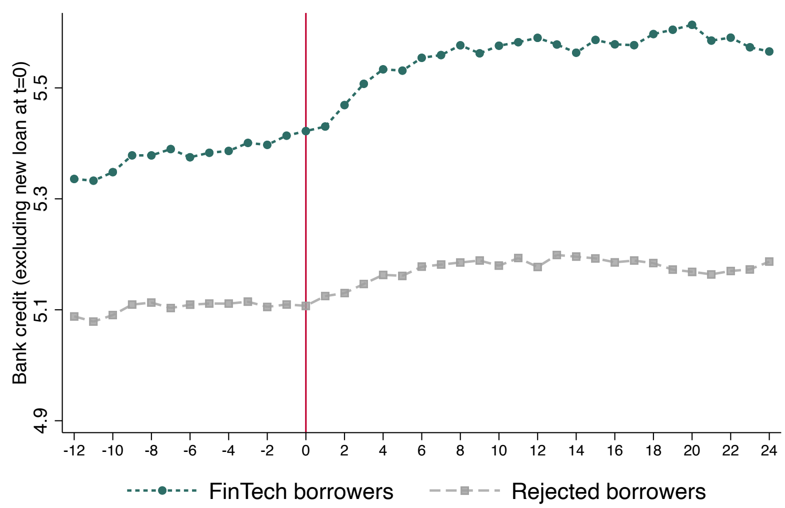
FIGURE 4

Evolution of bank loan amount for the matched firms

(a) FinTech borrowers vs. Bank borrowers



(b) FinTech borrowers vs. Rejected borrowers

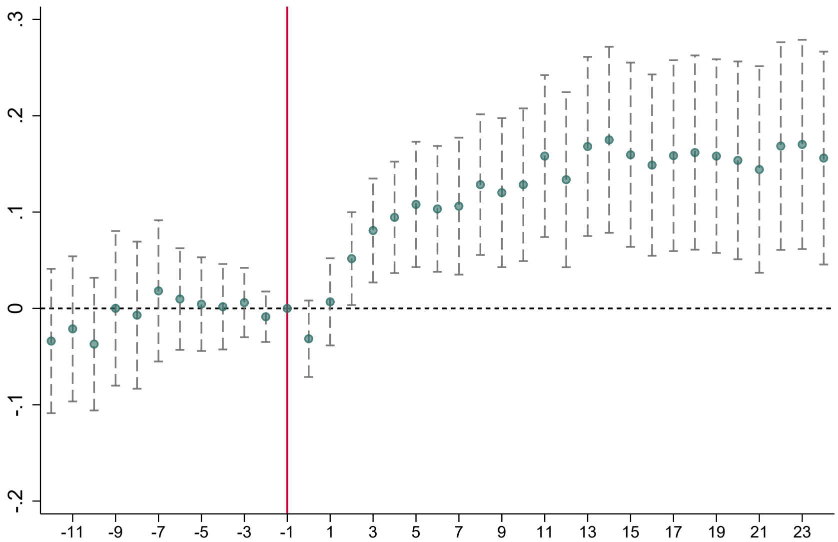


NOTE.—This figure presents the average log amount of bank credit by borrower type in the 36-month window around the origination of the outside loan at $t = 0$. Panel a (b) is based on the matched sample of FinTech and bank borrowers (resp. FinTech and rejected firms). An outside loan is a loan originated by a lender that has not previously extended credit to firm i. The figures plot the average of $\log(1 + y_{i,t})$, with $y_{i,t}$ equal to the amount of outstanding bank credit of firm i in month t. Firm i can either be a FinTech borrower (i.e., the new loan is a FinTech loan), a bank borrower (i.e., the new loan is a bank loan), or a rejected borrower (i.e., the firm applies for a FinTech loan but is rejected). Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We retain outside loans originated between January 2014 and June 2019.

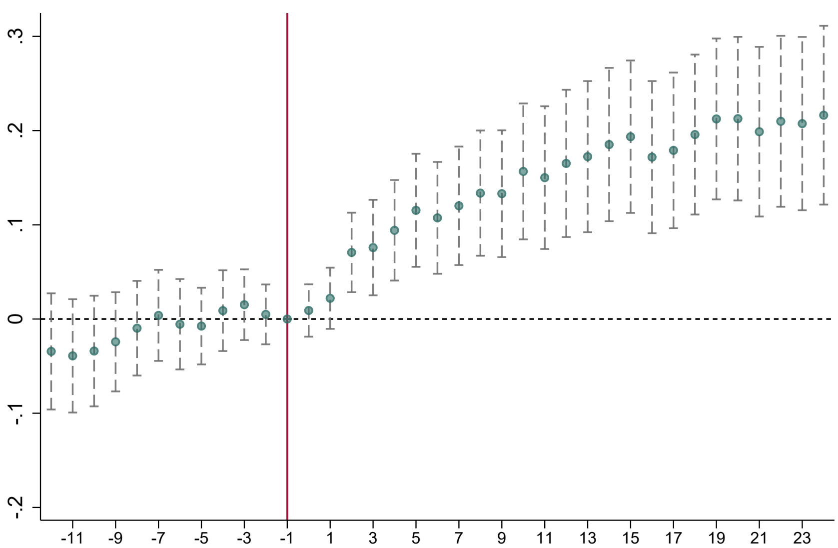
FIGURE 5

Credit dynamics: FinTech borrowers vs. benchmark firms

(a) FinTech borrowers vs. Bank borrowers



(b) FinTech borrowers vs. Rejected borrowers



NOTE.—The figure presents the estimation results of the following equation, using the 36-month window around the origination of the outside loan at $t = 0$:

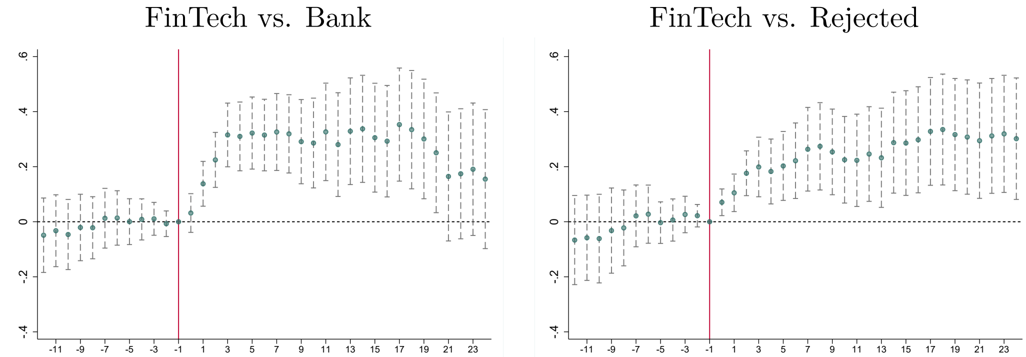
$$log(1 + y_{i,t}) = \sum_{t \in [-12,24]} \beta_t FinTech_i \times D_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t},$$

where $y_{i,t}$ is the total amount of outstanding bank credit of firm i at time t. The outside loan can either be a FinTech loan or a bank loan. In Panel a, the benchmark group is bank borrowers, and in Panel b, rejected borrowers. Coefficients are reported along with the 95% confidence intervals. Standard errors are clustered at the firm level. The base group in D_t is $t = -1$. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We retain outside loans originated between January 2014 and June 2019.

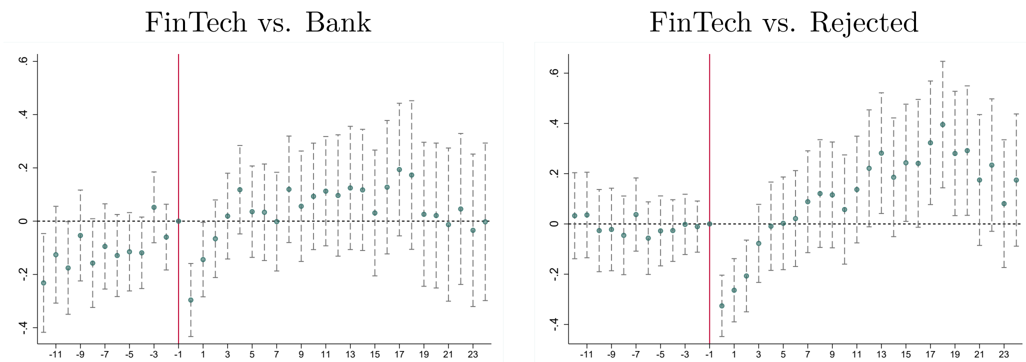
FIGURE 6

Firm credit dynamics by bank loan category

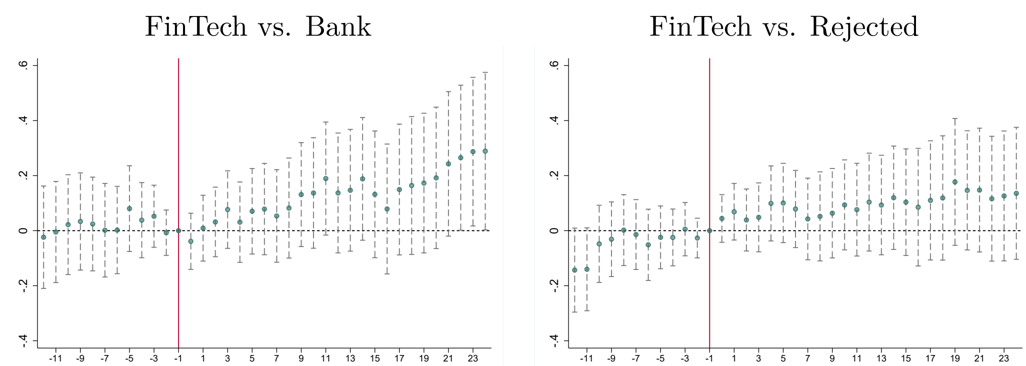
(a) Long-term loans



(b) Used line of credit



(c) Other loans



NOTE.— The figure presents the estimation results of the following equation, using the 36-month window around the origination of the outside loan at $t = 0$:

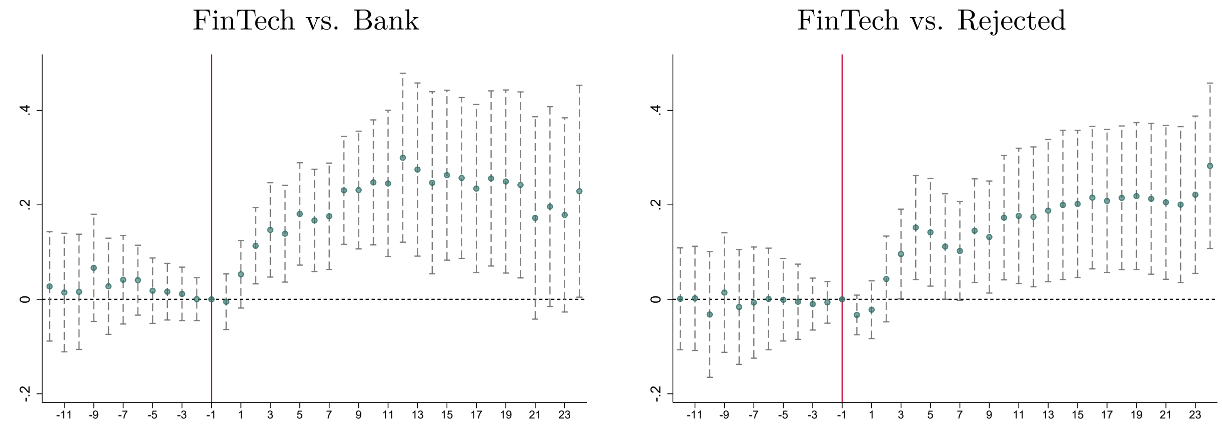
$$log(1 + y_{i,t}) = \sum_{t \in [-12,24]} \beta_t FinTech_i \times D_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t},$$

where $y_{i,t}$ is the amount of long-term loans, drawn credit lines, and other loans of firm i at time t, in the top, middle, and bottom panels. An outside loan is a loan originated by a lender that has not previously extended credit to firm i. Firm i can either be a FinTech borrower (i.e., the outside loan is a FinTech loan) or a bank borrower. In the left-hand figures, the benchmark group is bank borrowers, and in the right-hand figures, it is rejected. Coefficients are reported along with the 95% confidence intervals. Standard errors are clustered at the firm level. The baseline is set at $t = -1$.

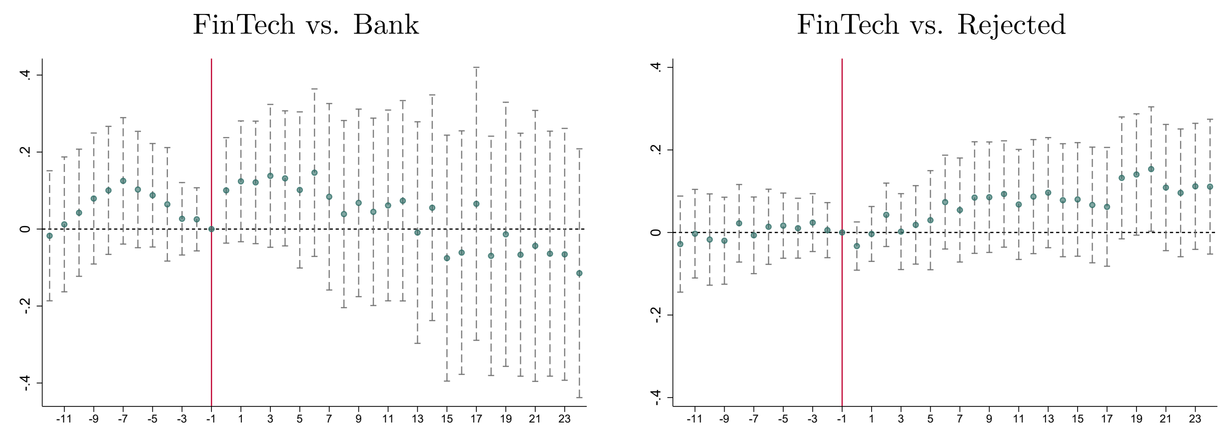
FIGURE 7

Firm credit dynamics by outside loan purpose

(a) Loan purpose: investments



(b) Loan purposes: Others



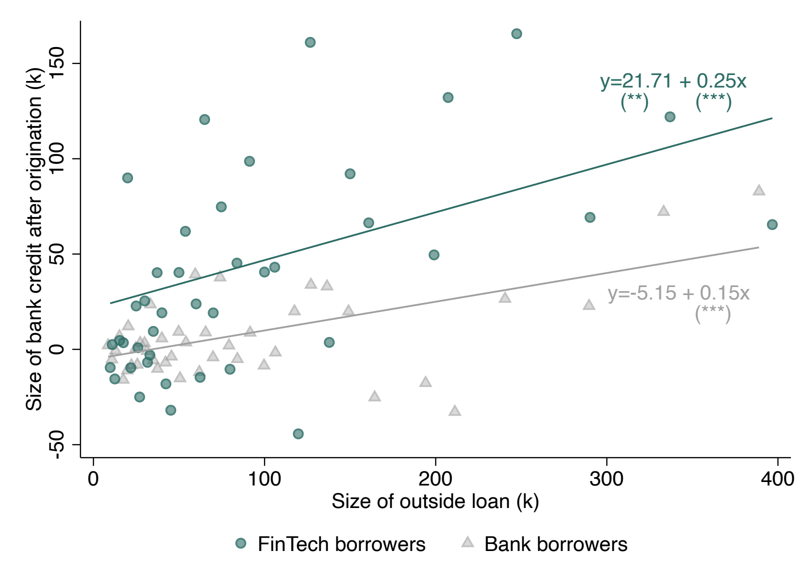
NOTE.— The figure presents the estimation results of the following equation, using the 36-month window around the origination of the outside loan at $t = 0$:

$$log(1 + y_{i,t}) = \sum_{t \in [-12,24]} \beta_t FinTech_i \times D_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t},$$

where $y_{i,t}$ is the amount of outstanding bank loans of firm i at time t, excluding the loans from the bank where the benchmark borrowers obtain an outside loan at $t = 0$. An outside loan is a loan originated by a lender that has not previously extended credit to firm i. Firm i can either be a FinTech borrower (i.e., the outside loan is a FinTech loan) or a bank borrower. In the left-hand figures, the benchmark group is bank borrowers, and in the right-hand figures, it is rejected borrowers. In panel a, the outside loans are used to finance the acquisition of news assets (investments), and in panel b, the loans are used for other purposes. Coefficients are reported along with the 95% confidence intervals. Standard errors are clustered at the firm level. The base group in D_t is $t = -1$. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We retain outside loans originated between January 2014 and June 2019.

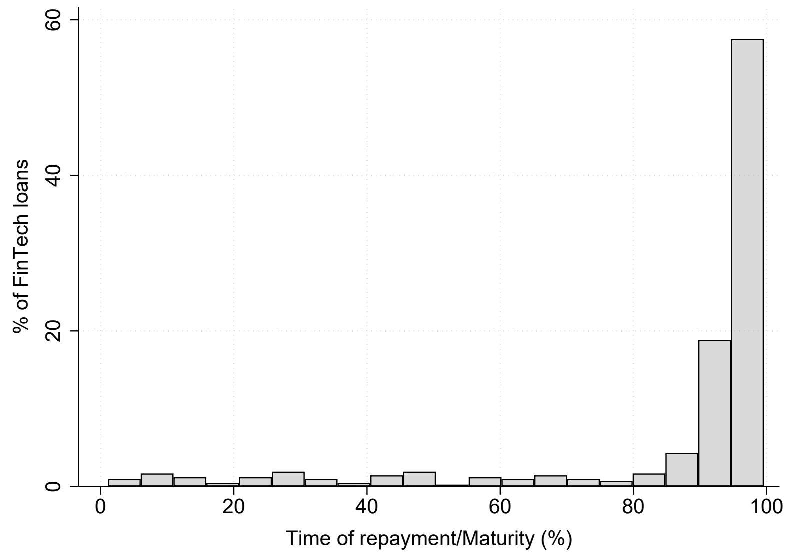
FIGURE 8

Relationship between outside loan size and subsequent bank loan size



NOTE.—This figure is a binned scatter plot of the amount of subsequent bank loans and the amount of outside loans, both in thousands of euros. The total amount of subsequent bank loans is calculated for the six-month period following the origination of the outside loan. Green dots represent FinTech borrowers, and gray triangles represent bank borrowers. The regression coefficients are reported with the significance levels. Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

FIGURE 9
Timing of repayment of FinTech loans



Note.—This figure gives the distribution of FinTech loans by the timing of repayment. The timing of repayment is the ratio of the number of months before the full repayment of the loan over the agreed maturity of the FinTech loan (in months). We exclude loans that are defaulted upon. We only include loans originated after 2016 and that matured before 2019 (that is, for which we observe the full repayment schedule). Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset.

TABLE 1
Characteristics of FinTech loans

	Min	Mean	p50	Max	S.D.	Count
Loan terms						
Loan amount (000' euro)	1.00	150.92	50.00	5000.00	346.07	2,013
Interest rate (%)	1.00	7.79	8.00	16.77	1.97	2,013
Maturity (months)	3	38	36	84	16	2,013
Investors						
Number of banks	0	0	0	1	0	2,013
Share of banks	0.00	11.57	0.00	100.00	25.55	2,013
Number of legal entities	0	2	0	37	5	2,013
Share of legal entities	0.00	1.61	0.00	100.00	7.42	2,013
Number of individuals	0	501	320	5141	554	2,013
Share of individuals	0.00	86.80	100.00	100.00	25.89	2,013

NOTE.—This table presents descriptive statistics on FinTech loans. Loan amounts are in thousands of euros. Interest rates are annualized and expressed in percentage points; rates are inclusive of fees. Loan maturity is in months. Investors can be individuals, banks, or other legal entities, such as FinTech platforms themselves. Data on FinTech loans come from the Banque de France FinTech dataset only. We retain only outside loans originated between January 2016 and July 2019.

TABLE 2
Comparing FinTech and bank loans

	Loan size (Mns EUR)		Maturity (years)		Rate (%)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FinTech	-0.14**	-0.14*	-2.00***	-1.58***	5.41***	5.48***	5.36***
	(0.07)	(0.07)	(0.10)	(0.09)	(0.02)	(0.02)	(0.02)
Maturity						0.03***	0.02***
						(0.00)	(0.00)
Loan size						-0.01***	-0.01***
						(0.00)	(0.00)
Constant	0.29***	0.29***	5.01***	4.96***	1.96***	1.80***	1.87***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry, County, Size, Rating FE	N	Y	N	Y	N	N	Y
N	12,811	12,778	12,811	12,778	12,811	12,811	12,778
R-sq	0.01	0.03	0.05	0.37	0.84	0.84	0.86

NOTE.—This table shows the difference in loan size (in millions of euros), maturity (in years) and interest rate (in %) between FinTech loans and bank loans received by firms in the unmatched sample between Jan 1., 2016, and Jan 1, 2019. All specifications include year fixed effects. In columns 2, 4, and 7, we control for industry, location, size, and rating fixed effects. Standard errors are clustered by industry. Data on new bank loans come from the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We retain outside loans originated between January 2014 and June 2019. Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 3
Testing the collateral channel

(a) Benchmark: Bank borrowers

	Loan category			Outside loan purpose	
	Long term loans	Credit lines	Other loans	For investments	Other purposes
	(1)	(2)	(3)	(4)	(5)
FinTech × Post	0.25***	0.09*	0.05	0.12***	0.06
	(0.05)	(0.05)	(0.05)	(0.04)	(0.06)
Post	-0.08**	-0.12***	0.05	-0.05*	-0.06
	(0.03)	(0.04)	(0.04)	(0.03)	(0.06)
Firm-Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
N	218,484	218,484	218,484	52,929	60,151
R-sq	0.93	0.77	0.91	0.95	0.95

(b) Benchmark: Rejected borrowers

	Loan category			Outside loan purpose	
	Long term loans	Credit lines	Other loans	For investments	Other purposes
	(1)	(2)	(3)	(4)	(5)
Accepted × Post	0.16***	-0.01	0.07	0.08**	0.03
	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)
Post	0.04	-0.03	0.03	-0.02	0.02
	(0.03)	(0.04)	(0.04)	(0.02)	(0.03)
Firm-Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
N	316,275	316,275	316,275	88,356	87,955
R-sq	0.93	0.79	0.92	0.96	0.95

NOTE.—This table presents the estimation results of the following equation, using the 36-month window around the origination of the outside loan at $t = 0$:

$$\log(1 + y_{i,t}) = \beta FinTech_i \times Post_t + \delta Post_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t}. \quad (7)$$

where $Post_t$ is equal to one when $t \geq 0$. In columns 1-3, $y_{i,t}$ is the total amount of long-term loans, line of credit, and other credit of firm i in month t. In the last two columns, the regressions are run on subsamples of firms for which the outside loan is used to either finance the acquisition of new assets (column 4) or for other purposes (column 5). An outside loan is a loan originated by a lender that has not previously extended credit to firm i. In Panel a, the benchmark group is bank borrowers, and in Panel b, it is rejected borrowers. Standard errors are clustered at the firm level. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We retain outside loans originated between January 2014 and June 2019. Coefficients are reported along with the standard errors (in parentheses). Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 4

FinTech loans and propensity to post collateral

	$\mathbb{1}(Secured)$			
Benchmark:	*Bank borrowers*		*Rejected borrowers*	
	(1)	(2)	(3)	(4)
FinTech × Post	0.036***	0.031***	0.016***	0.009
	(0.006)	(0.008)	(0.006)	(0.009)
Post	−0.060***	−0.069***	−0.007**	−0.010
	(0.002)	(0.005)	(0.003)	(0.007)
Matched Sample	N	Y	N	Y
Firm FE	Y	Y	Y	Y
Industry-Quarter FE	Y	Y	Y	Y
N	141,472	82,210	17,584	31,198
R-sq	0.11	0.11	0.11	0.13

NOTE.—This table presents the results of the estimation for the 4-year window around the origination of the outside loan at $t = 0$ (t is in quarters) :

$$\mathbb{1}(Secured)_{i,t} = \beta FinTech_i \times Post_t + \delta Post_t + \alpha_i + \mu_{s,year} + \varepsilon_{i,t}. \quad (8)$$

where $Post_t$ is equal to one when $t \geq 0$, γ_i denotes firm fixed effects, $\mu_{s,year}$ denotes industry-year fixed effects, and $\mathbb{1}(Secured)_{i,t}$ indicates whether firm i takes a new secured loan in quarter t. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We retain outside loans originated between January 2014 and June 2019. Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 5

Testing the information channel

(a) Benchmark: Bank borrowers

	Existing Lenders (1)	New Lenders (2)	Local Lenders (3)	Distant Lenders (4)	Rated (5)	Unrated (6)
FinTech × Post	0.10**	0.02	0.25***	-0.04	0.09**	0.13***
	(0.04)	(0.06)	(0.06)	(0.06)	(0.04)	(0.03)
Post	-0.06*	0.04	-0.12***	0.07	-0.04*	-0.06***
	(0.03)	(0.04)	(0.04)	(0.05)	(0.03)	(0.02)
Firm-Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
N	218,484	218,484	218,484	218,484	78,939	126,856
R-sq	0.97	0.94	0.94	0.94	0.97	0.94

(b) Benchmark: Rejected borrowers

	Existing Lenders (1)	New Lenders (2)	Local Lenders (3)	Distant Lenders (4)	Rated (5)	Unrated (6)
Accepted × Post	0.07**	0.10**	0.13***	0.05	0.09***	0.04
	(0.03)	(0.05)	(0.04)	(0.05)	(0.04)	(0.03)
Post	-0.01	0.01	0.00	0.01	-0.00	0.01
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Firm-Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
N	316,275	316,275	316,275	316,275	140,884	151,812
R-sq	0.97	0.94	0.93	0.95	0.97	0.94

NOTE.—This table presents the estimation results of the following equation, using the 36-month window around the origination of the outside loan at $t = 0$:

$$\log(1 + y_{i,t}) = \beta FinTech_i \times Post_t + \delta Post_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t}. \tag{9}$$

where $Post_t$ is equal to one when $t \geq 0$. In column 1 (resp. 2), $y_{i,t}$ is equal to the total amount of bank loans issued by banks that have an above-median lending relationship with the firm (resp., below-median). The median length of bank-firm lending relationships is 5 years in our sample. In column 3 (resp. 4), $y_{i,t}$ is the total amount of outstanding loans from banks located in the same (resp. a different) county as firm i. In columns 5-6, $y_{i,t}$ is equal to the total amount of bank loans, and the regressions are run on subsamples of firms that are rated and unrated the year before the outside loan origination. An outside loan is a loan originated by a lender that has not previously extended credit to firm i. In Panel a, the benchmark group is bank borrowers, and in Panel b, it is rejected borrowers. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We retain outside loans originated between January 2014 and June 2019. Standard errors are clustered at the firm level. Coefficients are reported along with the standard errors (in parentheses). Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 6
Liquidity shocks and demand for FinTech loans

	All motives			Customer illiquidity	Other motives
	(1)	(2)	(3)	(4)	(5)
FinTech × Customer default$_q$	0.02**			0.02**	0.01
	(0.01)			(0.01)	(0.01)
Customer default$_q$	0.00			-0.00	-0.00
	(0.00)			(0.00)	(0.00)
FinTech × Customer default$_{q-1}$		0.02**			
		(0.01)			
Customer default$_{q-1}$		-0.00			
		(0.00)			
Customer default$_{\textit{Before q-2}}$			0.00		
			(0.00)		
FinTech × Customer default$_{\textit{Before q-2}}$			-0.00		
			(0.01)		
Firm FE	Y	Y	Y	Y	Y
Industry × Quarter FE	Y	Y	Y	Y	Y
N	184,690	176,295	151,110	184,690	184,690
R-sq	0.00	0.01	0.01	0.00	0.00

NOTE.—This table presents the estimation results of the following equation:

$$\mathbb{1}(Outside\ loan)_{i,q} = \beta X + \delta FinTech_i \times X + \alpha_i + \mu_{s,q} + \varepsilon_{i,q},$$

where $\mathbb{1}(Outside\ loan)_{i,q}$ is a dummy equal to one if firm i takes a loan at time q, $FinTech_i$ is equal to one if the firm borrows from a FinTech platform, α_i denotes firm fixed effects, and $\mu_{s,q}$ denotes industry (s) × quarter (q) fixed effects. In column 1 (2), X is equal to $Customer\ default_{i,q}$ ($Customer\ default_{i,q-1}$), a dummy equal to one if at least one of the customers of firm i defaults on a trade bill in the quarter of the loan origination q (one quarter before the outside loan origination $q-1$). In column 3, X is equal to $Customer\ default_{Before\ q-2}$, a dummy equal to one if at least one of the customers of firm i defaults on a trade bill between times $q-4$ and $q-2$, but not at $q-1$ or q. In column 4 (5), X is equal to a dummy equal to one if at least one of the customers of firm i defaults on a trade bill default at time q due to illiquidity (due to motives not related to illiquidity –, e.g., omission, disagreement, or insolvency). An outside loan is a loan originated by a lender that has not previously extended credit to firm i. Data on trade credit default come from the CIPE dataset. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We retain outside loans originated between January 2014 and June 2019 and customer defaults between 2014 and 2020. Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 7
Other firm outcomes

(a) Benchmark: Bank borrowers

	Assets (1)	Tangible assets (2)	Employment (3)	Working capital (4)	WC: Payables (5)	WC: Others (6)
FinTech × Post	-0.011	-0.063	-0.036	0.016	-0.026**	-0.006
	(0.027)	(0.057)	(0.028)	(0.012)	(0.011)	(0.018)
Post	0.048***	0.128***	0.009	0.004	-0.012	-0.008
	(0.017)	(0.035)	(0.019)	(0.009)	(0.009)	(0.014)
Firm FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
N	15,619	15,619	15,182	12,428	12,424	12,429
R-sq	0.97	0.97	0.97	0.90	0.86	0.87

(b) Benchmark: Rejected borrowers

	Assets (1)	Tangible assets (2)	Employment (3)	Working capital (4)	WC: Payables (5)	WC: Others (6)
Accepted × Post	0.142***	0.137***	0.092***	0.021*	-0.023***	0.000
	(0.025)	(0.037)	(0.031)	(0.012)	(0.008)	(0.014)
Post	-0.031*	-0.061**	-0.037*	0.014	0.004	0.024*
	(0.017)	(0.028)	(0.021)	(0.010)	(0.007)	(0.013)
Firm FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
N	25,009	25,009	24,427	19,497	19,497	19,502
R-sq	0.99	0.98	0.97	0.89	0.88	0.90

NOTE.—This table presents the results of the estimation of

$$y_{i,t} = \beta FinTech_i \times Post_t + \delta Post_t + \alpha_i + \mu_{s,t} + \varepsilon_{i,t}. \tag{10}$$

where $Post_t$ is equal to one when $t \geq 0$ and $y_{i,t}$ is the outcome variable of i in year t (relative to the origination of the outside loan). The outcome variables are the log of one plus total assets (col. 1), log of one plus tangible assets (col. 2), log of one plus employment (col. 3), log of one plus employment, working capital/total assets (col. 4), accounts payable/total assets (col. 5), and other working capital/total assets (col. 6). In Panel a, the benchmark group is bank borrowers, and in Panel b, it is rejected borrowers. Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We include annual firm-level observations in the nine-year window around loan origination (four years before, four years after). Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 8
Propensity to default and credit rating

(a) Benchmark: Bank borrowers

	$\mathbb{1}$(Default)		Rating		$\mathbb{1}$(Rated)	
	(1)	(2)	(3)	(4)	(5)	(6)
FinTech × Post	0.048***	0.029**	0.414***	0.389**	0.041*	0.009
	(0.010)	(0.012)	(0.129)	(0.161)	(0.022)	(0.035)
FinTech × Post × High rate		0.041**		0.057		0.059
		(0.020)		(0.269)		(0.046)
High rate × Post		0.021*		0.160		-0.011
		(0.011)		(0.159)		(0.030)
Post	-0.014**	-0.025***	-0.103	-0.167	0.069***	0.075***
	(0.006)	(0.008)	(0.082)	(0.105)	(0.015)	(0.026)
Firm FE	Y	Y	Y	Y	Y	Y
Industry-Quarter FE	Y	Y	Y	Y	Y	Y
N	147,336	147,336	56,582	56,582	90,690	90,690
R-sq	0.49	0.49	0.71	0.71	0.42	0.42

(b) Benchmark: Rejected borrowers

	$\mathbb{1}$(Default)	Rating	$\mathbb{1}$(Rated)
	(1)	(2)	(3)
Accepted × Post	-0.062***	-0.358***	-0.013
	(0.011)	(0.108)	(0.021)
Post	0.060***	0.447***	0.129***
	(0.007)	(0.078)	(0.015)
Firm FE	Y	Y	Y
Industry-Quarter FE	Y	Y	Y
N	203,216	94,545	108,530
R-sq	0.54	0.71	0.44

NOTE.— This table presents the results of the estimation of

$$y_{i,t} = \beta FinTech_i \times Post_t + \delta Post_t + \alpha_i + \mu_{s,t} + \varepsilon_{i,t}$$

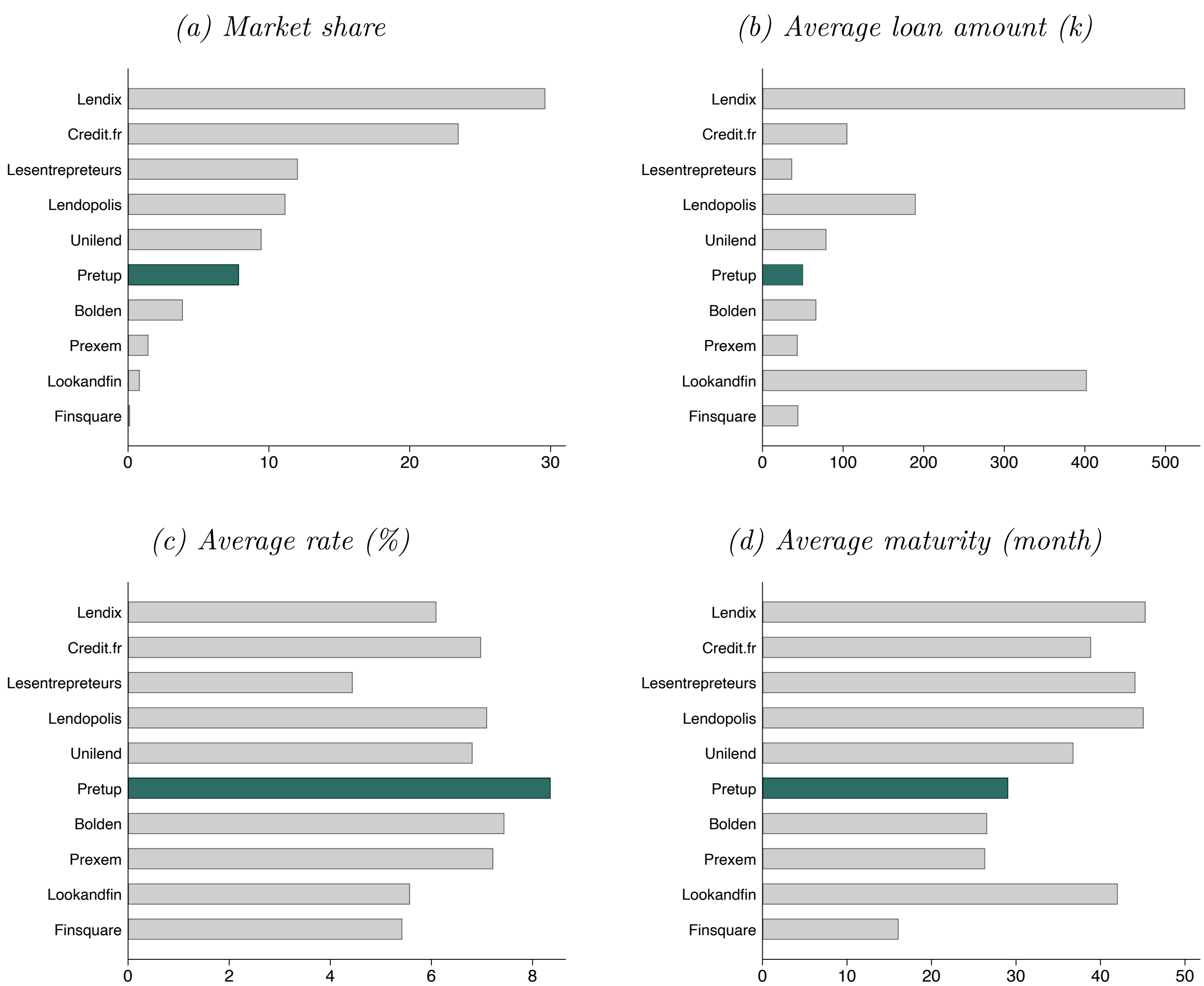
where y can be $\mathbb{1}(Default)$, *Rating* or $\mathbb{1}(Rated)$. The former is a dummy variable indicating whether firm i enters a liquidation or bankruptcy procedure at time t; *Rating* is the credit rating of firm i in quarter t (conditional on the firm being rated before the outside loan origination), and $\mathbb{1}(Rated)$ is an indicator variable that equals one if the firm becomes rated conditional on being unrated before the outside loan. *High rate* is equal to one when the FinTech (bank) loan rate is higher than the median FinTech (bank) loan. $Post_t$ is equal to one when $t \geq 0$. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We include annual firm-level observations in the nine-year window around loan origination (four years before, four years after). Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

The Role of FinTech in Small Business Lending

Online Appendix

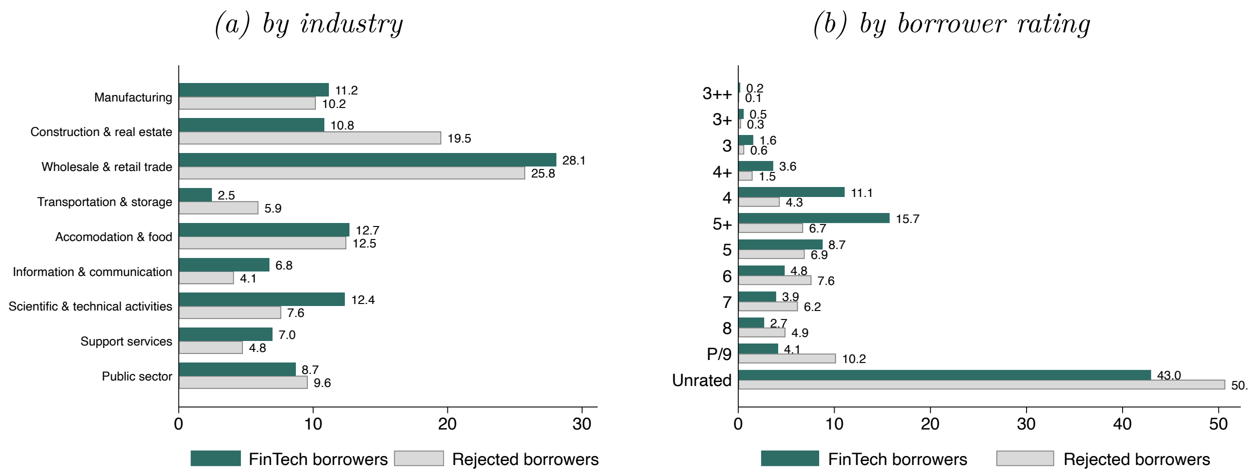
I Additional Figures

FIGURE A.1
Pretup versus other platforms



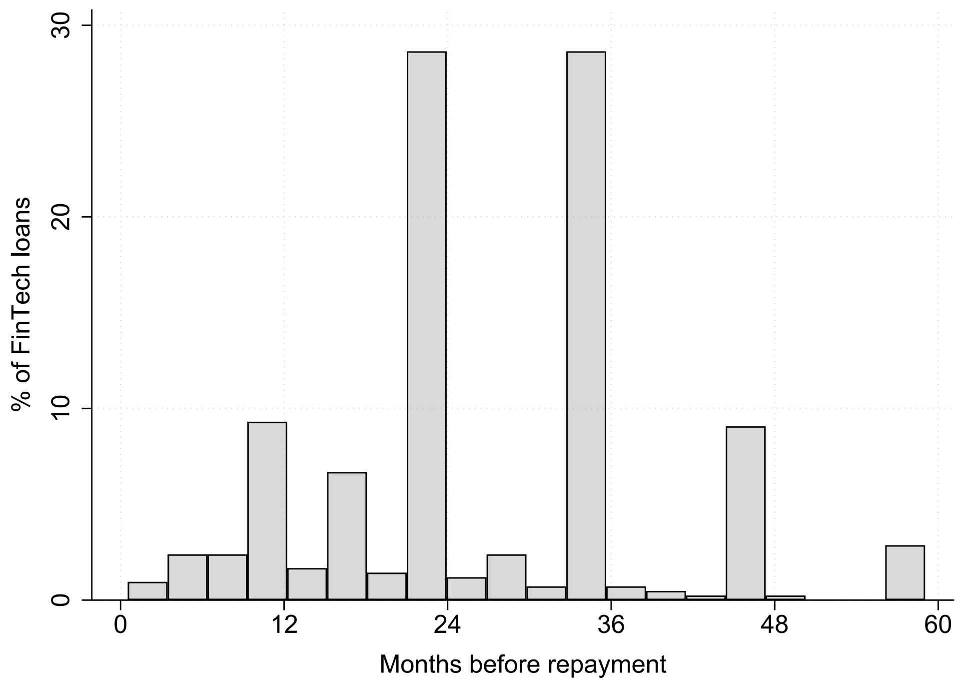
NOTE.—This figure presents the market share, average loan amount, interest rates and maturity of loans of the 10 FinTech platforms in our sample. We only include Fintech and bank loans originated between January 2016 and June 2019.

FIGURE A.2
FinTech and rejected borrowers composition



NOTE.—This figure presents the breakdown (%) of loans by firm industry (Panel a) and firm credit rating (Panel b). In both panels, green (white) bars represent the breakdown for FinTech (rejected) borrowers. The list of rejected firms is provided by PretUp. Data on firm characteristics come from FIBEN and Orbis. We only keep FinTech and bank loans originated between January 2016 and June 2019.

FIGURE A.3
Realized maturity of FinTech loans



Note.—This figure shows the distribution of FinTech loans by the number of months it takes for the loan to be fully repaid. We exclude loans that are defaulted upon. We only include loans originated after 2016 and that matured before 2019 (that is, for which we observe the full repayment schedule). Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset.

II Additional Tables

TABLE B.1

Comparing FinTech borrowers and benchmark firms - Before matching

(a) Benchmark: Bank borrowers

	(a) FinTech (1)	(b) Bank (2)	(a)-(b) (3)	t-statistic (4)	(a) Count (5)	(b) Count (6)
Rating	9.636	9.919	−0.283	−2.164**	1,078	6,042
Tangible assets	0.232	0.289	−0.057	−6.167***	755	3,229
Employment	2.741	2.762	−0.021	−0.405	508	2,189
Debt	0.693	0.665	0.028	2.638***	688	2,705
Investment	0.470	0.639	−0.169	−0.628	666	2,852
EBIT	0.057	0.060	−0.003	−0.679	676	2,633
Working capital	0.255	0.262	−0.007	−0.782	641	2,558
Age	13.662	14.031	−0.369	−0.919	1,071	5,947
Total Assets	7.332	7.247	0.085	1.483	755	3,229
Outside loan	148.448	299.169	−150.721	−1.451	1,078	6,042
𝟙(Credit line)	0.842	0.553	0.289	18.230***	1,078	6,042
N	1,078	6,042	7,120	7,120	1,078	6,042

(b) Benchmark: Rejected FinTech applicants

	(a) Accepted (1)	(b) Rejected (2)	(a)-(b) (3)	t-statistic (4)	(a) Count (5)	(b) Count (6)
Rating	9.636	10.888	−1.251	−12.039***	1,078	6,181
Tangible assets	0.232	0.241	−0.009	−0.979	755	2,307
Employment	2.741	2.745	−0.004	−0.072	508	1,501
Debt	0.693	0.787	−0.094	−8.057***	688	1,932
Investment	0.470	1.048	−0.578	−0.818	666	1,870
EBIT	0.057	0.016	0.042	6.717***	676	1,986
Working capital	0.255	0.239	0.016	1.609	641	1,839
Age	13.662	10.647	3.015	8.286***	1,071	6,152
Total Assets	7.332	6.978	0.354	5.252***	755	2,307
𝟙(Credit line)	0.828	0.794	0.035	2.621**	1,078	6,181
N	1,078	6,181	7,259	7,259	1,078	6,181

NOTE.—This table compares the characteristics of FinTech borrowers and two benchmark groups of borrowers before the matching. Panel a (resp., panel b) presents the t-test result of the differences in various variables between FinTech and bank borrowers (resp., between FinTech borrowers and rejected borrowers). *Rating* is the numerical equivalent of the Bank of France rating (1 for the best rating, 12 for the worse rating, 13 if the firm is unrated - see Table B.3). *Total Assets* and *Employment* are measured in logarithm. *Tangible assets*, *Debt*, *EBIT*, *Investment*, *Working capital* are normalized by total assets. *Age* is measured in years. 𝟙(*Credit line*) indicates whether the firm has a line of credit before the outside loan origination. *Outside loan* is the log amount of the outside loan. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. We only keep outside loans originated between January 2016 and June 2019.

TABLE B.2
Comparing FinTech borrowers and benchmark firms - After matching

(a) Benchmark: Bank borrowers

	(a) FinTech (1)	(b) Bank (2)	(a)-(b) (3)	t-statistic (4)	(a) Count (5)	(b) Count (6)
Rating	9.874	9.900	−0.027	−0.271	3,405	3,405
Tangible assets	0.240	0.239	0.001	0.190	2,125	2,150
Employment	2.409	2.378	0.032	0.953	1,305	1,290
Debt	0.670	0.660	0.010	1.247	1,935	1,974
Investment	0.761	0.844	−0.083	−0.318	1,835	1,811
EBIT	0.065	0.066	−0.001	−0.354	1,870	1,898
Working capital	0.271	0.272	−0.000	−0.056	1,755	1,678
Age	12.592	12.776	−0.184	−0.687	3,405	3,405
Total Assets	6.950	6.901	0.050	1.452	2,125	2,150
Outside loan	97.211	93.443	3.768	0.902	3,405	3,405
$\mathbb{1}$(Credit line)	0.806	0.806	−0.000	−0.031	3,405	3,405
N	3,405	3,405	6,810	6,810	3,405	3,405

(b) Benchmark: Rejected FinTech applicants

	(a) Accepted (1)	(b) Rejected (2)	(a)-(b) (3)	t-statistic (4)	(a) Count (5)	(b) Count (6)
Rating	9.815	9.947	−0.133	−1.803	4,800	4,800
Tangible assets	0.235	0.226	0.009	1.700	3,295	3,268
Employment	2.740	2.748	−0.008	−0.240	2,280	2,150
Debt	0.702	0.684	0.018	2.701**	3,040	3,012
Investment	0.324	0.407	−0.083	−1.071	2,915	2,696
EBIT	0.055	0.053	0.002	0.815	2,990	2,984
Working capital	0.250	0.266	−0.016	−2.743**	2,835	2,735
Age	13.520	13.645	−0.125	−0.513	4,800	4,800
Total Assets	7.323	7.303	0.019	0.534	3,295	3,268
$\mathbb{1}$(Credit line)	0.828	0.811	0.017	2.125*	4,800	4,800
N	4,800	4,800	9,600	9,600	4,800	4,800

NOTE.—This table compares the characteristics of FinTech borrowers and two benchmark groups of borrowers after the matching. Panel a (resp., panel b) presents the t-test result of the differences in various variables between FinTech and bank borrowers (resp., between FinTech borrowers and rejected borrowers). *Rating* is the numerical equivalent of the Bank of France rating (1 for the best rating, 12 for the worse rating, 13 if the firm is unrated - see Table B.3). *Total Assets* and *Employment* are measured in logarithm. *Tangible assets*, *Debt*, *EBIT*, *Investment*, *Working capital* are normalized by total assets. *Age* is measured in years. $\mathbb{1}$(*Credit line*) indicates whether the firm has a line of credit before the outside loan origination. *Outside loan* is the log amount of the outside loan. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. We only keep outside loans originated between January 2016 and June 2019.

TABLE B.3

FIBEN credit rating and firm size categories

(a) Firm size

Size category	Definition
1 Micro enterprises	The firms with less than 10 employees, that do not belong to a group and for which the revenue or the total asset do not exceed 2 million euros
2 Very small enterprises	The firms with less than 19 employees (so overlap with micro), that are neither one-person firm nor under the fiscal regime of a micro-enterprise and with less than 10 million euros in total assets.
3 Small enterprises	The firms with employees between 20 and 49 and less than 10 million euros of total assets.
4 Medium sized enterprises	The firms with employees between 50 and 249 and less than 43 million euros of total assets.
5 Large enterprises	The firms with more than 249 employees or more than 43 million euros of total assets.

(b) Credit rating

Credit score	Definition	Prob. of default	Coded as
3++	The company's ability to meet its financial commitments is deemed excellent.	0.04%	1
3+	The company's ability to meet its financial commitments is deemed very good.	0.08%	2
3	The company's ability to meet its financial commitments is deemed good.	0.16%	3
4+	The company's ability to meet its financial commitments is deemed to be quite good given the absence of major financial imbalances. There are, however, moderate factors of uncertainty or fragility.	0.52%	4
4	The company's ability to meet its financial commitments is deemed fair given the absence of financial imbalances. There are, however, moderate factors of uncertainty or fragility.	1.37%	5
5+	The company's ability to meet its financial commitments is deemed to be fairly good.	3.46%	6
5	The company's ability to meet its financial commitments is deemed to be poor.	8.18%	7
6	The company's ability to meet its financial commitments is deemed to be very poor.	12.42%	8
7	The company's ability to meet its commitments is cause for concern. At least one reported trade bill payment incident.	25.95%	9
8	The company's ability to meet its financial commitments is at risk given the trade bill payment incidents reported.	33.50%	10
9	The company's ability to meet its financial commitments is compromised as the reported trade bill payment incidents point to severe cash flow problems.	41.80%	11
P	The company is the subject of insolvency proceedings (recovery or judicial liquidation proceedings).	-	12
0	The firm is not rated by Banque de France.	-	13

Notes: This table describes the credit score (Panel a) and firm size categories (Panel b) as defined by Banque de France. In Panel a, we also report the predicted probability of default over a three-year horizon 2017-19 that is associated with credit score category. The last column shows how the ratings are coded as integers.

TABLE B.4
Matching Procedure - Robustness Checks

(a) Benchmark: Bank borrowers

	Unmatched	PSM no rep.	PSM with rep.	Five-nearest neighbor matching			Excl. Lendix & Lookandfin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FinTech × Post	0.12***	0.09***	0.06**	0.08***	0.14***	0.15***	0.07***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
Post	-0.02***	-0.03	-0.00	-0.01	-0.04*	-0.04**	-0.01
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Firm-Year FE	Y	Y	Y	Y	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	N	N	N	Y	Y	N
Industry-, Rating-, County-Year FE	N	N	N	N	N	Y	N
N	213,551	43,382	43,672	218,484	218,573	218,573	197,824
R-sq	0.97	0.96	0.95	0.96	0.89	0.89	0.96

(b) Benchmark: Rejected borrowers

	Unmatched	PSM no rep.	PSM with rep.	Five-nearest neighbor matching			Excl. Lendix & Lookandfin
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FinTech × Post	0.10***	0.07***	0.06**	0.07***	0.16***	0.13***	0.07***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
Post	0.00	-0.00	0.01	0.00	-0.03	-0.02	0.00
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Firm-Year FE	Y	Y	Y	Y	N	N	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Firm FE	N	N	N	N	Y	Y	N
Industry-, Rating-, County-Year FE	N	N	N	N	N	Y	N
N	237,684	63,066	63,426	316,275	316,426	316,426	279,880
R-sq	0.96	0.96	0.97	0.96	0.91	0.91	0.96

NOTE.—This table shows the results of the baseline DiD regressions on different samples. Column 1 is based on the unmatched sample. In columns 2 to 5, results are based on the matched samples using alternative propensity score matching specifications: PSM without replacement, PSM with replacement, and PSM with k-nearest neighbor ($k = 5$). In columns 5 and 6, we replace firm×year fixed effects with firm fixed effects and industry-, location-, rating- × year fixed effects, respectively. In column 7, we exclude FinTech loans from two platforms, Lendix and Lookandfin and repeat the matching. The number of unique firms is reported at the bottom of the table. Data on bank loans come from the M-Contran survey. Data on Fintech loans come from the Banque de France Fintech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We only include bank and Fintech loans originated between January 2016 and June 2019. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE B.5

Fraction of loans secured by assets

Loan category	% of loan volume	% of loan secured (volume)
Line of credit	2.52%	27.79%
Long-term loans	93.98%	40.65%
Other loans	3.50%	28.18%
Overall	100%	39.89%

Notes: This table shows the repartition of loan volume by credit category and the fraction of secured loan (in terms of loan volume) within each category. All numbers are calculated based on the loans originated between 2014-2019 in the M-Contran database.

TABLE B.6
Description of variables

Variables	Description
Borrower type:	
$FinTech_i$	Dummy variable that is equal to one if the outside loan taken by firm i is issued by a FinTech platform, 0 if it is issued by a bank.
$Post_t$	Dummy variable that is equal to one for any period t (month, quarter, or year) after the origination of the outside loan.
Credit variables:	
$Total\ loans_{i,t}$	Total amount of bank credit firm i has at time t (excluding the outside loan).
$Line\ of\ Credit_{i,t}$	Drawn overdraft facilities (excluding the outside loan).
$Long\text{-}term\ loans_{i,t}$	Long-term loans, with a maturity longer than one year (excluding the outside loan).
$Other\ loans_{i,t}$	Loans other than drawn credit lines or long-term loans (excluding the outside loan).
$\mathbb{1}(Secured)_{i,t}$	Dummy variable that equals to one if the bank loan i obtained in quarter t is secured.
$Investment\ loan_i$	Dummy variable that equals to one if the bank or FinTech loan obtained by firm i at time $t = 0$ is used to finance the acquisition of new assets.
$Total\ loans\ from\ new\ lenders_{i,t}$	Total loans granted to firm i observed at time t from banks that have a shoter-than-median length of relationship with firm i.
$Total\ loans\ from\ existing\ lenders_{i,t}$	Total loans granted to firm i observed at time t from banks that have a longer-than-median length of relationship with firm i.
$Total\ loans\ from\ local\ lenders_{i,t}$	Total loans granted to firm i observed at time t from banks that are located in the same county (département) as firm i.
$Total\ loans\ from\ distant\ lenders_{i,t}$	Total loans granted to firm i observed at time t from banks that are located in a different county (département) as firm i.
$\mathbb{1}(Credit\ line)_{i,t}$	Dummy variable that equals to one if firm i has an open bank line of credit at time t.
Balance sheet, profit & loss statements:	
$Total\ assets_{i,t}$	Logarithm of the total assets of the firm i at time t.
$Age_{i,t}$	Age in months of the firm i at time t.
$Working\ capital_{i,t}$	Ratio of working capital to lagged total assets of the firm i at time t.
$Accounts\ payable_{i,t}$	Ratio of account payable to lagged total assets of the firm i at time t.
$Other\ working\ capital_{i,t}$	Ratio of the sum of working capital and account payable to lagged total assets of the firm i at time t.
$EBIT_{i,t}$	Ratio of earnings before interests and taxes to lagged total assets of the firm i at time t.
$Investment_{i,t}$	Growth of fixed assets of the firm i between time t and $t-1$, normalized by lagged total assets.
$Leverage_{i,t}$	Ratio of total assets less equity to lagged total assets of the firm i at time t.
$Employment_{i,t}$	Logarithm of number of employees of the firm i at time t.
$Tangible\ assets_{i,t}$	Ratio of fixed assets to lagged total assets of the firm i at time t.
Customer defaults:	
$Customer\ default_{i,q}$	Dummy variable that indicates that firm i experiences at least one customer defaults at quarter q, when the outside loan is originated.
$Customer\ default_{i,q-1}$	Dummy variable that indicates that firm i experiences at least one customer defaults at quarter $q-1$, one quarter before the outside loan is originated.
$Customer\ default_{i,Before\ q-2}$	Dummy variable that takes the value one if firm i has experienced at least one customer default more than two quarters ago before the origination of the outside loan, but no customer defaults in the two quarters preceding the loan origination.
Defaults and rating:	
$Default_{i,q}$	Dummy variable that indicates whether firm i has entered a liquidation or bankruptcy procedure in quarter q.
$Rating_{i,t}$	Credit rating of the firm i at time t issued by Banque de France.
$\mathbb{1}(Rated)_{i,t}$	Dummy variable that equals to one if the Banque de France is rating the firm i at time t.