The Role of FinTech in Small Business Lending*

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Abstract

What is the role of FinTech lenders in small business lending markets? Using French administrative data, we show that, relative to similar firms taking new bank loans, SMEs that take a FinTech loan experience a 20% increase in bank credit after obtaining the new loan. The effect is more pronounced for low-collateral firms and when the FinTech loan finances the acquisition of tangible assets. This is consistent with firms using uncollateralized FinTech loans to acquire assets that they can then pledge to obtain bank loans. We also find evidence that firms use FinTech loans to meet urgent liquidity needs. In contrast, we find no evidence of a superior screening ability of FinTech lenders.

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1 Introduction

Financing is crucial for small business growth, yet small and medium-sized enterprises (SMEs) routinely report difficulty accessing credit. Since the 2008 financial crisis, increased regulatory burden and stricter scrutiny on bank lending have further exacerbated credit constraints of small businesses (Buchak et al., 2018; Cortés et al., 2020; Gopal and Schnabl, 2020) and hindered firm growth (Bord, Ivashina and Taliaferro, 2015; Chen, Hanson and Stein, 2017). In contrast, peer-to-peer FinTech lending platforms have been rapidly growing, thereby partially filling in the gap left by banks.[1] The development of FinTech platforms has been generally encouraged by regulators, with various regulatory measures being taken to scale up this market for its potential positive impact on SMEs and job creations.[2] Yet, despite the expansion of FinTech small business lending and regulatory efforts to facilitate its development, very little is known about the role FinTech lenders play in the access of SMEs to financing. Are FinTech platforms merely substituting banks, or do they have a comparative advantage over traditional banks? Understanding whether, and how, FinTech lenders differ from banks would help us better understand the implications of the arrival of new entrants for SMEs and the small business lending markets.

This paper identifies the comparative advantage of FinTech platforms over banks. FinTech platforms offer a new way of financing SMEs by matching firms and individual lenders. Platforms screen borrowers and pre-select loan applications, which are then submitted to lenders who decide to lend or not fund the projects.[3] This business model can offer two types of advantages over banks: technological and regulatory. The first potential source of technological advantage comes from the implementation of streamlined and semi-automated

[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] The EU commission's action plan on FinTech explicitly mentions job creations as a motive for fostering the growth of FinTech lenders (link). In light of the recent Pandemic of COVID-19, the French government unprecedentedly provides guarantees for new loans originated by crowd-funding intermediaries (link).

[3] While this system could lead some projects to be unfunded if not enough individual lenders decide to finance the project, most FinTech platforms currently 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 point of view, the screening is therefore carried out by the platform, not individual lenders.

screening processes, which allow FinTech platforms to make quicker decisions (*speed*). The second source of technological advantage could be the superior screening ability (*information*). One of the main promises of FinTech platforms is their reliance on new technologies (e.g., machine learning, big data) to better screen firms and therefore lend to profitable firms neglected by banks. In terms of regulatory advantage, compared to banks, FinTech platforms are subject to less stringent regulations because they do not take deposits. This explains why, unlike most traditional banks, FinTech platforms can offer non-collateralized loans to SMEs (*collateral*). According to the US Federal Reserve's Small Business Credit Survey (2019), SMEs understand these three advantages, with firms mentioning the fast application and funding processes, the high chance of getting funded, and the absence of required collateral as main reasons for applying to a FinTech lender.

To formally investigate the existence of these comparative advantages and their role in driving FinTech borrowing, we exploit the fact that these different hypotheses yield distinct testable predictions on banks' reaction to the approval of a new FinTech loan and the probability of default of FinTech borrowers. We find strong evidence for the collateral hypothesis. Total bank credit increases by 20% more for firms taking a new FinTech loan than for similar firms taking a new *bank loan*. This effect is smaller when the new *bank loan* is uncollateralized (as most FinTech loans) and is more pronounced for low-collateral firms and loans used to finance the acquisition of tangible assets. This is in line with the idea that compared to uncollateralized FinTech loans, collateralized bank loans are more likely to encumber assets, and therefore constrain future borrowing and investment (Donaldson, Gromb and Piacentino, 2019). We also find evidence supporting the speed hypothesis. However, we show that this channel alone cannot explain the increase in bank credit obtained by firms following a FinTech loan. In contrast, our results are inconsistent with the information hypothesis, suggesting that FinTech platforms' comparative advantage does not hinge on a superior screening ability. This paper, therefore, contributes to the existing literature investigating the determinants of the growth of FinTech lenders (e.g., Buchak et al., 2018) by documenting the role of FinTech lending in SMEs' access to financing and economic mechanisms at the micro-level.

We combine administrative data on FinTech loans, bank loans, trade credit, and firm characteristics to confront the different hypotheses to the data. Our data is unique in two ways. First, we observe the near-universe of bank loans and FinTech loans to SMEs along with a rich array of loan characteristics (e.g., collateralized or not, maturity, interest rate).[4] The quasi-exhaustive nature of the data allows us to investigate which type of firms borrow from FinTech platforms and why. Second, for one major lending platform in the sample, we observe all *rejected* applicants. This allows us to construct a potential benchmark group for FinTech borrowers when studying the impact of obtaining a FinTech loan.

The 12 FinTech platforms in our sample facilitated 2,897 projects by 2,283 unique firms for a total amount of 486 million euros between January 2014 and December 2019. We find that most FinTech borrowers have little or no credit history with banks (e.g., are unrated). Compared to bank loans originated during the same period, FinTech loans feature a shorter maturity (by two years on average) and a much larger interest rate inclusive of fees (+5.5 p.p.). The latter differences persist even if we control for observable loan characteristics or firm characteristics. While differences in costs in themselves do not inform us of the comparative advantage of FinTech platforms, they suggest that FinTech lending plays a distinct role from banks in the financing of SMEs.

To better understand whether FinTech lending improves firms' access to credit, we construct a matched sample of FinTech firms and comparable bank borrowers using a propensity score matching. We match borrowers based on recent credit dynamics, the size and date of the new loan, as well as a rich array of firm characteristics (e.g., rating, industry, size, and tangible assets). The propensity score matching allows us to plausibly control for time-varying differences in demand for credit. Our central result is that, compared to similar firms taking a bank loan from a *new* lender around the same date, firms that take a FinTech loan experience a 20% increase in bank credit following the new loan. The gap appears gradually over the first six months after the origination of the new loan and stays constant in the subsequnt 18 months. We refer to the new bank and FinTech loans taken by matched bank borrowers and FinTech borrowers as "new loans" throughout.[5] To further substantiate

[4]Our sample of FinTech loans represent over 82% of market, based on our own calculation using our FinTech loan sample and a portal website on FinTech loans *TousNosProjets*, provided by BPI (*Banque publique d'investissement*, the French Public Investment Bank).

[5]We exclude the new loan from the computation of bank credit. See Degryse, Ioannidou and von Schedvin (2016) for a similar setting.

this result, we construct an altnernative benchmark group that consists of rejected FinTech applicants. Our previous observation still hold. The magnitude of the increase in bank credit for FinTech borrowers is similar using either bank borrowers or rejected FinTech applicants as the benchmark group. In the following analysis, we use the bank borrowers as the main benchmark group.

Next, we try to shed light on why obtaining a FinTech loan leads to an increase in bank credit. The observed increase in bank credit could be explained by all the three different sources of comparative advantages of FinTech platforms, however, the mechanisms would be different. 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 new bank loan obtained with a lag. Under the *information* hypothesis, a successful FinTech loan application could serve as a positive signal for firm quality, prompting banks to lend more to FinTech borrowers. Under the *collateral* hypothesis, uncollateralized FinTech loans could allow firms to invest in new assets without posting collateral or personal guarantees, thereby expanding firms' borrowing capacity.

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 short-term loans (drawn credit lines) and no effect on leasing loans. The absence of effects on leasing loans is consistent with the collateral hypothesis, as leasing loans are by definition self-collateralized and should therefore not be affected by a change of the amount of pledgeable assets of the firm. The increase is also particularly strong for loans issued by banks from which firms were already borrowing (existing banks). This result suggests that the information hypothesis is not the main force at play since existing banks are likely to be already informed about the quality of borrowers through their repeated interactions with them (Diamond, 1991).

We then look at which types of *new loans* are driving the increase in bank credit. Our unique data set allows us to observe whether the new bank and FinTech loans are used to finance the acquisition of tangible assets.[6] Under the collateral hypothesis, we expect the relative increase in bank loans to be more pronounced when new loans are used to finance

[6] 21.5% of FinTech loans and 41.4% of bank loans are used to finance tangible assets.

tangible assets. This is because acquiring new assets through uncollateralized FinTech loans should expand firms' subsequent borrowing capacity more than through collateralized bank loans. Our results are in line with this hypothesis, with a positive and significant increase in bank loans when the FinTech loans are used to finance investments. In contrast, we found a precisely estimated zero change in bank credit when the new loans are not for investments.

Lastly, we identify for which types of *firms* the increase in bank credit is more pronounced. Under the collateral hypothesis, we expect the increase in bank credit to be larger for firms with less collateral, for whom collateral constraints are more likely to be binding. Our results support this hypothesis, with the credit expansion three times as large for low-collateral firms than for high-collateral ones (the effect being non-significant for the latter). Under the information hypothesis, we expect the increase in bank credit to be concentrated among firms with a thin credit history because banks should react more to information on opaque borrowers. We find the opposite pattern: the growth in bank credit is concentrated among rated borrowers. Lastly, the speed hypothesis predicts that the increase in bank credit is driven by FinTech borrowers that repay their FinTech loans early using cheaper bank loans. However, only five FinTech borrowers repay within the first six months of the loan, and only 11 firms take out a FinTech loan with a maturity equal to or shorter than six months in the full sample. Removing these firms from the analysis does not change the results.

We perform two additional tests to assess the role of collateral, speed, and information in the data. We first look at the ex-post probability of default. Under the collateral hypothesis, if collateral constraints imposed by banks effectively prevent firms from overborrowing, we should find that FinTech borrowers are more likely to default ex-post, as getting access to uncollateralized loans should lead some firms to reach unsustainable levels of leverage. Our results support this hypothesis, with FinTech borrowers 0.4 p.p. more likely than bank borrowers to enter a bankruptcy procedure in the two years following the new loan. By contrast, this evidence is difficult to reconcile with a superior screening ability of FinTech platforms. If FinTech platforms were able to identify creditworthy borrowers neglected by banks, we should observe similar or even lower default rates for FinTech borrowers than for bank borrowers in the matched sample (Balyuk, 2019; Chava et al., 2021).

Second, we test the speed hypothesis by determining whether, compared to bank borrowers, FinTech borrowers are systematically more likely to have recently experienced 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 p.p. more likely to borrow from a FinTech platform 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. The effect is also more pronounced for unexpected customer defaults than for predictable defaults resulting from trade disagreements between the customer and the supplier. Overall, these results suggest firms borrow from FinTech lenders rather than banks when facing urgent liquidity needs, but this channel alone cannot explain the cross-section of results described before.

Our results have important policy implications. While we find that the emergence of FinTech platforms improves SMEs' access to financing, we also find higher default rates among FinTech borrowers, alluding to the cost of relaxing firms' collateral constraints. This suggests that the long-term prospects of Fintech platforms will depend on whether the higher rate of defaults is sustainable for FinTech lenders and whether the negative externalities on bank lenders of FinTech borrowers are considered acceptable by regulators.

Literature Our paper exploits data on the near-universe of FinTech and bank loans to investigate the role of FinTech lenders in the small business lending market. The richness of our data allows us to uncover the mechanisms through which FinTech credit impact firms' access to financing. More generally, this paper contributes to a growing literature on the determinants of the growth of FinTech lending and its implications for credit markets.

A few studies explore the role of regulation in the growth of FinTech lending in mortgage markets and collateralized small business loan markets (see Buchak et al., 2018; Gopal and Schnabl, 2020, for example). In particular, Gopal and Schnabl (2020) find that non-bank and FinTech lenders substitute for banks in supplying collateralized loans as a result of the tightening of banking regulations following the Great Recession. In contrast with previous studies, we show that the regulatory advantage of FinTech companies can lead to a *comple-*

mentarity between FinTech and bank credit. Unlike Gopal and Schnabl (2020) which focuses exclusively on the collateralized business loan markets, we observe all types of bank loans to firms. This key aspect of the data allows us to investigate FinTech platforms' impact on firms' credit dynamics.

The second stream of work focuses on information production by FinTech lenders and investors, mostly in consumer credit markets. Some argue that FinTech lenders improve capital allocation efficiency by exploiting and producing more information than traditional lenders (Balyuk, 2019; Balyuk, Berger and Hackney, 2020; Berg et al., 2020; Ghosh, Vallee and Zeng, 2021). Chava et al. (2021), in contrast, do not find that FinTech lenders enjoy an informational advantage in screening borrowers. Our paper adds to this body of research by showing that the rise of FinTech platforms in the French small business lending market cannot be attributed to a superior screening technology of FinTech lenders. We believe that our results are likely to apply more generally in markets where relationship lending is the primary mode of financing of SMEs (e.g., continental Europe), as banks are likely to be already well informed on their pool of borrowers.

There has also been some work 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 to meet borrowers' liquidity needs, our results indicate that a faster reactivity of FinTech platforms is unlikely to be the main driving force behind the growth of FinTech lenders.

Last, our paper also speaks to the literature on the competition between FinTech and bank lenders. Tang (2019) and Di Maggio and Yao (2020) 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 supply of FinTech credit in the US during the COVID-19 pandemic. Using a similar dataset to ours, Havrylchyk and Ardekani (2020) find that FinTech borrowers are more dynamic and innovative but have lower borrowing capacity than bank borrowers. 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 exposure to traditional banks and thereby limit bank rents. In contrast with those studies, our paper links the growth of FinTech platforms to product differentiation. We find that by supplying uncollateralized loans, FinTech platforms act rather as a complement than a substitute for bank loans.

The rest of the paper is organized as follows. Section 2 provides institutional details on the FinTech SME loan market in France. Section 3 describes our novel data sources. Section 4 provides a detailed description of FinTech loan and borrower characteristics, and Section 5 presents the empirical results based on the matched sample. Section 6 presents the different tests of the economic mechanisms leading to the increase in bank credit. 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 non-bank 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 investment amount per individual investor. Effectively, this loan size cap restricts the borrower pool, which motivates our focus on SMEs. By law, FinTech platforms can only originate loans used to finance specific projects (such as the purchase of fixed assets), which excludes the possibility of issuing working capital loans.[7]

The French FinTech lending market has been growing since its inception. As of 2020, there were 157 active FinTech platforms which collectively intermediated around €200 million. However, FinTech platforms still account for a limited fraction of the small business

[7]See article L548-1 of the Monetary and Financial Code (Code monétaire et financier).

lending market. Figure 1 shows the aggregate volume of loans under one million intermediated by banks and by FinTech platforms in our sample. We see that newly originated FinTech loans represent about 2% of similar-sized bank loans originated during the same period.

The application process is exclusively online. Borrowers have to meet some minimum requirements to apply, which vary between platforms. For example, firms have to be more than three years old or have more than €250,000 of 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 the 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 point of view, 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 short 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 which 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.[8] FinTech platforms can charge

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

additional fees to borrowers in case of late or early repayments. Importantly, no collateral or personal guarantees are required on these loans.

3 Data

We combine various databases using a unique firm identifier "SIREN". These databases provide firm-level information on FinTech loans, newly originated bank loans, credit history, financials, and bankruptcy status.

FinTech loans We rely on two main datasets for tracking FinTech loans. First, we use information retrieved by scraping Crowdlending.fr, a French website founded in late 2014 to help individual investors get information on FinTech loans. Since 2016, the website has been automatically 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 bonds financing to ensure that we only keep credit instruments comparable to bank loans.[9] We also remove one platform (Agrilend) that focuses on industries that exclusively finance agricultural firms. This dataset allows us to observe the main characteristics of the loan (e.g., interest rate, maturity, face value), some information on the fund collection process (rating given by the platform, duration of the collection process), as well as a dummy indicating whether the loan is being reimbursed, already reimbursed in full, or has been defaulted upon.

We complete this dataset with additional data collected by the Banque de France (the French central bank). The Banque de France collects monthly data on corporate 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 7 platforms.[10] These platforms facilitated 2,011 projects by 1,519 unique firms for a total amount of 304 million euros. The Banque de France dataset completes the information coming from Crowdlending.fr in three ways: (i) the Banque de France

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

[10]There were 10 platforms at the beginning of our sample period. During 2016-19, Prexem and PretGo were acquired by Happy Capital and Unilend by Pretup. In addition, Lendix changed its name to October.

dataset covers the full repayment history of individual loans (e.g., monthly loan balance), which allows us to observe the actual fraction of payment made by firms and early repayments; (ii) because information on interest rates and maturities is not always reported on the Crowdlending.fr, we use the information provided by the Banque de France by default; (iii) the Banque de France provides additional information on the purpose of the loan based on the text analysis of the description of projects published on the platforms' website.

We focus in the main analysis on the outcome of the merge of the two datasets. The final dataset has 2,283 firms and 2,897 loan applications for a total amount of 458 million euros. These loans represent over 80% of FinTech loans to SMEs in France as of 2020.[11] We drop loans originated after Jan 1, 2020, so that we focus on the period before the coronavirus crisis and have at least one year of observations for each firm after the origination of a FinTech loan. For firms borrowing multiple times from FinTech platforms, we only keep the first FinTech loan.

FinTech applicants Unlike most other work on FinTech small business loans that only observe approved applicants, our study exploits a unique dataset on rejected FinTech applicants. One of the 10 lenders in our sample share with us the unique identifier of firms that did not pass the platform's initial screening process as well as the date of the rejection. For each firm, we only consider the first rejected application. Using the firm identifier SIREN, we merge this dataset with our other data sources. In total, there are 31,292 rejected applicants over the sample period 2016/01-2019/12, among which we identify 12,880 rejected firms which have a presence in the credit registry that we describe below. We use this dataset to construct our alternative benchmark group for FinTech borrowers: rejected FinTech applicants.

Bank loans: M-Contran The second database provides information on a sample of new loans originated by banks in the first month of each quarter. Bank branches are selected within a rotating panel to form a representative sample of corporate loans. On average, there are about 100,000 new loans each period. We observe a wide range of characteristics for each

[11] We merge the two datasets on the platform and firm names as well as the origination date. We allow origination dates to differ by two months between the two websites.

loan, such as the loan amount, the loan type (e.g., revolving, overdraft), the loan purpose (e.g., investment, leases), maturity, and whether it is secured or not. As with FinTech loans, we only keep loans originated before Jan 1, 2019.

Credit registry The French credit registry contains monthly information on the near universe of bank loans to non-financial firms. Specifically, the dataset covers any firm with a credit exposure exceeding 25,000 euros to at least one bank. We observe both credit effectively extended to the firm and banks' credit commitments. Loan balance is reported by categories, such as long-term loans, credit lines, or leasing loans. In addition, we observe some firm characteristics, including industry, location, and internal firm size category. 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 every firm in the sample.

Firm characteristics: FIBEN and Orbis The third dataset, FIBEN, reports the credit score, accounting, and financial information for all companies with an annual turnover of over €750,000 for the period 2015-20. The Banque de France constructs the credit score to reflect a firm's ability to meet its financial commitments in a three-year horizon. This score incorporates information on firms' balance sheets, trade bill payment incidents, 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. Appendix B.1 presents a description of each credit score category and the associated expected default probabilities.

We collect annual accounting data for the period 2015-19. The FIBEN dataset covers a smaller set of firms than the credit registry because of 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' defaults of payment 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 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 main categories: disagreement, omission, illiquidity, or insolvency. Disagreement refers to the case where 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 the sufficient provision on its bank account to pay the bill on time and in totality; last, insolvency occurs when the customer has filed for bankruptcy or is being liquidated.

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 keep 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 our P2P borrowing firms are the party being defaulted upon (359 firms) and 15,197 payment incidents in which our P2P borrowing firms are the defaulter (906 firms).

We aggregate the daily payment incidents records at the quarterly frequency. For each firm in each quarter, we construct the following four variables: a dummy for whether the firm defaults on its payment, the total euro amount the firm fails to pay, a dummy for whether the firm has been defaulted upon, and the total euro amount of the defaults incurred by the firm.

Bankruptcy status: BODACC BODACC ("Bulletin officiel des annonces civiles et commerciales") provides information on firm bankruptcy status based on commercial and civil court legal announcements. This dataset records the firm's name, the date of the announcement, and the type of legal procedure. Out of 869 FinTech borrowers (in our matched sample as introduced in Section 5), we manually identify 70 firms that entered a bankruptcy procedure, and among those, 53 were liquidated. This represents 8% and 6%

of FinTech borrowers in the sample, respectively. In contrast, 2% of the 2,411 firms in the matched sample that take a new bank loan in the same period entered a bankruptcy procedure, and 2.3% have been liquidated.

Construction of the dataset 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 at least three consecutive months in the credit registry before taking an *outside loan*. An outside loan is a loan originated by a lender from which the firm was not previously in a lending relationship. A firm is either a *FinTech borrower* if the outside loan is a FinTech loan or a *bank borrower* if the firm borrows from a new bank. New FinTech loans are observed in the Banque de France/Crowdlending.fr dataset. New bank loans are observed in the M-Contran dataset.[12] We only keep 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. We drop firms in the agricultural, finance, utility, and public administration sectors. After these filters, we are left with 1,080 FinTech firms and 6,379 Bank firms. We then complete this data set with information coming from CIPE, Orbis/FIBEN, and BODACC.

4 Descriptive statistics

4.1 FinTech loans

We first provide summary statistics on FinTech loans and of credit dynamics of FinTech borrowers. Table 1 Panel A presents descriptive statistics on the 2,011 FinTech loans for which we have detailed information from Banque de France. The average loan size is about €150,000, and the median amount is €50,000. The average annual percentage rate (APR), including fees, is 7.8% with a large variation: the maximum interest rate is 16.8%.[13] Loan maturity ranges between 6 and 84 months with an average of 38 months.

[12]We exclude renegotiated loans to focus on newly originated loans. We also exclude loans originated by public or quasi-public banks or banks with stakes in FinTech platforms.

[13]We use the terms interest rate and APR interchangeably in the following.

On the investor side, a project is financed by 501 individual investors on average. Individual investors provide 87% of total financing, the remaining 13% being supplied by institutional investors (non-bank legal entities, such as the platforms themselves, or banks). Panel a of Figure 2 shows the number and amount of loans by loan purpose. The top three purposes for FinTech loans, in terms of number of loans in each category, are intangible investment (27%), commercial development (26.5%), and tangible investment (19.9%). The distribution looks similar when we look at the breakdown by loan volume.

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 the same year. In columns 2, 4, 7, and 8 we add rating, location, industry, and size fixed effects to control for observable differences in the pool of borrowers. FinTech loans tend to be slightly 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, the difference being significant whether we control for observable characteristics (column 3-4). Finally, results in columns 5-8 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 5.4-5.5 p.p. higher (by comparison, the baseline bank interest rate is equal to 1.7%). Note that both FinTech and bank interest rates are inclusive of fees. The gap in interest rate remains essentially the same after restricting the sample to uncollateralized loans (column 8), suggesting that it cannot be explained by differences in security. In Table B.3, we show that maturity and interest rates differences are essentially the same after matching bank and FinTech borrowers using a propensity score procedure.

There are several reasons why FinTech loans are more expensive than bank loans even after controlling for observables. First, the higher price of FinTech loans may reflect that borrowers value the fast speed and convenience of FinTech services. 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. Liquidity-constrained firms may be willing to pay more in exchange for obtaining funds sooner. Second, FinTech platforms may face higher costs than banks due to the lack of economies of scale. This explanation, however, would contrast with the idea that the finance industry can be made more efficient by fostering the arrival of new incumbents (Philippon, 2018). The ensuing analysis provides some insight regarding the role of speed, collateral, and information in explaining the credit dynamics of FinTech borrowers.

Firm characteristics Panel b and c of Figure 2 show the distribution of FinTech and bank borrowers across industries and credit ratings. Most firms in the sample are unrated: firms without credit rating represent 61.4% and 75.6% of FinTech and bank borrowers respectively.

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 under-represented in the construction and real estate industries (10.8% versus 30.5% for bank borrowers). By contrast, they are over-represented in the wholesale and retail trade, accommodation and food, and scientific and technical activities industries.

We present descriptive statistics on the two groups of firms in Panel a of Table 3. Except for total assets, age, and rating, all other variables in the table is normalized by total assets. FinTech borrowers are of the same size (as measured by total assets or number of employees) as bank borrowers. They generate lower sales but similar EBIT, suggesting lower costs than their bank counterparts. They also feature similar working capital and investment ratios to their bank counterparts. However, they are younger, more levered, and have less tangible assets, suggesting a lower capacity to pledge collateral. They are also less likely to be rated, consistent with Figure 2. These distinctions in firm characteristics between the two groups of firms naturally leads to different credit access. Hence, we use propensity score matching to create a matched sample of bank borrowers and FinTech borrowers to better understand the role of the FinTech loan. We describe our matching procedure in detail in section 5.

In addition, using the rejected application sample, we shed light on the difference between accepted and rejected FinTech applicants. Panel b of Table 3 reveals that successful FinTech applicants have more assets, higher EBIT and R&D cost, and a lower leverage ratio. They do not differ in terms of age, employment, investment, working capital, rating, and importantly, leverage ratio. This suggest that profitability and leverage are the key determinant of the probability of obtaining an approval from the FinTech platform.

5 Firms credit dynamics

5.1 Credit dynamics of FinTech borrowers

In this section, we investigate how firms' bank credit evolves after they receive a FinTech loan. It is ex-ante not clear whether bank credit should increase or decrease after the FinTech loan origination. On the one hand, firms may value the streamlined process and speediness of FinTech services and switch from traditional lenders to FinTech lenders. In this case, bank credit is likely to decrease. On the other hand, the low collateral requirement associated with FinTech loans may allow firms to acquire new assets that they could pledge later to borrow more from banks. Moreover, a successful FinTech application could serve as a positive signal on firm quality, potentially mitigating information asymmetry between banks and firms. While the first channel reflects credit demand arising from preferences over speed and convenience, the two other channels operate through credit supply by banks.

Since we are interested in firm credit outcomes, our analysis starts with FinTech borrowers in the constructed dataset detailed in Section 3, which we will now refer to as the "unmatched sample". 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 only keep the first FinTech loan to identify the impact of the initial FinTech loan on bank credit access.

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

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

Firms' credit dynamics around the FinTech loan origination are shown in Figure 3. Panel (a) plots the evolution of the total amount of bank loans. In the 12-month period before $t = 0$, there is no significant change in how much they borrow from banks. In the first six months following the FinTech loan origination, firms experience a significant 30% increase in the total bank loan amount, and this effect persists throughout the two-year post period. Naturally, as we move further away from $t = 0$, the confidence interval widens as fewer firms have a continuous relationship with their banks during the three-year window.

To understand the source of the credit expansion, we break down total loan amount by credit types and investigate the dynamics in major loan categories such as long-term loans, credit lines, and leases. Results are presented in panels (b)-(d), respectively. We find that the increase is most pronounced for long-term loans, with a 30 % rise in the first six months after the FinTech loan origination. There is also a 20% increase in leases. On the other hand, panel (c) reveals that one immediate use of FinTech credit is to pay back credit lines. Consistent with the presence of liquidity needs, firms are increasingly drawing on their credit lines before obtaining the FinTech loan. Firms repay their credit lines immediately after receiving the loan. Credit line balances start increasing again after three months to reach their pre-loan levels at $t = 6$, suggesting that FinTech borrowers do not fully substitute bank line of credit with FinTech credit.

These patterns suggest that firms borrow more from banks after obtaining a FinTech loan. However, we cannot, at this point, conclude that this is a causal effect of a successful FinTech loan application. An alternative explanation is that SMEs that face investment opportunities borrow from FinTech platforms and banks simultaneously and obtain the FinTech loan shortly before the bank loans. In this case, the increase in bank lending reflects firms' unobserved credit demand rather than credit supply.

To distinguish between the credit demand and supply channels, we construct a matched sample that consists of FinTech borrowers and similar firms that obtain a bank loan in the same year as the FinTech loan. The underlying assumption is that firms with similar observable characteristics and credit history, which operate in the same industry and borrow around the same time, face similar investment opportunities. Therefore, by comparing subsequent credit dynamics between the two groups, we can isolate the effect of obtaining a FinTech loan on their access to bank credit.

5.2 Matching procedure

We construct a control group of firms that share similar credit dynamics to FinTech borrowers but obtain loans from a *new* bank lender at the same time. This matched sample serves two goals. First, it controls for credit demand by firms as we require control firms to have applied for a new loan of similar size in the same year as FinTech borrowers. Therefore, subsequent credit dynamics of the two groups of firms are more likely to be driven by credit supply. Second, requiring control firms to obtain a loan from a new lender allows us to control for the effects of a new lending relationship on subsequent credit supply (Degryse, Ioannidou and von Schedvin, 2016). By comparing the two groups, we identify the effects of a new FinTech loan (instead of any new loan) on credit dynamics.

The matching procedure is as follows. For each FinTech borrower, we keep only bank borrowers that took a new bank loan in the same year as the FinTech borrower. We then select bank borrowers using a propensity score matching with replacement (five-nearest neighbors) on multiple covariates. We use three sets of covariates. The first set is composed of variables obtained from either FIBEN or Orbis which are available at annual frequency. Those variables are size category, industry, credit rating, and ratio of tangible assets over total assets, taken for the year before the new loan. The second group of variables captures the monthly credit dynamics of firms: the total loan amount, the amount drawn from lines of credit, and long-term loans, in the three months preceding the new loan. Last, we match on the size of the new loan, which is the size of the FinTech loan for FinTech borrowers and that of the new bank loan for bank borrowers. We apply the matching procedure for each two-digit industry to obtain a matched sample within industry. In the estimation of the propensity score, size and credit rating categories are treated as categorical variables, and others are treated as continuous variables.

The final matched sample includes 26,028 unique firm-month observations for 244 FinTech borrowing firms and 551 control firms during the 36-month window around the new loan origination date. Because we allow for replacement in the propensity score matching, a control firm may be matched to several FinTech borrowers. Hence the weighted regression sample includes 81,265 firm-month observations. The number of FinTech borrowers drops significantly from the unmatched sample to the matched one for two reasons. First, for a small fraction of FinTech firms, neither FIBEN nor Orbis reports their accounting information. Second, some FinTech borrowers end up with no match within the same industry because of our stringent matching requirements. This leads to an upward bias in the size of the Fintech borrowers in the matched sample. To address this sample selection bias, we check the robustness of our results using alternative matching procedures (Table B.2).

To visualize the matching outcome, we plot in Figure 4 the credit patterns of the firms in the matched sample (Panel a) and the matched subsample in (Panel b). Both panels plot the average total loan amount of FinTech borrowers and control firms in the 36 month window around the new loan origination. The red dots represent FinTech borrowers, and the blue squares represent bank borrowers.

Several observations are worth noting. First, in the unmatched sample (top panel), the credit dynamics of the two groups of firms exhibit an overall similar trend, with the total amount of bank credit going down (up) before (after) the origination of the new loan at $t = 0$. Second, on average, FinTech borrowers borrow more than bank borrowers. This is consistent with the result in Table 2 that FinTech borrowers are more levered and are of similar size as bank borrowers. Third, in the bottom panel, once we perform the matching, the two groups of firms have similar amounts of bank loans not only in month -3 to month -1, but also in earlier months, showing that our matching is effective in controlling for systemic differences in their credit dynamics. Last, after obtaining a new loan, FinTech borrowers experience faster growth in total bank credit than bank borrowers in the first six month. In sum, these observations suggest that our matching process effectively controls for observable differences between the two groups of firms before the new loan, but that bank and FinTech borrowers exhibit differential credit dynamics after the new loan.

5.3 Results based on the matched sample

Using a standard difference-in-difference (DiD) approach, we investigate firms' credit dynamics in the 36-month window around the FinTech or bank loan origination. We estimate Equation (2), where we interact the $FinTech$ indicator with a series of dummy variables for the months relative to the time of the origination of the new loan:

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

The outcome variables are the logarithms of one plus the amount of bank credit obtained by firm i in relative month t. We include firm×year fixed effects to control for time-varying firm characteristics and unobservable investment opportunities that vary at the firm-year level (e.g., time-varying differences in credit demand). We also add month fixed effects to control for macro-economic shocks that are common to FinTech and bank borrowers. Standard errors are clustered at the firm level. This specification allows us to visualize the effects of a new loan on firms' credit dynamics at a monthly frequency and examine the pre-trends.

Regression coefficients β_t are plotted in Figure 5. Panel (a) shows no significant difference in credit dynamics between FinTech borrowers and bank borrowers in the 12 months before obtaining the new FinTech or bank loan. In addition, the pattern in Figure 5 is similar to that in panel (a) of Figure 3, where we do not include the benchmark group and fixed effects. Hence, including a benchmark group does not change the estimated impact of FinTech loan on firms' access to bank credit. This lends credence to our matching procedure and our assumption that matched bank and FinTech borrowers face similar growth opportunities with each other. After the origination of the new loan, relative to bank borrowers, FinTech borrowers experience a 20% increase in the total amount of bank credit, which persists for 24 months. The gap between bank and FinTech borrowers appears gradually and takes around six months before it stays constant.

As a robustness check, in Table B.2, we report the regression result based on our main matched sample along with the results using alternative samples mentioned in the previous section. We estimate a standard DID regression specification as in (5):

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

where we interact the $FinTech_i$ dummy with $Post_t$ in the interaction term. The total number of unique firms ranges between 8,395 in the unmatched sample to 429 in the sampled matching using PSM with replacements. Yet, the magnitude of the DID coefficients varies very little from our baseline estimate (0.17) across the different specifications. The coefficients vary from 0.12 to 0.17, and are all significant at 1% level. We conclude that our main results are robust to the choice of the matching procedure.

So far, the evidence shows that both FinTech and bank borrowers experience a credit expansion following the new loan. However, the increase is stronger for FinTech borrowers, suggesting that obtaining a FinTech loan improves firms' subsequent access to bank credit.

To further substantiate this result, we construct an altnernative benchmark group that consists of rejected FinTech applicants described in Section 3. If indeed FinTech loans improve firms borrowing capacity, we should expect a similar result from the comparison between successful and rejected FinTech applicants. Following the same propensity matching procedure, we obtained a sample of matched successful and rejected applicants and evaluate the impact of the FinTech loan on firms' total bank loan amount with Equation (2). The regression coefficients are reported in Panel (b) of Figure 5.

The pattern in Panel (b) is similar to that in Panel (a) in both the general pattern and economic magnitude. Relative to matched firms among the rejected FinTech applicants, successful FinTech borrowers experience a 20% increase in bank credit in the first six months following the loan origination. After month 6, there is continuing but mild growth trend in bank credit. While in the 12 months before the origination of the FinTech loan, the two group of firms exhibit similar credit dynamics.

Together, our results show that obtaining a FinTech loan expands firms future borrowing capacity, and this result holds when we benchmark FinTech borrowers against either either similar bank borrowers and rejected FinTech applicants. In the next section, we try to shed light on why this is the case.

6 Mechanisms

Why are FinTech borrowers able to expand subsequent access to bank credit relative to similar control firms? Several hypotheses can explain this result. First, as FinTech platforms and investors collectively exert efforts in screening firms, a successful application may signal good firm quality. Banks may be willing to extend more credit upon observing this signal. We refer to this as the *information channel*. A second channel relates to the fact that FinTech loans are unsecured. FinTech loans allow firms to seize investment opportunities without posting collateral. As a result, the newly acquired assets can be pledged to banks, expanding firms' borrowing capacity. Control firms, in contrast, face stringent collateral requirements from traditional banks (Davydenko and Franks, 2008). Obtaining a FinTech loan would therefore improve access to bank credit by alleviating collateral constraints. We refer to this mechanism as the *collateral channel*. Last, we may see an increase in bank credit if firms face urgent liquidity needs and FinTech platforms are faster in processing loan applications. Once firms receive a bank loan a couple of months later, they repay the more costly FinTech loan before maturity using bank loans. We refer to this last hypothesis as the *speed* channel.

We test the collateral and information hypotheses by dissecting the sample based on the characteristics of firms, the new loan, and subsequent bank loans they obtain. In addition, we examine the ex-post survival rates of bank and FinTech borrowers. We then examine the speed channel by testing whether the increase in bank credit can be explained by FinTech borrowers refinancing their FinTech loans and testing whether FinTech platforms are more reactive than bank borrowers at meeting firms' liquidity needs.

6.1 Information versus collateral: bank credit

We start by exploiting the heterogeneity in firm characteristics to distinguish between the three channels. To test the information channel, we focus on the degree of information asymmetry between banks and firms. We expect the information channel to be stronger when banks have little information on firms, as the incremental value of the good signal about firm quality in a successful FinTech loan application should be larger for opaque firms. To that end, we classify firms without a credit rating at the Banque de France (i.e., unrated firms) as opaque firms and those with credit ratings as more transparent. We also look at whether firms have a low or high ratio of tangible assets to total assets the year before the new loan. We expect the collateral channel to be stronger for low-collateral firms, as collateral constraints are more likely to be binding.

For both tests, we first split the unmatched sample based on the variables mentioned above and then perform the same propensity score matching on subsamples. This ensures that the two groups of firms in the subsamples are still comparable. This means that a rated (unrated) FinTech borrower will be matched to a rated (unrated) bank borrower, and a FinTech firm with above-median levels of collateral will be matched to a control firm with above-median levels of collateral.

The results on the subsamples are reported in panels a to d of Figure 7 and in panel a of Table 4. Each panel of Figure 7 presents the estimated coefficients in Equation (2) in the 36-month window for the two subsamples using the sample splits discussed above. Table 4 presents regression results using the standard $FinTech_i \times Post_t$ interaction term. Our results support the collateral channel and are less consistent with the information channel. In particular, columns 1-2 reveal that the credit expansion is not driven by opaque firms, with the effect being smaller both in economic and statistical significance for opaque firms. In contrast, the effects are stronger for firms with less collateral before obtaining the FinTech loan (columns 3-4), who are expected to benefit the most from the low collateral requirement of FinTech loans.

We then exploit the heterogeneity in lenders and loan characteristics. Under the collateral channel, we expect the increase in bank credit to be more pronounced for long-term loans, for which collateral requirements are common. By contrast, we expect little or no effect on leases since leases are automatically backed by the asset financed by leases (i.e., it is not necessary for the firm to have unencumbered assets to pledge as collateral). Under the information channel, we expect the increase in bank credit to be more pronounced for new lenders which had no lending relationship with the firm before the new FinTech/bank loans as they are likely to be less informed than existing lenders.

Panels a to c of Figure 6 show the estimation results of (2) for long-term loans, credit lines, and leases. Table 5 reports the impact of the FinTech loan on FinTech borrowers' credit access in the three credit categories by existing and new lenders. The dynamic regressions in (2) show that the increase in bank credit is mostly driven by long-term loans, which sharply rise in the first 3 months after the FinTech loan and stay relatively stable afterward. By contrast, there is no significantly different trend between FinTech and bank borrowers in leases or credit lines. Consistent with the dynamics in Figure 6, the results of Table 5 show that the increase in total bank credit is concentrated in the long-term loan category, with a 25% effects for existing lenders and 16% for new lenders (columns 3-4). We find again insignificant effects for leases. The estimates suggest a 16% increase on lines of credit issued by existing lenders, but the effect is marginally significant. We do not find a significant increase in line of credit issued by new lenders. Again, the results support the collateral channel rather than the information channel.

Lastly, we exploit the heterogeneity in the characteristics of the new loan. Under the collateral hypothesis, the effect should disappear when firms do not use the loan for investing in tangible assets (i.e., to purchase intangible assets or finance commercial growth – see Figure 2 for the list of loan purposes). We test this prediction in panels e to f of Figure 7 and in columns 5-6 of Table 4.

In line with the predictions of the collateral channel, we find a stronger effect when the FinTech loan is used to finance the purchase of tangible assets than for other purposes (0.17 vs. 0.01), although the effect is not significant at conventional level, with a t-statistics of 1.54. In sum, our findings are consistent with the collateral hypothesis, whether we exploit the heterogeneity across borrowers, credit categories, or loan characteristics.

6.2 Information versus collateral: probability of default

We further substantiate the collateral channel by examining the ex-post probability of default. The information and collateral channels generate opposite predictions regarding whether the observed increase in bank loans should lead to higher or lower default rates for FinTech firms. Under the information hypothesis, if FinTech platforms are able to mitigate information asymmetries and identify creditworthy firms overlooked by banks, we should observe that FinTech borrowers are equally or even less likely to default as bank borrowers after obtaining the new loan, controlling for the difference in loan prices (Balyuk, 2019).

By contrast, under the collateral hypothesis, if collateral constraints imposed by banks prevent firms from overborrowing, we should observe that FinTech borrowers are more likely to default after the new loan.

We assess the impact of FinTech loans on firms' ability to fulfill their debt obligations, measured by the probabilities of a trade credit default, a bankruptcy procedure, and liquidation. Information on trade credit default is from the CIPE database, and information on bankruptcy and liquidation status is manually collected from BODACC as mentioned in Section 3. Defaults are observed at the firm-year level. Table 7 compares the evolution of default rates between FinTech and bank borrowers in the four-year window around the new loan. The regressions include firm fixed effects as well as industry-year fixed effects. We find a positive relationship between receiving a Fintech loan and defaulting on trade bills (column 1). The results in columns 2 and 3 suggest that FinTech borrowers are 0.3% more likely to file for bankruptcy and 0.4% more likely to be liquidated (significant at the 5 and 10% levels, respectively). We conclude that the default dynamics are more consistent with the collateral channel than with the information channel.

6.3 Speed channel

Another explanation for why firms borrow from FinTech platforms is that FinTech platforms are quicker to process loan applications, which gives them a competitive edge to meet urgent firm liquidity needs. This speed channel can also lead to an increase in bank credit for FinTech borrowers if firms use FinTech loans as a form of bridge financing and refinance FinTech loans with less expensive bank loans. It is challenging to test this hypothesis directly because we do not observe the timing of the loan applications submitted to FinTech platforms and banks. Instead, we observe whether firms repay their FinTech loans before maturity. We perform, therefore, two sets of analysis to investigate the speed channel. First, we examine whether, compared to similar firms that take a new bank loan, firms that turn to FinTech are systematically more likely to have recently experienced a negative liquidity shock. Second, we verify whether the subsequent increase in bank credit is fully driven by FinTech borrowers refinancing their FinTech loans with 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 themselves on their suppliers or even to go bankrupt, suggesting that trade bills defaults constitute an economically meaningful liquidity shock.

Specifically, we compute a dummy $Customer\ default_{i,q}$ equal to one if at least one customer of firm i defaulted on a trade bill in quarter q. We define variables at the quarter-level instead of month-level because we only observe detailed information on new bank loans that are originated in the first month of each quarter, as described in Section 3. We estimate the following equation:

$$New\ loan_{i,q} = \beta Customer\ default_{i,q} + \delta FinTech_i \times Customer\ default_{i,q} + \alpha_i + \gamma_{s,q} + \varepsilon_{i,q},$$

where $New\ loan_{i,q}$ is a dummy equal to one if firm i takes a new loan at time q, $FinTech_i$ is equal to one if the firm borrows from a FinTech, α_i is a firm fixed effect, and $\gamma_{s,q}$ is an industry (s) time quarter (q) fixed effect.

The coefficient β measures how the probability of a firm taking on 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, compared to banks, firms are more or less likely to turn to FinTech platforms after experiencing such a liquidity shock. The firm fixed effect ensures that β and δ capture the correlation between liquidity shock and credit demand for a given firm in the time series. Last, industry $\times$ quarter fixed effects control for sectoral quarterly shocks that could lead to systematic relationships between customer default 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 is substantial, with 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 a new loan at quarter q and the probability of having experienced a customer default at quarter $q-1$ (column 2).

If indeed firms 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 $Customer\ default_{i,Before\ q-2}$. $Customer\ default_{i,Before\ q-2}$ is a dummy variable equal to one if at least one of the customers of firm i defaults on a trade bill between time $q-4$ 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 be affecting both customer defaults and firms' demand for credit. For instance, young firms may be more prone to take on new loans and less likely to deliver goods or services of the required quality, leading customers to refuse the payment of trade bills. In columns 4 and 5, we split customer payment incidents by the reason of the default. 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. By contrast, in case of disagreement or omission of payments, the cause of the default may be the supplier who did not deliver the expected products. Suppliers may also anticipate customers' insolvency.

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

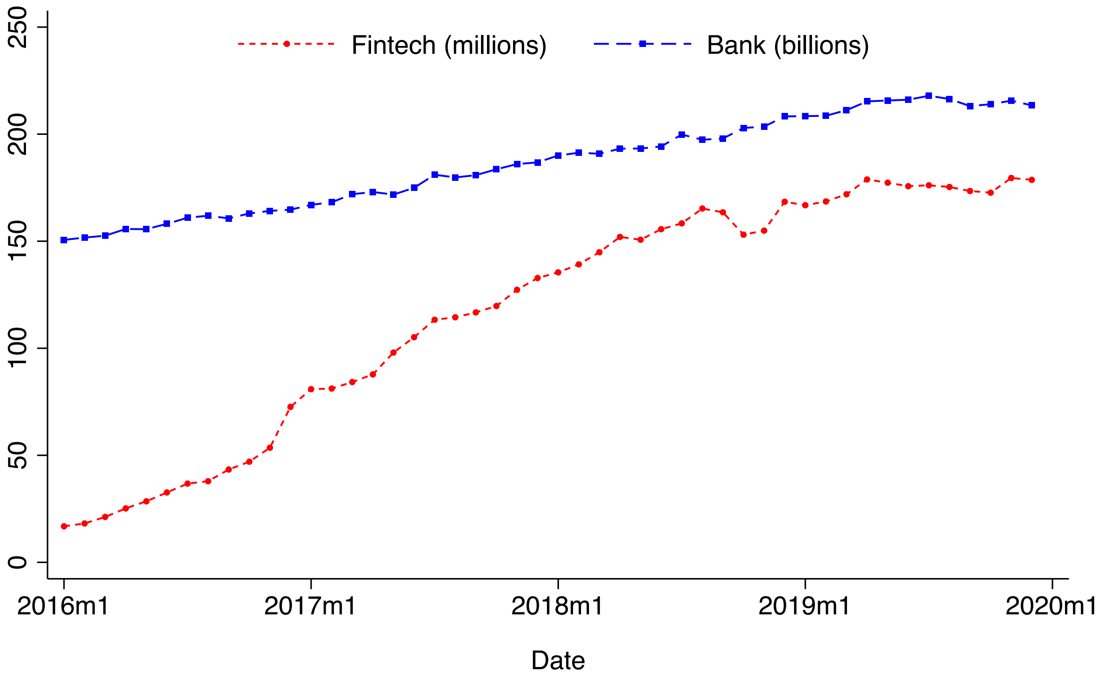
Next, we turn to examine whether the increase in bank credit is driven by FinTech borrowers who repay their loans before maturity. Figure 8 gives the distribution of FinTech borrowers based on the timing of repayment of the FinTech loan, that is, the ratio of the time (in months) it takes for a given firm to fully repay its FinTech loan over the agreed maturity of the FinTech loan (in months). The evidence suggests that the vast majority of FinTech loans 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. In the Appendix (Table B.4), we show that removing firms that repay their loans fully within 6 months does not change our main results. Overall, the small number of early repayers leads us to conclude that the speed channel alone is unlikely to explains our findings.

7 Conclusion

The simultaneous decline in bank lending to SMEs and the emergence of FinTech lending platforms suggest that FinTech platforms could play an important role in the SME lending markets. This paper attempts to identify that role. To that end, we provide a comprehensive description of the FinTech SME loan market, using administrative data from France. We document that FinTech borrowers tend to experience a larger increase in bank credit following the new loan compared to similar firms that borrow from banks. Looking at ex-ante firm and loan characteristics and ex-post default rates, we provide strong evidence supporting the idea that uncollateralized FinTech loans relax firms' collateral constraints by allowing firms to invest in tangible assets without posting collateral. The increase in default rates among FinTech borrowers, in particular, suggest that the growth of FinTech platforms will only be sustainable in the long run if investors consider themselves sufficiently compensated for the risk they take and if regulators consider that the excess defaults experienced by other lenders (e.g., banks) remain tolerable.

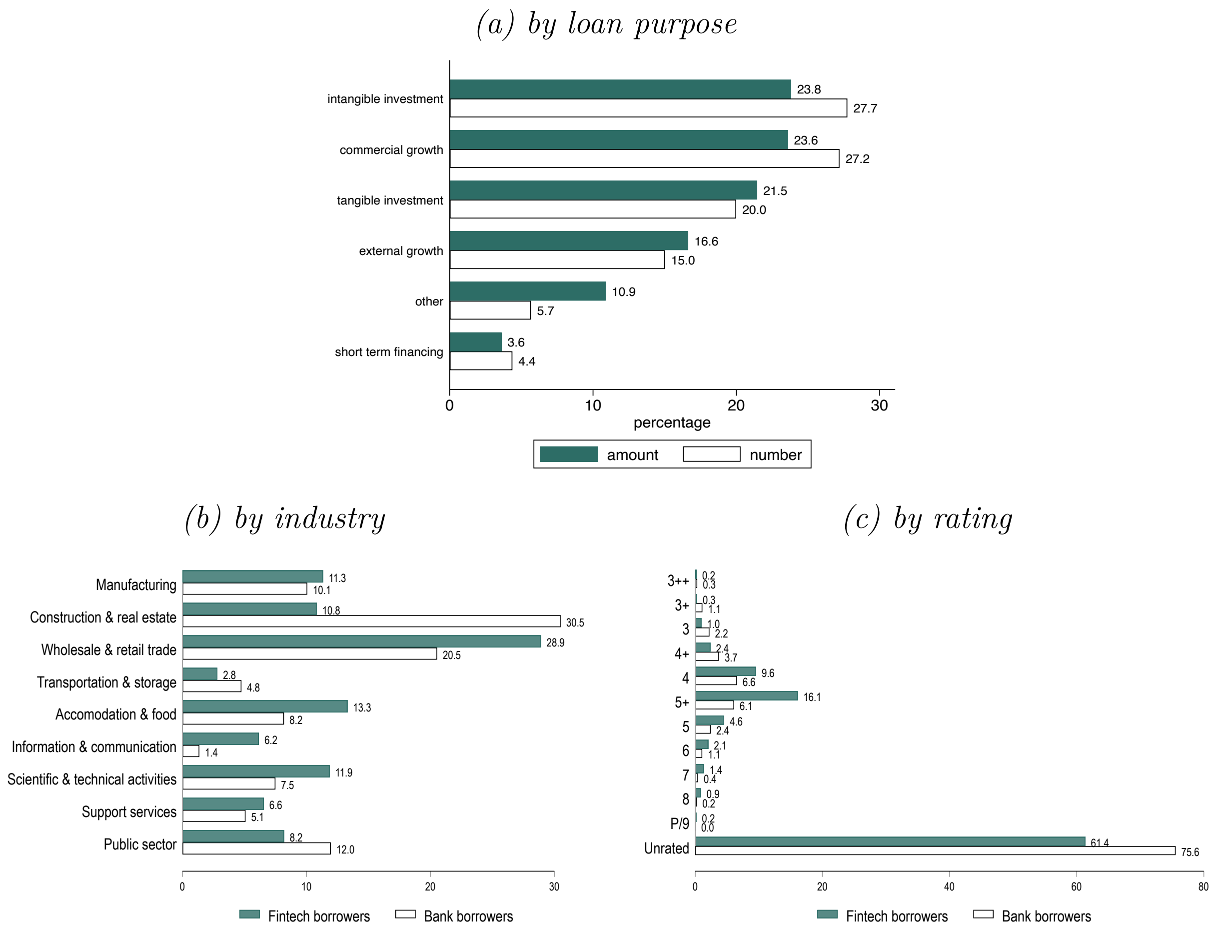
FIGURE 1

Aggregate loan volume by banks and FinTech platforms



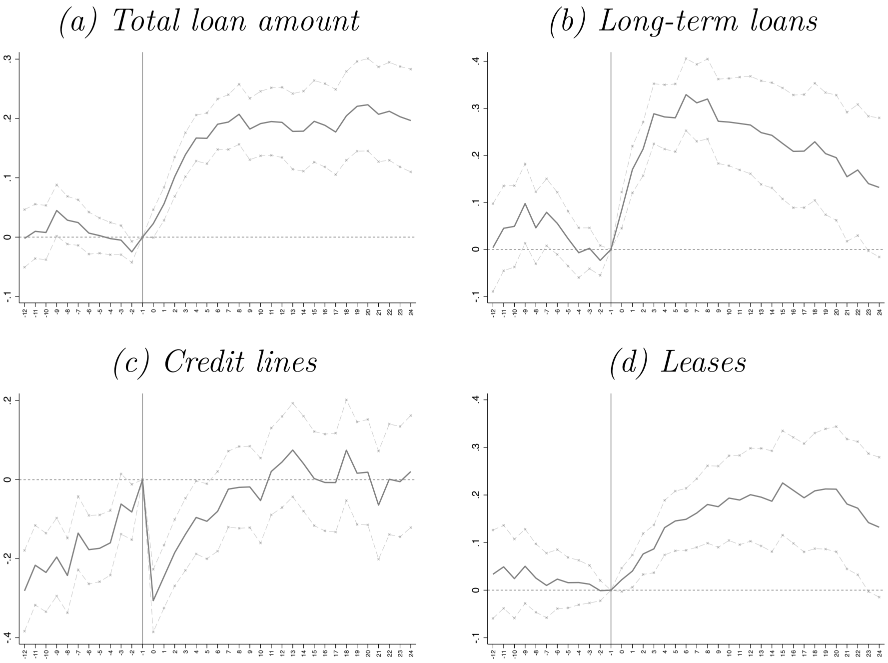
Note.—This figure presents the aggregate lending volume by banks and FinTech platforms to non-financial firms. We focus on loans under one million euros, since the French regulation prevents FinTech platforms from issuing loans with a face value exceeding one million euros. The red dots represent the FinTech borrowers, while the blue squares represent the bank borrowers. Lending volume by banks is computed using the French credit registry. Lending volume by FinTech platforms is computed using the FinTech dataset made available by the Bank of France. The FinTech dataset covers approximately 80% of the universe of FinTech loans.

FIGURE 2
Breakdown of loans



Note.—This figure presents the breakdown (in %) of loans by purpose category (panel a), by the borrower's industry (panel b), and by the borrower's credit rating (panel c). In panel a, percentages are computed both in terms of number of loans (white bars) and loan amount (green bars). Purpose categories are observed in the Banque de France FinTech dataset. The Banque de France attributes loan purposes based on a text analysis of the project descriptions posted by firms on platforms' websites when applying for a loan. In panel b, (white) bars give the breakdown of Fintech (bank) loans by the borrower's industry. In panel c, (white) bars give the breakdown of Fintech (bank) loans by the borrower's credit rating. New bank loans are observed in the M-Contran database made available by the Bank of France. The M-Contran dataset is a survey representative of the universe of new bank loans issued by banks to non-financial firms. Data on firms come from FIBEN and Orbis. We only keep Fintech and bank loans originated between Jan 1., 2016 and Jan 1., 2019.

FIGURE 3
Credit dynamics of FinTech borrowers



(a) Total loan amount *(b) Long-term loans* *(c) Credit lines* *(d) Leases*

NOTE.—The figures present the results of the estimation for the 36-month window around the FinTech loan origination ($t = 0$) of

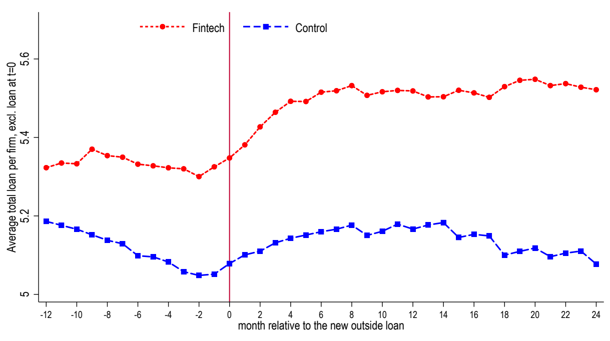
$$log(1 + x_{i,t}) = \sum_{t \in [-12,24]} \beta_t \times D_t + \gamma_{i,year} + \varepsilon_{i,t},$$

where $x_{i,t}$ is replaced respectively by total loans, credit lines, long-term loans, and leases. Only FinTech firms are included in the sample. Coefficients are reported along with the 95% intervals. Standard errors are clustered at the firm level. The baseline is set at $t = -1$. 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 only keep outside loans originated between Jan 1., 2016 and Jan 1., 2019.

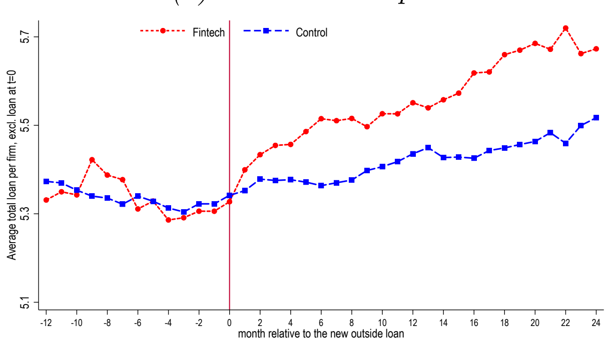
FIGURE 4

Bank credit dynamics before and after matching

(a) unmatched sample



(b) matched sample

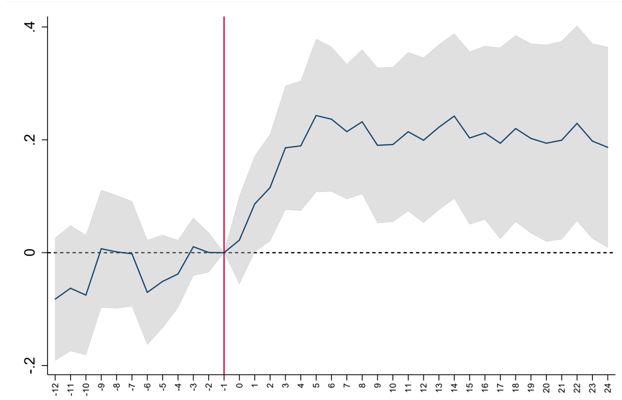


NOTE.—This figure presents the average amount of bank credit by borrower type in the 36-month window around the origination of the outside loan at $t = 0$ for the unmatched sample (panel a) and matched sample (panel b). An outside loan is a loan originated by a lender not present in the set of lenders of firm i before time 0. The figures plot the average of $\log(1 + x_{i,t})$, $x_{i,t}$ being the amount of bank credit of firm i at time t. Firm i can either be a FinTech borrower (i.e., the outside loan is a FinTech loan) or a bank borrower (i.e., the outside loan is bank loan). The red dots represent the FinTech borrowers, while the blue squares represent the bank 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 only keep outside loans originated between Jan 1., 2016 and Jan 1., 2019.

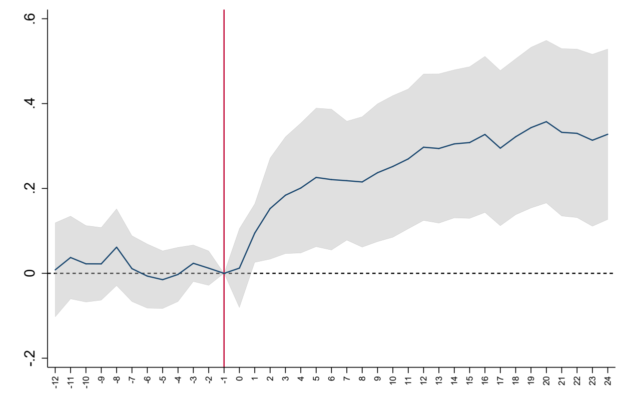
FIGURE 5

Credit dynamics: FinTech borrowers vs. benchmark firms

(a) FinTech borrowers vs. bank borrowers



(b) FinTech borrowers vs. rejected applicants



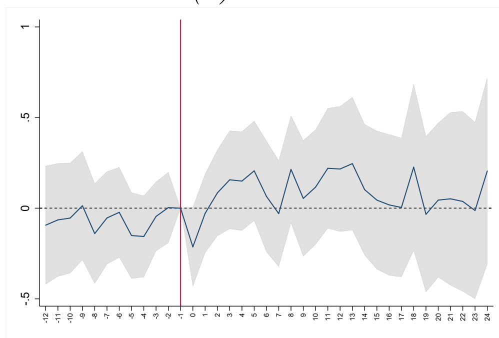
NOTE.—The figures present the results of the estimation for the 36-month window around the origination of the outside loan at $t = 0$ of

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

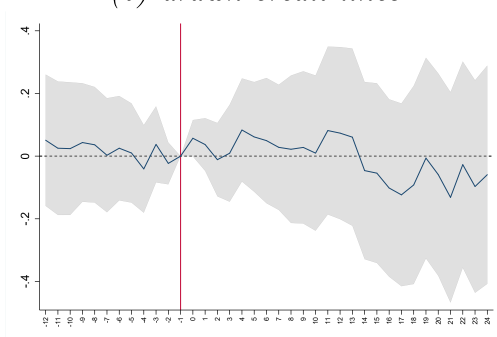
where $x_{i,t}$ is respectively the amount of total bank credit for firm i at time t. An outside loan is a loan originated by a lender not present in the set of lenders of firm i before time 0. Firm i can either be a FinTech borrower (i.e., the outside loan is a FinTech loan) or a bank borrower in panel (a) or a FinTech borrower or a rejected FinTech applicant in panel (b). Coefficients are reported along with the 95% intervals. Standard errors are clustered at the firm level. The baseline is set at $t = -1$. 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 only keep outside loans originated between Jan 1., 2016 and Jan 1., 2019.

FIGURE 6
Credit dynamics by loan types

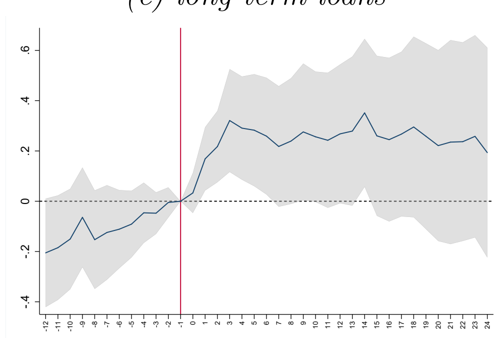
(a) leases



(b) drawn credit lines



(c) long-term loans

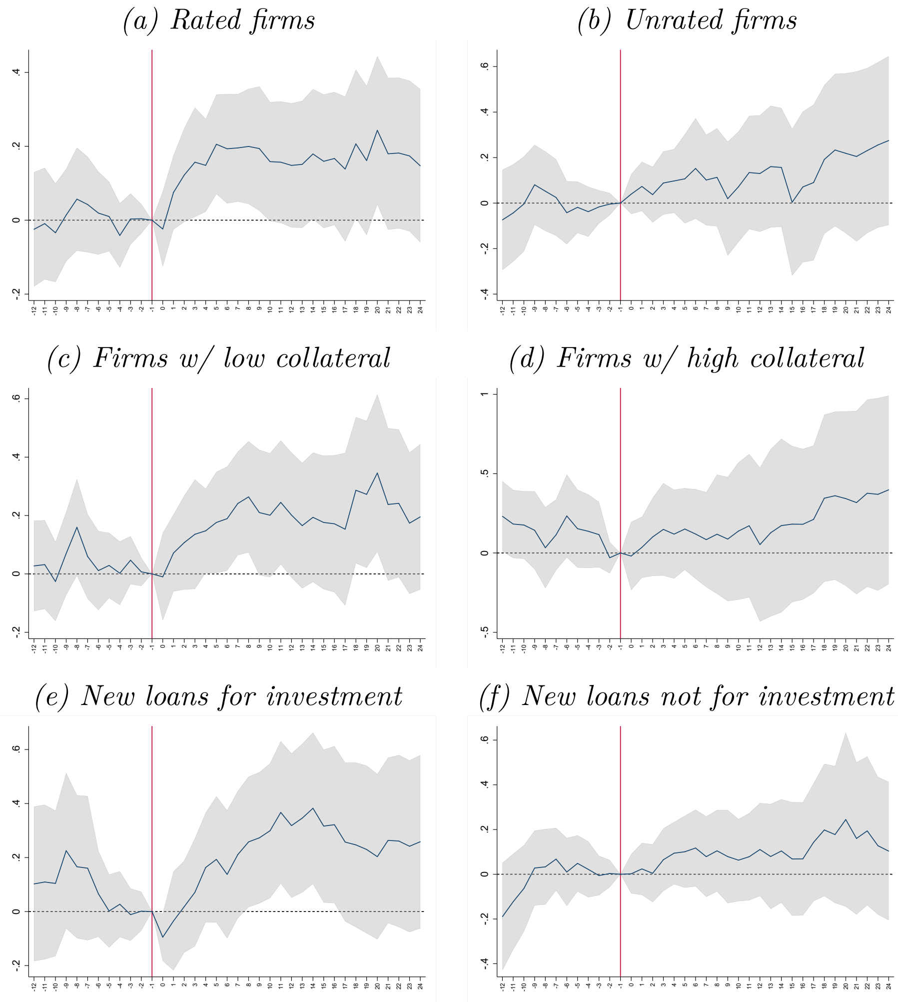


NOTE.—The figures present the results of the estimation for the 36-month window around the origination of the outside loan at $t = 0$ of

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

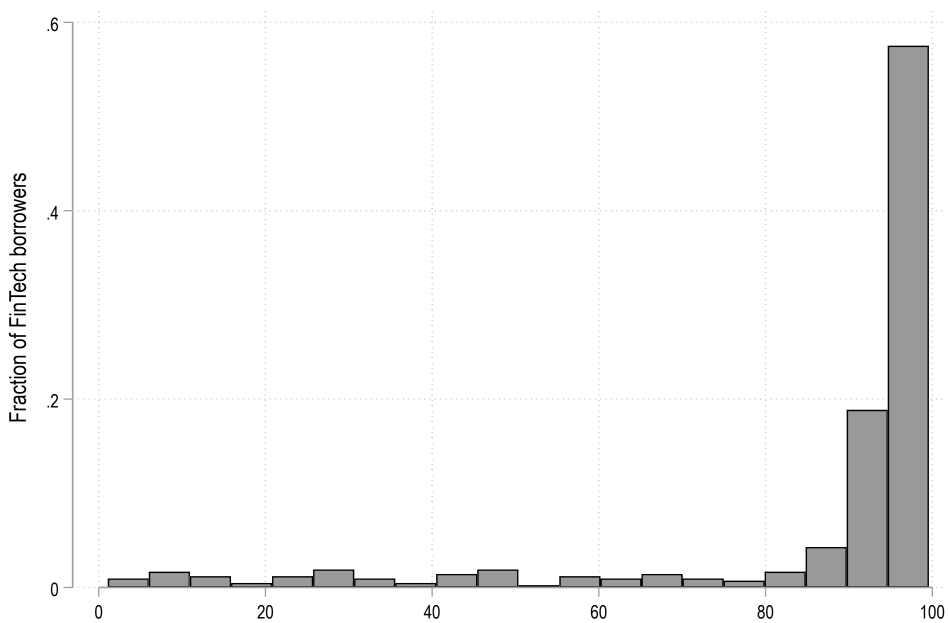
where $x_{i,t}$ is respectively the amount of total bank credit, drawn credit lines, long-term credit, and leasing loans of firm i at time t. An outside loan is a loan originated by a lender not present in the set of lenders of firm i before time 0. Firm i can either be a FinTech borrower (i.e., the outside loan is a FinTech loan) or a bank borrower (i.e., the outside loan is a bank loan). Coefficients are reported along with the 95% intervals. Standard errors are clustered at the firm level. The baseline is set at $t = -1$. 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 only keep outside loans originated between Jan 1., 2016 and Jan 1., 2019.

FIGURE 7
Heterogeneity in firms and new loan characteristics



NOTE.—The figures present the results of the estimation for the 36-month window around the origination of the outside loan at $t = 0$ of $log(1 + x_{i,t}) = \sum_{t\in[-12,24]} \beta_t FinTech_i \times D_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t}$ where $x_{i,t}$ is the amount of total bank credit of firm i at time t. An outside loan is a loan originated by a lender not present in the set of lenders of firm i before time 0. If firms take an outside loan to finance the purchase of tangible assets, the outside loan is called an "investment loan". Firm i can either be a FinTech borrower (i.e., the outside loan is a FinTech loan) or a bank borrower (i.e., the outside loan is bank loan). Coefficients are reported along with the 95% intervals. Standard errors are clustered at the firm level. The baseline is set at $t = -1$. 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 only keep outside loans originated between Jan 1., 2016 and Jan 1., 2019.

FIGURE 8
Timing of repayment of FinTech loans



NOTE.—This figure gives the distribution of FinTech borrowers based on the timing of repayment of the FinTech loan. The timing of repayment is the ratio of the number of months it takes for a given firm to fully repay its FinTech loan over the agreed maturity of the FinTech loan (in months). We exclude FinTech borrowers that defaulted on their loans. 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
FinTech loans characteristics

	Min	Mean	p50	Max	S.D.	Count
Loan terms						
Loan amount (000' euro)	1.00	151.04	50.00	5000.00	346.22	2,011
Interest rate (%)	1.00	7.79	8.00	16.77	1.97	2,011
Maturity (months)	6	38	36	84	16	2,011
Investors						
Number of banks	0	0	0	1	0	2,011
Share of banks	0.00	11.59	0.00	100.00	25.56	2,011
Number of legal entities	0	2	0	37	5	2,011
Share of legal entities	0.00	1.61	0.00	100.00	7.42	2,011
Number of indiviudals	0	501	321	5141	554	2,011
Share of individuals	0.00	86.79	100.00	100.00	25.90	2,011

NOTE.—This table presents descriptive statistics on FinTech loans. Loan amounts are in thousands of euro. Interest rates are annualized and expressed in percentage points. Interest rate are inclusive of fees. Loan maturity is in month. 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 and the Crowdlending.fr dataset. We only keep Fintech loans originated between Jan 1., 2016 and Jan 1., 2019.

TABLE 2
Comparing FinTech and bank loans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loan size (Mns)		Maturity (years)		Rate (%)			
								Uncollateralized
FinTech	-0.14**	-0.14*	-1.96***	-1.52***	5.41***	5.48***	5.36***	5.51***
	(0.07)	(0.07)	(0.10)	(0.09)	(0.02)	(0.02)	(0.02)	(0.03)
Maturity						0.03***	0.02***	0.02***
						(0.00)	(0.00)	(0.00)
Loan size						-0.01***	-0.01***	-0.02***
						(0.00)	(0.00)	(0.01)
Constant	0.29***	0.29***	5.01***	4.96***	1.96***	1.80***	1.87***	1.50***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE		Y		Y			Y	Y
Location FE		Y		Y			Y	Y
Size FE		Y		Y			Y	Y
Rating FE		Y		Y			Y	Y
N	13,435	13,399	13,435	13,399	13,435	13,435	13,399	5,417
R-sq	0.01	0.04	0.05	0.37	0.83	0.84	0.85	0.91

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, 7, and 8, we include industry, size, location and rating fixed effects. In column 8, the regression sample only includes uncollateralized loans. There are 9 industries and 12 credit ratings. 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 only keep bank and Fintech loans originated between Jan 1., 2016 and Jan 1., 2019. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 3

Comparing FinTech borrowers and Benchmark firms

(a) Main benchmark: Bank borrowers

	(a) FinTech borrower	(b) Bank borrower	(b)-(a)	t-statistic	(a) count	(b) count
Total Assets	7.332	7.242	−0.090	−1.594	757	3,434
Age	18.895	21.519	2.624	4.347***	651	3,060
Working capital	0.256	0.264	0.009	1.030	642	2,721
EBIT	0.057	0.059	0.002	0.487	678	2,797
Sales	1.455	1.602	0.147	3.514***	729	3,321
Investment	0.644	0.605	−0.039	−0.143	667	3,049
Leverage	0.693	0.665	−0.028	−2.679**	690	2,869
Employment	2.742	2.777	0.035	0.687	509	2,341
Tangible assets	0.232	0.288	0.056	6.104***	757	3,434
R&D costs	0.037	0.012	−0.025	−9.194***	521	2,395
Rating	3.751	2.979	−0.772	−8.627***	1080	6,379
N	1,080	6,379	7,459	7,459	1,080	6,379

(b) Alternative benchmark: Rejected FinTech applicants

	(a) Rejected applicants	(b) FinTech borrowers	(b)-(a)	t-statistic	(a) count	(b) count
Total Assets	6.888	7.326	0.438	6.539***	2489	775
Age	17.986	18.831	0.845	1.415	1761	655
Working capital	0.238	0.255	0.017	1.745	1949	661
EBIT	0.016	0.057	0.041	6.613***	2120	696
Sales	1.621	1.478	−0.144	−3.020**	2464	747
Investment ratio	0.974	0.459	−0.514	−0.761	2009	679
Leverage	0.787	0.696	−0.090	−7.495***	2052	708
Employment	2.732	2.729	−0.003	−0.048	1561	526
Tangible assets	0.238	0.230	−0.008	−0.905	2489	775
R&D costs	0.025	0.036	0.011	2.597**	1613	540
Rating	3.532	3.610	0.078	0.690	7094	1184
N	7,094	1,184	8,278	8,278	7,094	1,184

NOTE.—This table presents firm characteristics for FinTech borrowers and two benchmark groups of borrowers: bank borrowers and rejected FinTech applicants as defined in Section 4. Panel a. present the t-test in firm characteristics for FinTech and bank borrowers, while panel b. present that for FinTech borrowers and rejected FinTech applicants. *Assets* are measuredin logarithm. *Working capital, EBIT, Debt, Net income, Investment, Fixed assets, Cash flow, R&D*, and *Collateral* are all normalized by total assets.

TABLE 4
Cross-sectional tests: firm and loan characteristics

	Unrated	Rated	Low collateral	High collateral	Investment purpose	Other purposes
	(1)	(2)	(3)	(4)	(5)	(6)
FinTech × Post	0.09	0.15**	0.12*	0.04	0.17	0.01
	(0.06)	(0.06)	(0.07)	(0.08)	(0.11)	(0.12)
Post	-0.12**	-0.04	-0.03	-0.02	-0.02	0.13
	(0.05)	(0.03)	(0.04)	(0.08)	(0.04)	(0.09)
Firm-Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
N	25,043	50,271	32,409	6,892	28,246	17,922
R-sq	0.95	0.96	0.97	0.98	0.96	0.95

NOTE.—This table presents the results of the estimation for the 36-month window around the origination of the new loan at $t = 0$ of

$$\log(1 + \textit{Total bank loans})_{i,t} = \beta FinTech_i \times Post_t + \delta Post_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t}. \tag{4}$$

where $Post_t$ is equal to one when $t \geq 0$. The regressions are run on subsamples of firms that are unrated the year before the new loan (column 1), rated the year before the new loan (column 2), have a ratio of fixed assets over total assets below the sample median (column 3), for which the new loan is used to finance the acquisition of tangible assets (column 5) or for other purposes (column 6). A new loan is a loan originated by a lender not present in the set of lenders of firm i before time 0. Firm i can either be a FinTech borrower (i.e., the new loan is a FinTech loan) or a bank borrower (i.e., the new loan is bank 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. Data on firms come from FIBEN and Orbis. We only keep new loans originated between Jan 1., 2016 and Jan 1., 2019. Standard errors are clustered at the firm level. Coefficients are reported along with the standard errors (in parentheses). Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 5
Bank credit by loan category

	Credit lines		Long-term loans		Leases	
	Existing Lenders	New Lenders	Existing Lenders	New Lenders	Existing Lenders	New Lenders
	(1)	(2)	(3)	(4)	(5)	(6)
FinTech × Post	0.16*	0.03	0.25***	0.16**	0.01	0.08
	(0.08)	(0.02)	(0.08)	(0.08)	(0.06)	(0.05)
Post	-0.07	-0.05***	-0.07	-0.01	0.05*	-0.05*
	(0.05)	(0.02)	(0.05)	(0.04)	(0.03)	(0.03)
Firm-Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y
N	81,265	81,265	81,265	81,265	81,265	81,265
R-sq	0.81	0.70	0.94	0.85	0.96	0.83

NOTE.—This table presents the results of the estimation for the 36-month window around the origination of the new loan at $t = 0$ of

$$\log(1 + x_{i,t}) = \beta FinTech_i \times Post_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t}. \quad (5)$$

where $Post_t$ is equal to one when $t \geq 0$, and $x_{i,t}$ is replaced by the value for firm i at time t of short-term loans, long-term loans, and leasing loans issued by banks from which firm i was already borrowing at $t = -1$ (columns 1, 3, and 5) and from which firm i was not already borrowing at $t = -1$ (columns 2, 4, and 6). A new loan is a loan originated by a lender not present in the set of lenders of firm i before time 0. Firm i can either be a FinTech borrower (i.e., the new loan is a FinTech loan) or a bank borrower (i.e., the new loan is bank loan). 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 only keep new loans originated between Jan 1., 2016 and Jan 1., 2019. Coefficients are reported along with the standard errors (in parentheses). Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 6
Liquidity shocks and demand for FinTech loans

	All motives			Customer illiquidity	Others
	(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$_{Before\ q-2}$			0.00		
			(0.00)		
FinTech × Customer default$_{Before\ q-2}$			-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 results of the estimation for the 36-month window around the origination of the new loan at $q = 0$ of

$$New\ loan_{i,q} = \beta X + \delta FinTech_i \times X + \alpha_i + \gamma_{s,q} + \ \varepsilon_{i,q},$$

where $New\ loan_{i,q}$ is a dummy equal to one if firm i takes a new loan at time q, $FinTech_i$ is equal to one if the firm borrows from a FinTech, α_i is a firm fixed effect, and $\gamma_{s,q}$ is an industry (s) time quarter (q) fixed effect. 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 at time q $(q-1)$. 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 time $q-4$ 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 motives (due to motives not related to illiquidity – e.g., omission, disagreement, or insolvency). A new loan at $t = 0$ is a loan originated by a lender not present in the set of lenders of firm i before time 0. Firm i can either be a FinTech borrower (i.e., the new loan is a FinTech loan) or a bank borrower (i.e., the new loan is bank 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. Data on firms come from FIBEN and Orbis. We only keep new loans originated between Jan 1., 2016 and Jan 1., 2019. Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 7
Firm-level defaults

	(1) Default on suppliers	(2) Bankruptcy procedure	(3) Liquidation
FinTech × Post	0.014	0.003**	0.004*
	(0.010)	(0.001)	(0.002)
Post	0.007	0.001	-0.000
	(0.007)	(0.001)	(0.001)
Firm FE	Y	Y	Y
Industry-Year FE	Y	Y	Y
N	53,680	53,680	53,680
R-sq	0.24	0.06	0.08

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

$$y_{i,t} = \beta FinTech_i \times Post_t + \delta Post_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t}. \tag{6}$$

where $Post_t$ is equal to one when $t \geq 0$ and $y_{i,t}$ is a dummy variable for whether the firm enters a bankruptcy procedure (column 1) or is being liquidated (column 2). 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 only keep new loans originated between Jan 1., 2016 and Jan 1., 2019. Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

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TABLE B.1
FIBEN credit score categories

Credit score	Description	Pr(Default)
3++	The company's ability to meet its financial commitments is deemed excellent	0.04%
3+	The company's ability to meet its financial commitments is deemed very good	0.08%
3	The company's ability to meet its financial commitments is deemed good	0.16%
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	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+	The company's ability to meet its financial commitments is deemed to be fairly good	3.46%
5	The company's ability to meet its financial commitments is deemed to be poor	8.18%
6	The company's ability to meet its financial commitments is deemed to be very poor	12.42%
7	The company's ability to meet its commitments is a specific cause for concern. At least one reported trade bill payment incident	25.95%
8	The company's ability to meet its financial commitments is at risk given the trade bill payment incidents reported	33.50%
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%
P	The company is the subject of insolvency proceedings (recovery or judicial liquidation proceedings)	-
0	The rating is given to firms that have not been analyzed by Banque de France rating team over the observation period	-

Notes: This table describes the credit score categories and their associated probability of default over a three-year horizon, based on Banque de France data from 2017 to 2019.

TABLE B.2
Matching Procedure - Robustness Checks

	Unmatched	PSM w/o rep	PSM w/ rep	PSM k-nearest neighbor
	(1)	(2)	(3)	(4)
FinTech × Post	0.12***	0.15***	0.14***	0.17***
	(0.02)	(0.05)	(0.05)	(0.05)
Post	-0.01	-0.05*	-0.04	-0.06***
	(0.01)	(0.03)	(0.04)	(0.02)
#Unique FinTech borrowers	1,202	244	244	244
#Unique control firms	7,193	244	182	551
Firm-Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
N	246,824	16,205	16,335	81,265
R-sq	0.97	0.95	0.95	0.95

Note.—This table shows the results of the DID regressions on different samples. Column 1 is based on the unmatched sample. In Columns 2-4, the regression samples are the matched sample based on PSM without replacement, PSM with replacement, and PSM with k-nearest neighbor ($k = 5$). The number of unique firms is reported at the bottom of the table. 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 only keep bank and Fintech loans originated between Jan 1., 2016 and Jan 1., 2019. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE B.3
Comparing FinTech and bank loans - Matched sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Loan size (Mns)		Maturity (years)		Rate (%)			
								Uncollateralized
FinTech	0.04	0.08***	-0.32*	-1.13***	5.37***	5.40***	5.30***	5.32***
	(0.02)	(0.03)	(0.17)	(0.17)	(0.05)	(0.05)	(0.06)	(0.07)
Maturity						0.04***	0.04***	0.06***
						(0.01)	(0.01)	(0.01)
Loan size						-0.24***	-0.19***	-0.48***
						(0.05)	(0.05)	(0.09)
Constant	0.12***	0.12***	3.17***	3.32***	1.83***	1.75***	1.76***	1.80***
	(0.01)	(0.01)	(0.07)	(0.06)	(0.02)	(0.03)	(0.03)	(0.04)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	N	Y	Y
Location FE	N	Y	N	Y	N	N	Y	Y
Size FE	N	Y	N	Y	N	N	Y	Y
Rating FE	N	Y	N	Y	N	N	Y	Y
N	1,714	1,711	1,714	1,711	1,714	1,714	1,711	1,321
R-sq	0.05	0.17	0.09	0.35	0.86	0.87	0.89	0.89

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 matched sample between Jan 1., 2016 and Jan 1, 2019. All specifications include year fixed effects. In columns 2, 4, 7, and 8, we include industry, rating, location, and size fixed effects. In column 8, the regression sample only includes uncollateralized loans. There are 9 industries and 12 credit ratings. 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 only keep bank and Fintech loans originated between Jan 1., 2016 and Jan 1., 2019. Standard errors are clustered by firm. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE B.4
Early repayment of FinTech loans

	Early repayers	Other firms
	(1)	(2)
FinTech × Post	0.17	0.14***
	(0.21)	(0.05)
Post	-0.05**	-0.05**
	(0.02)	(0.02)
Firm-Year FE	Y	Y
Month FE	Y	Y
N	40,800	47,285
R-sq	0.96	0.96

NOTE.—This table presents the regression results using subsamples of firms that repay their FinTech loan in full before and at maturity. Column 1 includes FinTech borrowers that repay the FinTech loan in full before maturity and the full set of control firms in the matched sample. Column 2 excludes from the matched sample firms that do not repay their FinTech loans early. 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 only keep new loans originated between Jan 1., 2016 and Jan 1., 2019. Coefficients are reported along with the standard errors (in parentheses). Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE B.5
Description of variables

Variables	Description
Main dependent variables:	
D_t	Dummy equal to 1 when the relative time between the calendar month and the month of the new loan is equal to t, 0 otherwise.
$FinTech_i$	Dummy variable that takes value one if the new loan taken by firm i is issued by a FinTech platform, 0 if it is issued by a bank.
$Post_t$	Dummy variable that takes value one if the month is after the origination of the new loan.
$\gamma_{i,year}$	Firm-year fixed effects.
Credit variables:	
Credit lines$_{i,t}$	Drawn overdraft facilities
Long-term loans$_{i,t}$	Drawn long-term loans, with a maturity longer than one year.
Leases$_{i,t}$	Drawn leases loan for equipment and real-estate.
Drawn loans$_{i,t}$	Drawn loans, regardless of their maturity. They are the sum of credit lines, factoring, trade receivables, other short-term loans, leasing, and long-term loans.
Available loan$_{i,t}$	Available loans, regardless of their maturity.
Total loans$_{i,t}$	Total loans are defined as the sum of drawn and available loans.
Number of banks$_{i,t}$	Number of bank relationships of firm i at date t.
Collateralized loan$_i$	Dummy equal to one if the bank loan i is collateralized.
Investment loan$_i$	Dummy equal to one if the bank or FinTech loan i is used for the acquisition of tangible assets.
Total loans from new lenders$_{i,t}$	Total loans granted to firm i observed at time t from banks that were not lending to firm i before the new loan.
Total loans from existing lenders$_{i,t}$	Total loans granted to firm i observed at time t from banks that were lending to firm i before the new loan.
Balance sheet, profit & loss statements:	
Total assets$_{i,t}$	Logarithm of the total asset 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 total assets of the firm i at time t.
EBIT$_{i,t}$	Ratio of earnings before interests and taxes to total assets of the firm i at time t.
Sales$_{i,t}$	Ratio of sales to total assets of the firm i at time t.
Investment ratio$_{i,t}$	Growth rate of fixed assets of the firm i at time t.
Leverage$_{i,t}$	Ratio of total assets less equity to 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 total assets of the firm i at time t.
Rating$_{i,t}$	Banque de France rating of the firm i at time t.
Rated$_{i,t}$	Dummy which is equal to one if the Banque de France is rating the firm i at time t.
High collateral$_{i,t}$	Dummy which is equal to one if the tangible assets ratio of firm i at time t is above the median of the tangible assets ratio of the firms in the candidate sample.
Default:	
$Customer\ default_{i,q}$	Dummy variable that indicates that firm i has been a victim of at least one of its customers defaulting at quarter q.

Continued next page

Description of Variables (continued)

Variables	Description
$Customer\ default_{i,Before\ q-2}$	Dummy variable that takes the value one if firm i has experienced at least one customer default at more than two quarters ago, but none during the last previous two quarters.
$Procedureopening_{i,q}$	Dummy variable that indicates that a collective procedure has been opened for firm i at quarter q. A procedure opening can lead to the liquidation or the restructuring of the company.
$Liquidation_{i,q}$	Dummy variable that indicates that a liquidation procedure is opened for firm i at quarter q.
Early repayment:	
$Early\ repayment_i$	Dummy variable that indicates that firm i fully repays its FinTech loan in less than 6 months.