# Collateral Effects:
# The Role of FinTech in Small Business Lending*

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**Abstract**

This paper investigates the impact of introducing junior unsecured loans (i.e., FinTech loans) in the small business lending market. Using French administrative data, we find that FinTech borrowers experience a 20% increase in bank credit following FinTech loan origination. We establish causality using a shift-share instrument exploiting firms' differential exposure to banks' collateral requirements. The credit expansion only occurs when FinTech borrowers invest in new assets, and Fintech borrowers are subsequently more likely to pledge collateral to banks. This suggests that firms use FinTech loans to acquire assets that they then pledge to banks, thereby increasing their total borrowing capacity.

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# 1 Introduction

Banks provide the primary source of credit for small and medium-sized enterprises (SMEs). In view of tightening bank regulations, therefore, policymakers have become increasingly concerned that banks may not be able to offer a wide enough range of products to meet SMEs' financing needs (G20, 2015, 2022). Can non-banks complement the range of products offered by banks? Does supplying new credit products to SMEs facilitate their access to financing, or does it merely replace bank financing? Answering these questions is essential to understanding the potential of product innovation in the small business lending market for firms' access to credit.

One type of credit product historically absent from the small business lending market is junior unsecured debt. Indeed, one of the defining characteristics of bank credit is that it is senior (Welch, 1997; Hackbarth, Hennessy and Leland, 2007). Moreover, banks typically require collateral, especially from young or small firms (Berger and Udell, 1995; Schmalz, Sraer and Thesmar, 2017; Caglio, Darst and Kalemli-Ozcan, 2022).[1] Can providing junior unsecured loans facilitate SMEs' access to financing? The fact that bank credit is senior and secured means that the assets of SMEs cannot easily be pledged to other creditors, which protects banks against dilution from new creditors. However, since encumbered assets cannot be pledged again, bank credit also reduces borrowers' ability to fund future investment opportunities. In contrast, junior unsecured debt can finance the acquisition of new, unencumbered assets that can be pledged to future creditors, including banks. Therefore, supplying junior unsecured credit products to SMEs could alleviate collateral constraints and improve firms' access to bank credit.

In this paper, we study the impact of the introduction of junior unsecured loans by FinTech platforms on SMEs' access to bank credit. Differences in regulation explain why FinTech lenders do not offer the same credit products to SMEs as banks. Under the Basel III framework, banks must set aside twice as much capital for unsecured loans to SMEs as for secured loans, making unsecured loans an unattractive product for banks. Because FinTech platforms do not take deposits, they are not subject to regulatory capital requirements.[2] Our main finding is that SMEs use FinTech loans to acquire assets that they then pledge to obtain bank credit. The resulting bank credit increase

[1] While large firms have access to junior unsecured credit products under the form of bonds, SMEs typically do not have access to the bond market (Caglio, Darst and Kalemli-Ozcan, 2022).

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

is equivalent to 20% of a firm's credit balance prior to the FinTech loan origination. Throughout the paper, we refer to this mechanism as the "collateral channel".

We study the French SME lending market, which offers three main advantages for our analysis. First, France has both a developed banking and FinTech market. According to Ziegler et al. (2021), France is the second largest market for FinTech lending and the largest market for bank lending to SMEs in the European Union. Second, banks and FinTech lenders are the only two types of lenders operating in the French small business lending market. Specifically, only banks were allowed to engage in lending activities to French firms until 2014, when the government amended the law to allow FinTech lenders to enter the small business lending market. Third, FinTech loans are 100% junior and unsecured in France, meaning that the entry of FinTech lenders made it possible for SMEs to access credit products that were virtually inaccessible to them before.[3]

We rely on administrative and commercial datasets to study the interactions between FinTech and bank lending. Our data allow us to observe the near universe of loans originated by French FinTech platforms between 2014 and 2019, with the 10 FinTech platforms in our sample facilitating 82% of the FinTech lending volume in France. In addition, we obtain the identity of all rejected applicants from one major FinTech platform. We combine this dataset with information on bank loans, such as volume, collateral, and interest rate, from the French Credit Registry and detailed firm-level information from administrative tax records.

In the first part of the paper, we track firms' bank credit dynamics around the origination of a FinTech loan. We find that for an average FinTech borrower, the FinTech loan is followed by an 8% increase in bank credit. The increase appears gradually and reaches a plateau at 20% six months after the FinTech loan origination. Is this increase in bank credit caused by the origination of the FinTech loan? An alternative explanation is that firms with investment opportunities simultaneously apply to multiple lenders, including FinTech platforms and banks, and obtain the FinTech loan before the bank loan. In this case, the increase in bank credit reflects firms' unobserved credit demand rather than banks' reaction to the FinTech loan origination. We address the role of credit demand in two ways.

Our first strategy is to compare FinTech borrowers' credit dynamics to those of firms that did

[3]Outside of France, OECD (2015) or World Economic Forum (2015) describe FinTech lending to SMEs as being mostly unsecured. In the Small Business Credit Survey (2019), 45% of the firms that applied for a FinTech loan mentioned the absence of collateral as a factor influencing their decision to turn to a FinTech platform. Currently, among the 9 FinTech lenders that have issued more than \$50Mns in loans to SMEs in the US (source), eight platforms report unsecured financing solutions on their website. While FinTech loans are not explicitly described as junior or senior outside of France, the fact that they are typically unsecured suggests they are not repaid first during bankruptcy proceedings.

not obtain a FinTech loan but presumably had similar credit demand. We consider two groups of "benchmark borrowers". The first group is composed of firms that obtained a new bank loan during the sample period, the "bank borrowers". We refer to the new bank and FinTech loans taken as "outside loans" throughout, and we exclude outside loans from the computation of total bank credit.[4] The second group is composed of firms that applied for a FinTech loan but were rejected, the "rejected borrowers". We ensure that FinTech and benchmark borrowers are observably similar before the outside loan. Specifically, we use propensity score matching to match FinTech and benchmark borrowers based on recent credit dynamics, the size and origination year of the outside loan, and a rich array of firm characteristics, such as rating, industry, size, and tangible assets.

Our identifying assumption is that observably similar FinTech and benchmark borrowers have similar credit demand. Comparing FinTech and bank borrowers allows us to test whether bank credit increases systematically after firms obtain an outside loan or whether the increase only follows FinTech loans. In contrast, comparing FinTech borrowers and rejected applicants allows us to control for factors driving both the decision to borrow from FinTech platforms and firms' subsequent access to bank credit. Using both benchmark groups, we show that FinTech borrowers experience a larger increase in bank credit than benchmark borrowers. This long-term increase is close to 20%, our simple-difference estimate. Importantly, we find no evidence of pre-trends for both benchmark groups. Credit line utilization rates, a measure directly related to firms' credit demand, remain parallel between groups in the pre and post periods.

In our second strategy, we address potential differences in unobservable credit demand between FinTech and bank borrowers exploiting exogenous variations in the decision to apply for a FinTech loan. The premise of our identification strategy is that firms are more likely to turn to FinTech lenders when their existing banks are more likely to require collateral against new loans. Since bank collateral requirements are likely orthogonal to an individual firm's credit demand, this identification strategy allows us to neutralize the role of credit demand from our estimations. We measure a firm's exposure to banks' collateral requirements using a shift-share instrument, the "share" being the firm's credit exposure to a given bank and the "shift" the bank-level fraction of newly originated loans to SMEs that are secured. Our first-stage coefficient is strongly significant, in line with FinTech platforms catering to firms facing tightening collateral requirements by banks.

Turning to the second stage, we find that the instrumented propensity to borrow from a FinTech

[4] Since FinTech borrowers are by construction first-time borrowers on FinTech platforms, we impose in this approach that bank borrowers also take a loan from a new bank lender to control for factors associated with the creation of a new lending relationship (Degryse, Ioannidou and von Schedvin, 2016).

lender still predicts an increase in subsequent bank borrowing. Our identifying assumption in this shift-share strategy is that absent the changes in banks' collateral requirements ("shift"), firms with higher exposure to high-collateral-requirement banks ("share") and firms with lower exposure to those banks would have experienced similar credit dynamics.[5] Our placebo tests substantiate this assumption: the second-stage coefficients become statistically insignificant when we replace the shifts by their lags, suggesting that it is indeed the concurrent collateral requirement shocks that are driving the effects, and not firm exposure to specific banks. Overall, our results show that the increase in bank credit is attributable to the origination of the FinTech loan and not to FinTech borrowers' credit demand.

In the second part of the paper, we explore why FinTech borrowers obtain more bank credit after receiving a FinTech loan. The collateral channel states that acquiring new assets using junior unsecured FinTech loans expands firms' subsequent borrowing capacity more than acquiring the same assets using bank credit, as junior unsecured loans allow firms to acquire assets without encumbering them.[6] This hypothesis yields two testable predictions.

First, the collateral channel predicts that FinTech borrowers should be more likely to pledge assets in subsequent bank borrowing than benchmark borrowers. In line with this prediction, we show that the increase in bank credit is almost exclusively driven by long-term loans, which are more likely to be backed by assets than other loan types.[7] In contrast, we find weak effects on used lines of credit and no effect on other loan types, such as leasing. In addition, using a subset of loans for which we observe the collateral, we find that FinTech borrowers are more likely to borrow against specific assets than benchmark borrowers after the origination of the outside loan.[8]

Second, the increase in bank credit should be more pronounced when the firm uses the new loan to acquire additional assets than to meet short-term financing needs. We test this hypothesis by exploiting the purpose of bank and FinTech loans, that is, whether they are used to finance the acquisition of new assets.[9] Our results are in line with the prediction. There is a positive

[5]We add a measure of the supply of new loans to SMEs by the existing banks of the firm as an independent variable to control for banks' credit supply.

[6]Note that the collateral channel does not imply that firms cannot finance the acquisition of new assets by secured banks loans. The collateral channel states that conditional on buying an asset, financing the asset with a FinTech loan rather than a bank loan will lead to higher subsequent borrowing capacity.

[7]For instance, Benmelech, Kumar and Rajan (2020) report the share of secured loans for various debt categories and find that long-term loans are more likely to be secured than other categories. We document similar patterns in our data.

[8]Our dataset only allows us to observe whether loans are backed by specific assets, such as machines or real estate. In practice, banks can ask for "cash collateral" in the form of personal guarantees; in that case, the loan is not tied to a specific asset.

[9]The purpose of FinTech loans available in our sample is based on the loan purpose description posted on the

and significant increase in bank loans when FinTech loans are used to finance new assets and no significant change in bank credit when the new loans are used for other purposes, such as commercial growth. Similarly, the increase in the propensity to pledge assets is entirely driven by firms that use the FinTech loan to acquire new assets.

An alternative interpretation of the increase in bank credit is that FinTech lenders produce new information on firms. Unlike banks who typically engage in relationship lending, FinTech lenders often leverage new technologies (e.g., machine learning, big data) to better screen firms and lend to profitable businesses overlooked by banks. As a result, a successful FinTech loan application could, in theory, serve as a positive signal about firm quality, prompting banks to lend more to FinTech borrowers (Balyuk, 2023).[10] Under this hypothesis, we should observe that the increase in bank credit is more pronounced when banks have less information on firms. Instead, we find that the increase in bank credit is driven by banks that have been lending to FinTech borrowers for more than five years, that are geographically close to FinTech borrowers, and concentrated among FinTech borrowers with a rating issued by Banque de France, suggesting that the increase in bank credit is not caused by additional information brought by FinTech lenders.[11]

In the last part of the paper, we study whether introducing junior unsecured loans in the small business lending market is sustainable for firms and lenders. We start by investigating how FinTech firms use the additional funding they obtain from banks. On average, compared to bank borrowers, FinTech borrowers obtain €15,000 additional bank credit. While both bank borrowers and FinTech borrowers invest more after receiving a new loan, FinTech borrowers do not seem to invest more, suggesting that they do not use the additional bank credit to invest in additional assets. This has two implications. First, the fact that FinTech borrowers do not invest more than banks but are more likely to pledge collateral strongly suggests that the assets acquired with FinTech loans are less encumbered. Second, the absence of differences in investment rates between FinTech and bank borrowers provides further support for the idea that the increase in bank credit is due to the FinTech loan itself and not to superior growth opportunities of FinTech borrowers.

platforms' website. The purposes of bank loans are also available in the administrative data. We classify bank loans as being "for investment" if they are reported as equipment loans and "not for investment" otherwise.

[10] FinTech lenders and banks have access to similar "hard" information on firms. If anything, banks have an edge in terms of access to "soft" information through their past interactions with firms.

[11] Another difference between FinTech and banks is the speed at which they process loan applications. Since FinTech platforms rely on streamlined and semiautomated screening processes, they typically make decisions faster than banks (Fuster et al., 2019). This could lead bank credit to increase for FinTech borrowers if FinTech borrowers use the FinTech loan to meet urgent liquidity needs and then refinance it at a lower rate with a bank loan (Liu, Lu and Xiong, 2022). However, we find that only 3% of FinTech borrowers repay within the first six months of the loan, during which the bank credit increase occurs. Removing these firms from the analysis does not change the results.

Instead, we find that FinTech borrowers use most of the additional funding they receive from banks to substitute away from expensive sources of short-term financing (i.e., supplier trade credit), suggesting that firms actively consolidate debt to limit the risk of default.[12] In line with this idea, we find no difference in default rates between FinTech and bank borrowers with low ex-ante credit risk (i.e., interest rate below median). In contrast, firms with high ex-ante credit risk default more following a FinTech loan origination, potentially due to the larger repayment burden associated with the higher cost of FinTech loans. Taken together, these findings suggest that obtaining junior unsecured loans alleviates firms' borrowing constraints, which can have heterogeneous effects on their probability of default depending on their ex ante financial health.

Since FinTech loans are junior to bank loans, most of the credit risk will be borne by FinTech lenders. We estimate that after excluding platforms' fees and accounting for firms' repayment profiles, an average loan delivers a 4.90% internal rate of return. By comparison, average yields of US corporate bonds for firms with similar credit ratings to FinTech borrowers (i.e., Baa) were 4.54% over the 2017-2019 period.[13] This suggests that despite the low creditor protection associated with FinTech loans, funding FinTech loans is profitable for investors.

Overall, our findings suggest that fostering the supply of junior unsecured loans in the small business lending market has the potential to alleviate SMEs' financing constraints, which reduce aggregate output and productivity (Catherine et al., 2022). Instead of replacing bank credit, junior unsecured loans can facilitate firms' access to bank credit by allowing them to acquire assets that they then can pledge to banks. More generally, our results support the view that the arrival of new, less regulated entrants in the finance industry has the potential of generalizing access to services (e.g., "bond-like" securities) that were previously reserved for the largest firms (e.g., Philippon (2018)).

**Related literature** Our paper falls within a large body of literature exploring the role of collateral constraints in firms' access to credit. Donaldson, Gromb and Piacentino (2020, 2022) show

[12]Previous work has estimated trade credit to be a very expensive source of short-term financing, with annual interest rates ranging between 25% and 50% (Ng, Smith and Smith, 1999; Giannetti, Burkart and Ellingsen, 2011; Klapper, Laeven and Rajan, 2012). Trade credit is implicitly secured on the inputs purchased in the transaction (Burkart and Ellingsen, 2004; Maksimovic and Frank, 2005).

[13]While bonds are junior to bank loans, they can be secured by collateral, meaning that bond yields may be an imperfect benchmark for the internal rate of return of FinTech loans. However, Schwert (2020) estimates that secured bonds only represent 11% of bonds and finds a 0.4 p.p. difference in yields between secured bonds and unsecured bonds, suggesting that unsecured bond yields are on the same order of magnitude as FinTech loans' rates of return. Moreover, since bond yields are estimated for 10-year maturity bonds, our estimates are likely to be an upper bound of the yields of unsecured bonds with a similar maturity to FinTech loans (i.e., three years).

how collateral requirements protect creditors from dilution but can, in turn, limit firms' borrowing capacity. Rampini and Viswanathan (2013) and Rampini and Viswanathan (2022) investigate firms' financing and risk management behavior when liabilities are explicitly or implicitly backed by collateral. In particular, Rampini and Viswanathan (2022) predict that financially constrained firms should rely more on secured debt, in line with the empirical evidence in Benmelech, Kumar and Rajan (2020, 2022).[14] We contribute to that literature by showing that allowing firms to dilute creditors (FinTech lenders) can boost firms' borrowing capacity and alleviate collateral constraints, in line with Donaldson, Gromb and Piacentino (2020, 2022).

Our results then shed light on how firms use debt of different levels of seniority. Diamond (1993), Welch (1997), and Hackbarth, Hennessy and Leland (2007) explore why firms may prefer to give seniority to some creditors. In a setting similar to ours, Degryse, Ioannidou and von Schedvin (2016) show that existing banks' willingness to lend decreases when firms start borrowing from a new bank, supporting the idea that taking on new bank loans does not increase firms' total borrowing capacity. Following the seminal contributions of Diamond (1991) and Rajan (1992), a large theoretical literature has explored the determinants of the choice between senior bank debt and junior bonds, particularly the role of renegotiation upon bankruptcy (Bolton and Scharfstein, 1996; Hackbarth, Hennessy and Leland, 2007; Crouzet, 2018). Empirically, Adrian, Colla and Shin (2013) and Becker and Ivashina (2014) provide evidence that firms substituted bank credit with bond financing during the Great Recession. While the literature typically studies large firms that already have access to both junior and senior debt, our setting allows us to explore how obtaining access to junior debt affects small firms' use of senior debt.

This paper also adds to a strand of research exploring the role of bank regulation in the growth of FinTech lending. In the context of consumer lending, Buchak et al. (2018) and De Roure, Pelizzon and Thakor (2022) show that the growth of FinTech platforms is more pronounced when traditional banks are more constrained by regulations. In contrast, Begley and Srinivasan (2022) show that small banks, which were less affected by new bank regulations, played a larger role than FinTech lenders in filling the void left by big banks. In the context of small business lending, Gopal and Schnabl (2022) find that nonbank and FinTech lenders substitute for banks to supply secured loans as a result of the tightening of banking regulations following the Great Recession. Unlike Gopal and Schnabl (2022), who focus on the supply of secured loans, the FinTech platforms in

[14] Relatedly, Berger and Udell (1995),Schmalz, Sraer and Thesmar (2017), and Caglio, Darst and Kalemli-Ozcan (2022) show that access to collateral is key for SMEs to obtain bank credit. Benmelech (2009),Kermani and Ma (2022), and Luck and Santos (2023) study the determinants of the pledgeability of firms' assets.

our data exclusively offer unsecured loans. Analyzing the supply of unsecured loans by FinTech lenders is important, as firms report the absence of required collateral as being one of the main reasons to apply for a FinTech loan (Small Business Credit Survey, 2019). Moreover, in contrast with previous studies, our focus is on the type of products offered by FinTech lenders. We show that FinTech lenders offer products that banks typically cannot provide in the current regulatory framework and that fostering the supply of junior unsecured products can alleviate the collateral constraints firms face. Lastly, we find that lighter regulation for FinTech lenders does not lead them to engage in excessive risk-taking, in contrast with existing evidence on regulatory arbitrage.

Our paper eventually contributes to a growing literature on the interplay between FinTech lenders and banks (see Thakor (2020) or Berg, Fuster and Puri (2021) for a review). Tang (2019) and Di Maggio and Yao (2021) investigate whether FinTech platforms and banks serve different borrowers in the US consumer credit market. Ben-David, Johnson and Stulz (2021) and Erel and Liebersohn (2020) focus on the supply of FinTech credit in the US during the COVID-19 pandemic. Erel and Liebersohn (2020), in particular, find that FinTech lenders provided more PPP loans to SMEs in areas where banks were less present, suggesting that FinTech lenders complemented banks in supplying PPP loans. Eça et al. (2021) show that in the Portuguese corporate lending market, FinTech borrowers tend to be higher quality firms than regular bank borrowers and use FinTech lenders to reduce their dependence on banks. Using a similar dataset to ours, Havrylchyk and Ardekani (2020) also find that FinTech borrowers have less tangible assets than bank borrowers. Huang (2021) shows that borrower segmentation can arise from the different enforcement technologies of bank and FinTech lenders, leading to efficiency gains. To our best knowledge, this is the first paper that documents the complementarity between FinTech and bank loans at the firm level.

The remainder of the paper is organized as follows. Section 2 provides institutional details on the FinTech SME loan market in France. Section 3 describes our data sources and provides detailed summary statistics on FinTech loans and borrowers. In Section 4, we compare the credit dynamics of FinTech and benchmark borrowers. Section 5 presents evidence on the collateral channel and discusses alternative channels. In Section 6, we study firm performance. We also discuss the external validity of our results. Section 7 concludes.

# 2 FinTech SME loan market in France

Since 1945, lending activities in France have been regulated under a "banking monopoly" (*monopole bancaire*) regime, which prohibits nonbank entities from carrying out lending activities. This regulation was relaxed in 2014 to introduce a new lender category – crowdfunding intermediaries (hereafter "FinTech platforms"). Such platforms are subject to neither capital nor liquidity requirements, as they are not classified as banks. However, they are only allowed to intermediate corporate loans of less than one million euro, with a €2,000 limit on the amount invested per individual investor. Effectively, this loan size cap restricts the borrower pool, which motivates our focus on SMEs. We estimate that between 2016 and 2019, there were 14 active FinTech platforms that collectively issued €530 million in loans. The number of FinTech borrowers is still low compared to that of bank borrowers. On average, FinTech borrowers account for only 0.5% of the borrowing base of banks, including solely SMEs.

The application process is exclusively online. Borrowers must meet some minimum requirements to apply. For example, on Lendix, one of the major French FinTech platforms, firms must be over three years old or have more than €250,000 in sales. To qualify for a loan, firms submit a loan request specifying the project they seek funding for and the amount of funding. Upon receiving the application, platforms collect information on applicants and make a decision, typically within 48 hours. Platforms in our sample have access to applicants' accounting data and credit history from the Banque de France. Some FinTechs (e.g., Lendix) also conduct interviews with applicants to assess the quality of the firm and its future profitability. Overall, therefore, FinTechs use similar information to Banque de France to evaluate firms' credit risk.[15] This suggests that if FinTech lenders have a superior screening technology, their comparative advantage resides in the algorithms they use, not the data they use as input.

Most FinTech platforms guarantee full funding of the project conditional on passing the screening stage.[16] The platforms complement the funds advanced by individual lenders either by advancing their own funds or funds from institutional investors partnering with the platform. This guarantee of total funding makes FinTech financing more attractive to borrowers. From the borrower's perspective, the screening is therefore carried out by the platform, not by individual lenders.

[15] The Banque de France also conducts interviews to rate firms (about 50,000 interviews per year - see link). The interviews allow analysts to evaluate companies on several criteria such as the "potential of the market in which the company operates", the "positioning of the company in that market", or the "strength of the shareholder base."

[16] On average, platforms report on their website that they approve 2% of submitted applications.

Once accepted by the platform, the borrowers' project is displayed online to lenders. Both individual and institutional investors can invest in FinTech platforms. Lenders have access to a brief description of the project, 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).

Borrowing costs typically have three components. The first part is a fixed application fee incurred upon application submission. 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 usually set the interest rate based on their internal credit scoring algorithm.[17] FinTech platforms can charge additional fees to borrowers in the case of late or early repayment. Importantly, no collateral or personal guarantee is required on these loans. Moreover, by law, FinTech loans are junior to bank loans.

# 3 Data and Descriptive Statistics

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

## 3.1 Data sources

**FinTech loans.** Our data on FinTech loans come from two sources. First, we collect information on FinTech loans by scraping Crowdlending.fr, a French website founded in late 2014 that aggregates information on FinTech loans for individual investors. Since 2016, the website has collected information from platforms' websites on individual loans for the universe of French FinTech lenders, including those that originated before 2016. We exclude platforms that provide equity or convertible bond financing to have credit instruments comparable to bank loans.[18] We also remove one platform (Agrilend) that exclusively finances agricultural firms. We observe the main characteristics of the loan (e.g., interest rate, maturity, face value) and information on repayment status, such as whether the loan is still being repaid, repaid in full, or has been defaulted upon.

We complete this dataset with additional data collected by the Banque de France (the French

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

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

central bank). Since 2016, the Banque de France has collected monthly data on loans intermediated by FinTech lending platforms. FinTech lending platforms report the information voluntarily in exchange for access to the credit score created by the Banque de France. In total, this database covers 10 platforms.[19] The Banque de France dataset completes the information from Crowdlending.fr in three ways: (i) the Banque de France dataset covers outstanding loan balances at a monthly frequency, which allows us to observe the actual fraction of payment made by firms and early repayments; (ii) information on interest rates and maturities is not always reported on Crowdlending.fr, so we use the information provided by the Banque de France whenever it is available; and (iii) the Banque de France dataset reports the purpose of the loan.

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

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

**Rejected FinTech applicants.** Our data also allow us to observe rejected FinTech applicants. One of the 10 lenders in our sample (PretUp) shared with us the list of firms that did not pass the platform's initial screening process and the date of the rejection decision. For each borrower, we only consider the first rejected application. In total, there are 30,539 rejected firms between January 2014 and July 2019.

**Credit registry.** We obtain data on firm credit using the French credit registry. It contains monthly information on the near universe of bank-firm lending relationships. Specifically, the dataset covers any firm with credit exposure exceeding €25,000 to at least one bank. We observe that both credit effectively extended to the firm and banks' credit commitments. Loan balance is

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

reported by categories, such as long-term loans and lines of credit. In addition, we observe some firm characteristics, including industry, location, and the internal firm size category defined by the Banque de France. Firms are classified as microenterprises, very small, small, medium-sized enterprises, or large enterprises based on their number of employees, revenues and total assets. We provide the definition of the size categories in Appendix Table C.2. We use the internal firm size category to identify SMEs. We compute the total credit exposure across all banks by credit category at the monthly frequency for each firm in the sample and only retain observations in the 2013-2020 period.

**Details of individual bank loans: M-Contran.** The M-Contran survey provides details on individual bank loans. All main credit institutions report exhaustive information for all individual loans originated in the first month of each quarter by the reporting bank branches.[20] On average, there are approximately 100,000 new loans in each reporting period. We observe a wide range of characteristics for each loan, including the loan amount, the loan type (e.g., revolving, overdraft), the loan purpose (e.g., investment), or its maturity. We also observe whether a loan is secured by specific assets (i.e., machine, real estate). However, M-Contran does not allow us to know whether a loan is secured by cash collateral (i.e., personal guarantees; see Davydenko and Franks (2008)). As with FinTech loans, we only retain loans originated before July 2019.

**Firm characteristics: FIBEN and Orbis.** FIBEN reports the credit score, accounting, and financial information for all companies with an annual turnover of over €750,000 for the period 2014-2020. The Banque de France constructs the credit score to reflect a firm's ability to meet its financial commitments in a three-year horizon. This score incorporates information on firms' balance sheets, trade bill payment incidents, the micro- and macroeconomic environment, and the quality of business partners and managers. Firms that are below the turnover threshold do not receive a credit score. Table C.2 presents a description of each credit score category and the associated expected default probabilities.

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

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

**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 (e.g., bankruptcy or liquidation).

**Construction of the datasets.** We construct our main sample as follows. First, we remove firms in the following industries: agriculture, finance, public administration, mining, and utilities. Second, we restrict our sample to firms that are present for at least three consecutive months in the credit registry before applying to obtain an *outside loan.* An outside loan is a loan originated by a lender with which the firm was not previously in a lending relationship. A firm is a *FinTech borrower* if the outside loan is a FinTech loan and the loan application is accepted, a *rejected applicant* if the outside loan is a FinTech loan and the loan application is rejected, or a *bank borrower* if the firm borrows from a new bank. New bank loans are observed in the M-Contran dataset.[21] We focus only on fixed-term bank loans (e.g., we exclude revolving credit lines or overdrafts). We do not include working capital loans or leasing loans as outside bank loans because FinTech loans are, in practice, not backed by specific assets such as accounts receivable or assets on lease. 97% of bank borrowers only obtain one outside loan during the sample period, and when they receive multiple outside loans, we randomly keep one outside loan per firm. Throughout the paper, we exclude outside loans (either bank or FinTech) from the computation of bank credit when studying firms' credit dynamics (i.e., we study how the origination of an outside loan by a new lender affects credit dynamics with other lenders). We then complete this dataset with information from Orbis/FIBEN and BODACC.

### 3.2 Descriptive statistics

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

On the investor side, a project is financed by 501 individual investors on average. Individual

[21] We exclude renegotiated loans and loans originated by public or quasipublic banks.

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

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

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

The presence of a premium for FinTech loans is consistent with previous evidence on mortgage loans (Buchak et al., 2018). In the context of small business loans, the presence of a premium can be explained by the fact that FinTech loans are riskier: they are not backed by any collateral and are junior to bank loans in the event of bankruptcy.[22]

**Firm characteristics.** Panels b and c of Figure 1 show the distribution of FinTech and bank borrowers across industries and credit ratings. Most firms in the sample are not rated by the Bank of France: firms without credit ratings represent 61.4% and 75.6% of FinTech and bank borrowers, respectively. This suggests that if anything, FinTech borrowers are less opaque than bank borrowers. Among rated firms, the modal credit rating is 4 or 5+, that is, firms for which the probability of default in a three-year horizon is estimated to be between 1.5 and 3.5%. This corresponds to ratings just above the speculative (or "junk") categories (Baa3/Ba2) in the US rating system. FinTech

[22] An alternative explanation for the presence of a premium is that borrowers are willing to pay for the speed and convenience of the FinTech loan origination process. It typically takes the platforms less than a week, sometimes less than a day, to approve a FinTech loan application, while the processing time is more than one month with banks.

borrowers tend to be underrepresented in the construction and real estate industries (10.8% versus 30.5% for bank borrowers). In contrast, they are overrepresented in the wholesale and retail trade, accommodation and food, and scientific and technical activities industries.

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

The average bank borrower in our sample is 14 years old, has approximately 1 million euros in total assets, and employs 14 workers, which is consistent with the fact that FinTech platforms cater mostly to SMEs. The average leverage ratio is 67% and the average asset tangibility ratio is 29%, in line with the capital structure of the average French firm in Rajan and Zingales (1995)[23]. FinTech borrowers are of the same size (either in terms of total assets or employment) as bank borrowers. They also feature similar EBIT, working capital, employment, and investment ratios. However, they are more levered, are more likely to have credit lines, and have fewer tangible assets, suggesting that they may face more difficulty obtaining additional bank financing. We then compare accepted and rejected FinTech applicants. Panel b of Table B.1 shows that successful FinTech applicants have more assets, generate more liquidity, are older, are more profitable, and are less levered. Figure A.2 shows that rejected borrowers are less likely to be rated and, when they are, have worse ratings than FinTech borrowers.

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

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

matching procedure in detail in Section 4.

# 4 Credit dynamics

In this section, we exploit the panel dimension of the data to track firms' credit dynamics around FinTech loan originations. We start by focusing on FinTech borrowers and show that FinTech loan originations are followed by an increase in bank credit. We then show that the increase in bank credit cannot be explained by differences in credit demand using propensity score matching and a shift-share instrument approach.

## 4.1 Credit dynamics of FinTech borrowers

We first investigate how firms' bank credit evolves after they receive a FinTech loan. We focus on FinTech borrowers present in the dataset detailed in Section 3. We require firms to be present for at least three consecutive months in the credit registry before taking out a FinTech loan. When a firm borrows multiple times from FinTech platforms, we retain only the first FinTech loan. We refer hereafter to this dataset as the "unmatched sample".

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

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

Figure 2 plots the evolution of the amount of bank credit around the FinTech loan origination. Bank credit remains constant in the 12-month period preceding the FinTech loan. Six months after loan origination, firms experience a significant 20%

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

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

We exploit two approaches to distinguish between these explanations. First, we rely on the richness of our data and compare FinTech borrowers to observably similar non-FinTech borrowers. We construct two benchmark groups: 1) firms that obtain a bank loan the same year as FinTech borrowers ("bank borrowers") and 2) FinTech applicants that were rejected the same year as FinTech borrowers ("rejected borrowers"). Second, we exploit firms' exposure to banks' collateral requirements for new loans as an instrument for the decision to apply for a FinTech loan. We present these two identification strategies in the next two sections.

### 4.2 Propensity score matching

*FinTech borrower vs. Bank borrower* We start by constructing a benchmark group of similar bank borrowers. We tightly control for credit demand by requiring the bank borrowers to have applied for and received an outside bank loan of similar size the same year as FinTech borrowers. We also impose that bank borrowers obtain an outside loan from a *new* bank lender. This condition allows us to control for the effects of a new lending relationship on subsequent credit supply (Degryse, Ioannidou and von Schedvin, 2016). Moreover, firms that turn to new lenders might already have exhausted their borrowing capacity with their existing banks. Hence, by imposing that benchmark bank borrowers also resort to new lenders, we control for factors driving this decision.

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

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

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

In summary, when comparing FinTech borrowers to bank borrowers, the underlying assumption is that observably similar firms face similar investment opportunities and, hence, have similar credit demand. Therefore, comparing FinTech and bank borrowers should allow us to determine whether the increase in bank credit systematically occurs after the origination of an outside loan or whether it is specific to FinTech loans. The comparison between FinTech borrowers and rejected applicants, in contrast, allows us to control for the factors that simultaneously drive firms' decision to specifically borrow from FinTech platforms and firms' subsequent access to bank credit.

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

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

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

### 4.3 Comparing the credit dynamics of FinTech, banks, and rejected borrowers

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

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

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

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

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

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

We then examine firms' credit line utilization rates, a direct measure of firms' credit demand. As shown in Appendix Figure E.1, the trends remain parallel between groups in both the pre and post periods. If anything, FinTech borrowers use their credit line slightly less than rejected borrowers. Taken together, our results suggest that the increase in bank credit observed for FinTech borrowers is unlikely to be driven by unobservable differences in credit demand between FinTech and benchmark borrowers.

In Appendix D, we show that the results are robust to alternative matching procedures, including one-nearest neighbor propensity score matching without replacement and with replacement, and the inclusion of alternative fixed effects such as firm fixed effects and industry-, location-, rating×year fixed effects. We also exclude two platforms that originate loans with larger loans. Although the set of matched firms varies across samples, the results are quantitatively similar.

### 4.4 Exploiting variations in banks' collateral requirements

In this section, we isolate a plausibly exogenous source in the decision to apply for a FinTech loan to rule out potential differences in unobservable credit demand between FinTech and bank borrowers. Our instrument is based on the idea that firms are more likely to turn to FinTech lenders to obtain junior unsecured loans when their existing banks are more likely to require collateral against new loans. Since bank collateral requirements are likely orthogonal to an individual firm's credit demand, this identification strategy allows us to purge the role of credit demand from our estimations.

Using the M-Contran survey, we first compute for each bank $b$ and quarter $t$ the fraction of newly issued loans to SMEs that are secured ("secured ratio")

$$\textit{Secured ratio}_{b,t} = \frac{\#\textit{New secured loans}_{b,t}}{\#\textit{New loans}_{b,t}}.$$

A high secured ratio means that a large fraction of new loans issued by bank $b$ require collateral.[25] For each firm, we compute the "shift-share" version of the secured ratio as

$$\textit{Secured ratio}_i = \sum_b \omega_{b,i,t=\text{-}2} \cdot \textit{Secured ratio}_{b,t=0}$$

where $\omega_{b,i,t=\text{-}2}$ is the share of total credit outstanding for firm $i$ that comes from bank $b$ two quarters before the firm receives the outside loan, and the *Secured ratio* is taken in the quarter of the outside loan origination. We used lagged instead of contemporaneous credit exposure because firms may endogenously respond to the tightening in collateral requirements by reducing their credit exposure. A high value of $\textit{Secured ratio}_i$ means that the collateral requirements from the mix of banks lending to firm $i$ are more stringent during the quarter of the outside loan.

A potential threat for identification is that banks' collateral requirements could be correlated to banks' credit supply. In particular, if banks require more collateral when they issue more loans, the instrumented FinTech coefficient could be positive not because of a causal effect of the FinTech loan but because firms exposed to banks with strict collateral requirements are more likely to receive a loan. To address this concern, we control for banks' credit supply by constructing $\textit{Credit supply}_i$ in a similar fashion to $\textit{Secured ratio}_i$:

$$\textit{Credit supply}_i = \sum_b \omega_{b,i,t=\text{-}2} \cdot \textit{log(New loans)}_{b,t=0}$$

where $\textit{log(New loans)}_{b,t=0}$ is the logarithm of the volume of all new loans issued by bank $b$ to SMEs at time $t = 0$.

[25] We use the number of loans instead of the amount of loans to construct this ratio, as the former is more likely to be representative of the composition of new loans to small firms.

We begin by testing whether firms facing tightening collateral requirements are more likely to turn to FinTech (i.e., $\theta > 0$) by estimating the following regression:

$$\begin{aligned} FinTech_{i,t} &= \theta Secured\ ratio_i \times Post_t + \delta Post_t + \alpha_i \\ &\quad + \gamma Credit\ Supply_i \times Post_t + \text{Interacted Fixed effects} + \mu X'_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

This constitutes the first stage of a two-stage least squares estimation. We then instrument $FinTech_{i,t}$, which is equal to $FinTech_i \times Post_t$, by $Secured\ ratio_i \times Post_t$ to estimate the second stage equation:

$$\begin{aligned} log(1 + Credit_{i,t}) &= \beta FinTech_i \times Post_t + \delta Post_t + \alpha_i \\ &\quad + \gamma Credit\ Supply_i \times Post_t + \text{Interacted Fixed effects} + \mu X'_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{4}$$

We estimate those regressions on the unmatched sample of FinTech and bank borrowers. We control for firm observables in two ways. First, we include firm- and interacted-fixed effects (industry $\times$ quarter, region $\times$ quarter, and size $\times$ quarter) to purge the estimates from time-invariant firm characteristics and aggregate time-varying shocks, respectively. Second, we use as control variables $X_t$ the same set of variables used for the propensity score procedure. This set of estimation results is reported in column 1 of Appendix Table F.1.[26]

Table 3 reports the main estimates. Column 1 provides the first-stage estimation result, column 2 the reduced-form, and columns 3 to 5 the second-stage results. In line with FinTech platforms catering to firms facing tightening collateral requirements from their banks, we find a strong positive relationship between the intensity of collateral requirements and the probability of taking a FinTech loan. Specifically, a one-standard-deviation increase (0.13) in collateral requirements leads to a 0.024 p.p. increase in the probability of receiving a FinTech loan relative to a bank loan. The second stage and reduced-form estimation deliver consistent results: firms that turn to FinTech lenders because of tight bank collateral requirements experience an increase in bank credit following the origination of the FinTech loan. The reduced-form estimate indicates that a one-standard-deviation increase in collateral requirements leads to an 8.3% increase in bank credit. In Appendix Table F.1, we show that the results are robust to changing the construction of the shift-share instrument (i.e.,

[26] Specifically, the set of control variables includes a dummy indicating whether the firm has a line of credit with any bank at the time of the outside loan origination, the firm's age, credit rating, total assets in logarithm, total debt, tangible assets, and EBIT, all taken at the last year-end before the outside loan is originated. Total debt, tangible assets, and EBIT are divided by total assets. We do not include variables that are directly related to firm credit dynamics, such as the logarithm of the total amount of bank loans in the six months preceding the outside loan and the log amount of the outside loan.

measuring the shares three or four quarters before the origination of the outside loan, or letting the shifts and the shares vary over time).

Our identifying assumption is that absent the changes in banks' collateral requirements, the credit outcomes of firms with higher exposure to these banks would have evolved similarly to firms with lower exposure to these banks (Borusyak, Hull and Jaravel, 2022).[27] The results of the placebo tests in columns 4 and 5 of Table 3 support our identifying assumption. Specifically, instead of using the bank secured ratio in the quarter of the outside loan ($t = 0$) to compute *Secured ratio*$_i$, we use the value of the bank secured ratio at $t = -1$ (column 4) and the average value of the bank secured ratio before $t = -2$ (column 5). Both estimates are economically small and statistically insignificant, suggesting that banks' collateral requirements are driving the effects, not the exposure to specific banks.

The shift-share approach aims at neutralizing unobservable differences in credit demand between FinTech and bank borrowers. However, it is possible that FinTech borrowers experience an increase in bank credit not because FinTech borrowers have higher credit demand but because FinTech lenders only serve firms with better growth opportunities (i.e., superior screening technology of FinTech lenders). Assuming that unobservable credit demand and growth opportunities are positively correlated (i.e., firms with higher credit demand tend to have better growth opportunities), the shift-share instrument strategy should also mitigate the impact of selection by FinTech lenders. The intuition is that if marginal borrowers turning to FinTech platforms due to the shift-share shock face similar growth opportunities as marginal borrowers turning to banks, differences in screening technologies should have a limited impact.[28]

The shift-share approach, however, may not be sufficient to address the selection issue if there are still large residual variations in firm growth opportunities after controlling for credit demand. To address this concern, we test a prediction of the superior screening technology hypothesis: FinTech borrowers would have a better growth trajectory than bank borrowers. In Section 6.1, we show that FinTech borrowers do not perform better than bank borrowers: specifically, they do not invest more and do not hire more workers. Therefore, differences in growth opportunities due to a better

[27] We are therefore assuming that bank-level collateral requirements (i.e., shifts) are "as-good-as-randomly assigned". In other words, they do not correlate with average unobservable characteristics impacting firms' credit demand. In contrast, the repartition of firms' credit exposure across banks may be correlated to other factors affecting firms' credit demand, suggesting that shares cannot be considered exogenous as required by the approach of Goldsmith-Pinkham, Sorkin and Swift (2020). In contrast, the approach of Borusyak, Hull and Jaravel (2022) allows shares to be endogenous.

[28] This should be the case if the presence of growth opportunities is correlated to credit demand, and credit demand is orthogonal to the exposure to banks' collateral requirements.

screening of applicants by FinTech platforms cannot explain our results.[29]

Taking stock of the results in this section, we demonstrate that the FinTech loan origination is followed by an expansion in bank credit. Importantly, this result holds when (i) we compare FinTech borrowers to either similar bank borrowers or rejected FinTech applicants and (ii) we exploit exogenous variations in the propensity to borrow from FinTech platforms. Therefore, the increase is unlikely to be driven by credit demand. In the next section, we explore the economic mechanisms for this finding.

# 5 Why does bank credit increase following a FinTech loan?

In the previous section, we show that firms are able to borrow more from banks following the origination of a FinTech loan. Two hypotheses can explain the complementarity between bank credit and FinTech credit. The first explanation relates to FinTech loans being junior and unsecured. Obtaining a FinTech loan allows firms to invest in new assets without encumbering them. Therefore, the newly acquired assets can then be pledged to banks, expanding firms' borrowing capacity. In contrast, assets financed by bank loans cannot be easily pledged to other creditors, meaning new bank loans do not increase firms' future borrowing capacity. We refer to this mechanism as the *collateral channel*.

An alternative interpretation of the credit increase is that since FinTech platforms typically leverage new technologies to screen firms, they may identify profitable businesses neglected by banks, making a successful FinTech loan application a good signal of firm quality. As a result, banks may be willing to extend more credit upon observing this signal. Importantly, FinTech loan originations are recorded in firms' credit reports, which are available to bank loan officers. We refer to this as the *information channel*.

These two channels would apply differently depending on firm characteristics, loan purposes, loan types, and lending relationships. In the following subsections, we test the collateral and information hypotheses.[30]

[29] An alternative interpretation could be that banks lend more to FinTech borrowers not because FinTech borrowers have better growth opportunities but because banks (mistakenly) believe FinTechs are better at screening firms. In Section 5.2, however, we find that the increase in bank credit is driven by banks that are already informed of firm quality, suggesting that the role of banks' learning about firm quality is limited.

[30] All the tests in this section are performed on the matched sample for two reasons. First, we perform various sample splits that are more straightforward with the propensity score matched sample than with the instrumental variable approach. For any given sample split, we redo the matching to ensure that the FinTech borrowers are still comparable to benchmark groups within each subsample. Second, the visualization of the dynamic DiD estimates is only possible with the matched sample.

## 5.1 Collateral hypothesis

The collateral channel hypothesis yields three main testable predictions: (i) the increase in bank credit should be driven by collateral-intensive lending products, (ii) FinTech borrowers are expected to pledge more collateral, especially when they use the FinTech loan to acquire new assets, and (iii) the increase in bank credit should be stronger when firms invest in new assets. We test these predictions in turn.

First, we expect the increase in bank credit to be driven by long-term loans, which are more likely to be secured by collateral than other credit types.[31] Accordingly, we study how the different credit types evolve following the origination of the outside loan. We replace the outcome variable in Equation D.1 with the log amount of long-term loans, used lines of credit, and other loans and report the results in columns 1-3 of Table 5. In Panel (a), the benchmark group is bank borrowers; in Panel (b), it is rejected FinTech applicants. As predicted, we observe strong growth in long-term credit for FinTech borrowers relative to both benchmark groups. Specifically, compared to similar bank borrowers (resp., rejected FinTech applicants), FinTech borrowers experience a 25% (resp., 16%) increase in long-term credit. In contrast, we only find a marginally significant increase in credit lines when we use bank borrowers as the benchmark group and no effect on other credit types.

Figure 6 visualizes the timing of the increase in long-term loans, estimated using Equation (2). The left and right parts of Figure 6 correspond to the two benchmark groups. In both figures, we observe that FinTech borrowers exhibit a sharp increase in long-term credit relative to the benchmark groups immediately after FinTech loan origination. The loan amount gradually increases for 3-6 months and then remains constant. Importantly, we do not observe differential trends between the FinTech borrowers and benchmark firms before outside loan origination.

In addition, we report the dynamics of used lines of credit and other types of credit in Panels (b) and (c) of Figure 6. In line with the regression results in Table 5, FinTech borrowers experience mild yet insignificant growth in these two credit categories. Note that the construction of our dataset leads to a mechanical reduction in FinTech borrowers' used lines of credit use after loan origination. This is because we exclude the outside loan and, more generally, any loans associated

[31] M-Contran provides information on whether a loan is secured by specific assets. Consistent with Benmelech, Kumar and Rajan (2020), we show in Table H.1 that long-term loans are more likely to be secured by specific assets than lines of credit and other types of loans. The fractions of secured loans for these three categories are 40.65%, 27.88%, and 28.2%, respectively. The fraction of secured loans in total is consistent with what Ivashina, Laeven and Moral-Benito (2022) document using Spanish data.

with the new lender in the computation of total bank credit. When a firm receives a new loan (either from a FinTech or a new bank lender), it will deposit the amount received in its current account. This mechanically reduces the amount drawn on overdrafts, a component of used credit lines. For FinTech borrowers, the reduction in the used lines of credit appears in the data since the new lender is the FinTech platform. For bank borrowers, the reduction in the used credit lines does not appear in the data since the new loan will be deposited in the current account at the new bank, which we exclude from the computation of bank credit.[32] The same argument applies to the comparison between FinTech borrowers and rejected borrowers, as the latter do not receive any outside loan.[33]

Second, we directly test whether firms are more likely to pledge collateral after the origination of the FinTech loan, using the detailed loan-level data from M-Contran (see Section 3). We proceed as follows. First, for each firm in our sample, we identify all loans issued to the firm in the M-Contran database and whether they are secured by specific assets. Second, we estimate

$$\mathbb{1}(Secured)_{i,t} = \beta FinTech_i \times Post_t + \delta Post_t + \alpha_i + \mu_{s,year} + \varepsilon_{i,t}. \tag{5}$$

where $\gamma_i$ is a firm fixed effect, $\mu_{s,year}$ is an industry-year fixed effect, and $\mathbb{1}(Secured)_{i,t}$ is an indicator variable equal to one if the firm pledges assets as collateral in a given quarter and zero if the firm does not pledge any specific assets or does not obtain any loan in that quarter. Including firm fixed effects allows us to tease out differences across firms in the probability of being included in M-Contran and to focus instead on within-firm differences over time in the probability of receiving a secured loan sampled into M-Contran.[34] Matching our baseline regression sample to M-Contran, however, leads us to lose a fraction of our sample firms, especially among rejected applicants.[35] For this reason, we primarily focus on the comparison between FinTech and bank borrowers in this test.

Table 4 shows the results. The first column is based on the full sample. The estimated coefficient

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

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

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

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

for the interaction term is positive and significant, in line with our expectations. We split the sample in columns 2-3 based on outside loan purposes and perform the same propensity score matching procedure on the subsamples (see Figure 1 for the repartition of loan purposes). As a result, FinTech borrowers that use the loan to acquire assets are matched only to bank borrowers that do the same.[36] Consistent with the collateral hypothesis, FinTech borrowers exhibit a higher propensity to subsequently pledge collateral only when they use the FinTech loan to acquire assets. Note that the coefficient on *Post* is negative, suggesting that the ability of bank borrowers to pledge collateral decreases after obtaining a new bank loan. One interpretation is that firms progressively exhaust the set of assets they can pledge, leading them to resort less and less to secured loans (Donaldson, Gromb and Piacentino, 2020).

We also perform the test for FinTech borrowers and rejected applicants in Appendix Appendix H. To deal with the loss of observations described above, we additionally report the results based on the unmatched sample that include the universe of FinTech borrowers and rejected applicants. As shown in Table H.2, the results are qualitatively similar: the point estimates are positive when the FinTech loans are used to acquire assets, although only significant for the unmatched sample. In contrast, firms that use the FinTech loan for other purposes do not exhibit a higher capacity to pledge assets.

Third, we examine whether the growth in bank credit is stronger when the FinTech loan is used to finance the acquisition of new assets. We split the unmatched sample depending on whether the outside loan is used to finance investment in new assets and, again, perform the propensity score matching procedure on the sub-samples. The results are reported in columns 4-5 of the two panels of Table 5. In line with the predictions of the collateral channel, we find a significant effect only when the FinTech loan is used to finance the acquisition of new assets. Long-term loans grow by 12% and 8% relative to bank borrowers and rejected borrowers, respectively. Firms do not enjoy improved access to bank credit when the outside loan is used for other purposes. We also plot the evolution of bank credit for these two subsamples in Figure 7. As expected, there is no difference between FinTech borrowers and benchmark firms before $t = 0$. Consistent with our previous results, FinTech borrowers experience a relative increase in total bank credit immediately after outside loan origination.

Can firms acquire new, unencumbered assets with unsecured bank loans instead of FinTech

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

loans? Even when bank debt is unsecured, it is "implicitly" secured on the unpledged assets of the firm since it is senior (Rampini and Viswanathan, 2022). Moreover, banks typically ask for personal guarantees in substitution or complement to pledged assets (Davydenko and Franks, 2008), effectively limiting the ability of firms to take on additional debt.[37] In line with this idea, we show in Appendix Figure G.1 that our estimates do not quantitatively change when imposing that bank borrowers take bank loans that are not secured on specific assets. This suggests that this type of loan still encumbers assets, either because it is senior or protected by other forms of securities.

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

In summary, our findings are in line with the collateral hypothesis, as the three testable predictions of that hypothesis are verified in the data.

### 5.2 Information hypothesis

In this section, we show that the increase in bank credit is not explained by banks reacting to the information on firm quality contained in a successful FinTech loan application.[38]

Under the information channel, we expect the increase in bank credit to be more pronounced when the degree of information asymmetry between firms and banks is large: banks should react more to the information brought by the origination of the FinTech loan if they have less information

[37] As explained in Section 3, M-Contran only allows us to observe whether loans are secured by specific assets. The dataset does not allow us to observe whether loans are backed by cash collateral (i.e., personal guarantees).

[38] Note that this does not imply that successful FinTech loan applications do not convey any useful information on firm quality.

on the quality of the firm. Following the convention in the literature, we measure the severity of information asymmetry in three ways: (i) the length of the lending relationship, (ii) the distance between borrowers and bank branches, and (iii) the presence of a credit rating for the firm.[39]

Exploiting comprehensive information on firm-bank lending relationships in the credit registry, we distinguish existing lenders from new lenders who recently started lending to the firm and close lenders from distant lenders. We define existing lenders as banks with a lending relationship longer than five years with the firm as of the origination of the outside loan (sample median of the length of lending relationships) and new lenders otherwise. Last, we consider a lender to be local if it is in the same county ("département") and remote otherwise. On average, 59% of firm-level credit is from existing lenders, and 72% is from local lenders. Following the literature, our assumption is that banks with a short lending relationship with the firm and banks located far from the firm are less informed about the firm and are, therefore, less likely to react to an external signal of firm quality.

We then measure the opaqueness of the firm by whether the firm has received a credit rating from the Banque de France. An attractive feature of the French credit market is that Banque de France is the single provider of credit ratings to firms, which implies that a firm that is unrated by Banque de France will be considered opaque by all lenders. Over half of the small firms do not receive a credit rating from the Banque de France due to a lack of credit history (see Figure 1 and Figure A.2). If the increase in bank credit for FinTech borrowers is mainly driven by a reduction in information asymmetry, we should observe that the new bank loans are mostly extended to firms that were previously opaque for banks.

Table 6 presents the results for the two matched samples. We find that FinTech borrowers receive more credit from existing lenders relative to both benchmark groups, and they also receive more credit from new lenders relative to rejected borrowers. In columns 3-4 of the two panels, we split banks into local and distant banks and find that the increase in bank credit is driven by local lenders. FinTech borrowers obtain 25% (resp., 13%) more credit from local lenders than bank borrowers (resp., rejected FinTech applicants), and there is no significant change in the amount of credit from distant lenders. If anything, therefore, the increase in bank credit is more pronounced when banks are more likely to be informed, in contradiction with the information channel.

We then exploit the heterogeneity in firms' rating status and implement propensity matching

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

in the two subsamples of rated and unrated firms. In this way, we only compare unrated (rated) FinTech firms to unrated (rated) benchmark borrowers. Columns 5-6 of both panels show that both rated and unrated FinTech borrowers experience a credit expansion, and the magnitudes are similar. The presence of an increase in bank credit for rated firms in both panels is difficult to reconcile with the information hypothesis, as the degree of information asymmetry should presumably be limited for those firms. In contrast, the collateral hypothesis could be at play for both rated and unrated firms. Moreover, we show in Appendix Table I.1 that if anything, FinTech borrowers' ratings decrease compared to bank borrowers after the FinTech loan, indicating that the increase in bank credit cannot be explained by the FinTech loan having a positive impact on firms' credit scores.

Taking stock of all the cross-sectional tests, we do not find the information channel to be a plausible explanation for credit expansion. Another alternative explanation is that FinTech lenders are faster in application processing and origination. This could lead bank credit to increase for FinTech borrowers if FinTech borrowers use the FinTech loan to meet urgent liquidity needs and then refinance it at a lower rate with a bank loan (Liu, Lu and Xiong, 2022). In Appendix J, we show evidence that firms facing liquidity shocks are more likely to receive FinTech loans than bank loans. However, only 3% of FinTech borrowers repay within the first six months of the loan, during which the bank credit increase occurs. Removing these firms from the analysis does not change the results. Hence, the speed advantage of FinTech lenders cannot explain the increase in bank credit for FinTech borrowers.

# 6 Additional results and discussion

In this section, we show that the introduction of junior unsecured loans in the small business lending market is sustainable for both firms and FinTech lenders. We first examine the performance of FinTech relative to benchmark borrowers after the loan origination. Then, we analyze the profitability of FinTech loans. We discuss the external validity of our results at the end of the section.

## 6.1 Firm performance

**Non-credit outcomes** In the previous sections, we show that FinTech borrowers are able to borrow more from banks after receiving a FinTech loan. But is this expansion of borrowing capacity sustainable for firms? The answer to this question depends on what firms do with the extra money they receive from banks. Specifically, we expect the relaxation of borrowing constraints to be more sustainable if firms reinvest the extra money to increase their performance or consolidate debt. We study this question by estimating the following equation where the outcome variables are the firm's total assets, tangible assets, employment, and working capital, all observed at a yearly frequency:

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

We apply the logarithm transformation to these variables, except for working capital, which can be negative. Hence, we normalize working capital with lagged total assets. The regression results are reported in Table 7.

We start by comparing FinTech borrowers to bank borrowers. By construction, FinTech and bank borrowers obtain outside loans of similar size. The only difference between the two groups of firms, therefore, is that FinTech borrowers experience an additional 20% increase in bank credit after the origination of the outside loan, which corresponds approximately to an extra €15,000 for FinTech borrowers.[40]

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

We do not find that FinTech borrowers employ more workers. The fact that FinTech borrowers do not spend more factors of production (i.e., labor and capital) suggests that they do not face better growth opportunities than bank borrowers. This result lends credence to the identification assumption behind the propensity score matching procedure: FinTech borrowers do not seem to have better ways to spend money (i.e., higher credit demand) than bank borrowers.

[40] We calculate the level change in the amount of bank credit for FinTech borrowers using two different methods. First, we take the median amount of bank credit for FinTech borrowers (€180,000) in the month before FinTech loan origination (we choose the median and not the mean because bank credit is highly skewed). Multiplying this figure by the average percentage increase in bank credit after the outside loan origination (8% - see column 4 of Table D.1), we obtain an increase of €14,400. Alternatively, relying on Table 1 and Figure 8, we calculate that an average FinTech loan of €150,000 translates into €15,000 (=(0.25-0.15)*150,000) in additional bank credit for FinTech borrowers.

In contrast, we find that firms pay their suppliers faster after receiving a FinTech loan (i.e., reduction in trade credit over assets). There is no change in the other components of working capital (e.g., cash holdings, accounts payable, or inventory), as shown in columns 4-6. These results suggest that FinTech firms use the additional funding to reduce their reliance on trade credit, a costly source of short-term financing. In terms of economic magnitude, the estimated coefficient in column 5 implies that FinTech borrowers experience a 2.6-p.p.reduction in the account-payables-to-asset ratio relative to bank borrowers. This represents a €8,400 decrease in the use of account payables by the average firm, that is, over 50% of the subsequent increase in bank credit experienced by FinTech borrowers.

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

**Default probability** How does the credit expansion experienced by FinTech borrowers affect their probability of default? Compared to bank borrowers, FinTech borrowers use extra money to cut back on trade credit, suggesting that they are less likely to default on suppliers. On the other hand, FinTech borrowers face higher interest expenses due to the higher cost of FinTech loans. Therefore, whether firms default more or less after receiving a FinTech loan will depend on their ability to meet the interest payments to FinTech lenders (e.g., credit risk).

We measure the occurrence of defaults using information on firm liquidation and bankruptcy from BODACC. We construct a dummy variable that is equal to one if a firm enters a liquidation or bankruptcy procedure in a given quarter. We estimate Equation (6), where $t$ represents the quarter relative to the outside loan origination. The regressions include firm fixed effects and industry-quarter fixed effects.

Table 8 reports the estimation results. Column 1 shows that FinTech borrowers are 4.8 p.p. more likely to enter a liquidation or bankruptcy procedure than bank borrowers. To test whether the higher default rates are explained by higher interest expenses, we split FinTech and bank loans based on the interest rate they pay for the outside loan. Column 2 reports the coefficients interacted with an indicator variable for loans with above-median rates *High rate* (the median is computed separately for bank and FinTech borrowers). By summing the coefficients of *Post* and *High rate* $\times$ *Post*, we see that bank borrowers who receive high-rate loans do not experience an increase in liquidation and bankruptcy probability compared to the pre-origination period. The same result holds for FinTech borrowers who receive low-rate loans, as indicated by the sum of the coefficients of *Post* and *FinTech* $\times$ *Post*.

This suggests that there is no difference in default rates between FinTech and bank borrowers with low ex-ante credit risk, despite the higher repayment burden faced by FinTech borrowers. In contrast, ex-ante risky FinTech borrowers (i.e., those receiving high-rate loans) are 6.6 p.p. more likely to be liquidated or enter bankruptcy, consistent with the idea that the average higher default rates are driven by the riskiest FinTech borrowers. Overall, these findings support the view that obtaining FinTech loans alleviates firms' borrowing constraints, which can have heterogeneous effects on their probability of default depending on their ex-ante financial health.

We then compare accepted and rejected FinTech borrowers. Accepted FinTech borrowers grow more than FinTech borrowers (Table 7), suggesting that they should default less. In line with this, we find that compared to rejected borrowers, FinTech borrowers are 6.2 p.p. less likely to default (column 3).

Taken together, our findings suggest that the credit expansion induced by junior unsecured FinTech loans is sustainable for firms with low ex-ante credit risk.

### 6.2 Profitability of FinTech loans

How profitable is it to lend to FinTech borrowers? Since FinTech loans are junior to bank loans, most of the credit risk will be borne by FinTech lenders. Whether providing junior unsecured loans to SMEs proves a viable business model, therefore, depends on the ability of FinTech platforms to compensate lenders for the credit risk they take. If interest rates are set too low, investors will not participate, limiting the ability of FinTech lenders to finance SMEs. On the other hand, if interest rates are set too high, firms will not borrow from FinTech platforms.

We start by estimating FinTech loans' internal rates of return. While we do observe a higher default rate among FinTech borrowers than bank borrowers, default risk is likely to be priced into the interest rate. Among loans for which we observe the entire repayment profile, we find a default probability of 4.6% and an average charged-off amount representing 21.4% of the loan principal. Taking into account defaults and early repayments, we find that the internal rate of return of

FinTech loans is 5.9% for the platform and the investors combined. Assuming a 3% origination fee and a 0.04% monthly management fee, as charged by the largest platform in our sample (i.e., Lendix), we find that the internal rate of return for investors alone is 4.9%.

It is difficult to know whether such returns fairly compensate investors without a model for required returns. Instead, we compare FinTech loans' returns to bond yields of firms with comparable credit ratings.[41] We find that over the 2017-2019 period, the average yield of US corporate bonds for firms with similar credit ratings to FinTech borrowers (i.e., Baa) was 4.54%. There are, however, two limitations with this comparison. First, bond yields are estimated for 10-year maturity bonds, while FinTech loans typically have a maturity of three years. Since the yield curve is typically upward sloping, however, bond yields for shorter maturities are likely to be lower. Second, while bonds are junior to bank loans, they can be secured by collateral. This means that bond yields may be an imperfect benchmark for the internal rate of return of FinTech loans. However, Schwert (2020) estimates that secured bonds only represent 11% of bonds and finds a 0.4 p.p. difference in yields between secured bonds and unsecured bonds, suggesting that unsecured bond yields are on the same order of magnitude as FinTech loans' rates of return. Overall, this exercise indicates that FinTech lenders are compensated similarly to bond market investors, suggesting that lending on Fintech platforms is profitable.

### 6.3 External validity

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

We first discuss whether our results can be generalized to other FinTech markets. The French FinTech sector is representative of the European market in general. According to Ziegler et al. (2021), France is the second-largest market in the EU in terms of the volume of FinTech lending to SMEs, behind Italy. Outside Europe, the largest market for SMEs remains the United States, with $8.27 billion in issued loans. One reason for the relatively small size of the French market compared to the US or UK market is that FinTech lending platforms have only been given accreditation by the French banking authority since 2014, which is seven years after the creation of the first FinTech lending platforms in the US and the UK. Another reason is the presence of institutional investors. Unlike the US and UK, platforms in continental Europe are currently dominated by individual

[41] Bond yields can be understood as bonds' internal rate of return.

investors. Despite the cross-country differences in market size and investor composition, the characteristics of FinTech credit are considered relatively homogeneous across countries. Specifically, FinTech lending to small firms is typically unsecured (OECD, 2015; World Economic Forum, 2015). In the US, SMEs cite lower collateral requirements as one of the main factors influencing their decisions to apply to a FinTech lender (Small Business Credit Survey, 2019). Moreover, among the 9 FinTech lenders having issued more than $50Mns in loans to SMEs in the US (source), eight platforms report unsecured financing solutions on their website. Since unsecured loans encumber assets less, we believe the credit expansion mechanism described in the paper is likely to hold outside France, including in the US.[42]

There are also reasons to believe that the collateral constraints faced by small firms are not uniquely present in France. We find that FinTech credit improves access to credit by allowing firms to acquire assets without encumbering them. FinTech lenders could play a similar role outside France for three reasons. First, there has been extensive literature showing that collateral is a key determinant of SMEs' access to credit in a wide range of countries.[43] Second, collateral requirements are largely determined by banking regulations, which are common to all European Union countries (Capital Requirements Directive - IV) and, more generally, follow the Basel III agreement adopted by the G20 countries. Finally, the French banking sector is the largest in Europe in terms of total assets, with four Global Systematically Important Banks ("G-SIBS"; e.g., see EBF (2020)). Liberti and Mian (2010) show that more developed banking systems tend to be associated with lower collateral requirements for firms. If anything, therefore, collateral constraints should be tighter in countries with less developed banking sectors.

Lastly, we think our results apply not only to firms already in a relationship with banks but also to unbanked firms. In our analysis, we impose that firms are already borrowing from banks before the outside loan. This is due to the fact that since FinTech firms typically require at least three years of fiscal data, very few FinTech borrowers are unbanked at the time of the FinTech loan. However, if anything, we expect collateral constraints to be stronger for unbanked firms. Unbanked firms are typically young and, as such, are likely to have limited pledgeable assets. Therefore, we expect unbanked firms to benefit more from introducing junior unsecured credit products (provided that they can access them).

[42] To our knowledge, there is no clear priority of FinTech loans regarding bank loans in the US.

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

# 7 Conclusion

In this paper, we investigate the impact of junior unsecured loans introduced by FinTech platforms on small and medium-sized enterprises' (SMEs) access to bank credit. Our findings suggest that fostering the supply of junior unsecured loans has the potential to facilitate SMEs' access to bank credit. Specifically, we find that FinTech borrowers experience a bank credit expansion amounting to a 20% increase in bank credit following the FinTech loan origination. Using propensity score matching procedures and an instrumentation strategy based on variation in exposure to banks' collateral requirements, we find that the increase in bank credit is unlikely to be driven by credit demand and instead caused by the FinTech loan.

We argue that junior unsecured loans improve firms' borrowing capacity by enabling firms to acquire assets without encumbering them. We show that SMEs use FinTech loans to acquire assets that they subsequently pledge to secure bank credit by establishing that the increase in bank credit (i) is driven by secured debt and (ii) is more pronounced when FinTech loans are used to finance new assets. In contrast, we find no evidence that the increase in bank credit is due to FinTech loans alleviating information asymmetries between banks and firms.

In conclusion, our results suggest that expanding the scope of lending products SMEs have access to can improve their overall access to financing. Instead of replacing bank credit, junior unsecured loans enable firms to acquire assets that can be pledged to banks, thus complementing the range of financial products offered by traditional financial institutions. Moreover, our findings underscore the potential benefits of new, less regulated entrants in the finance industry, such as FinTech platforms, in democratizing access to financial services and addressing the financing needs of SMEs.

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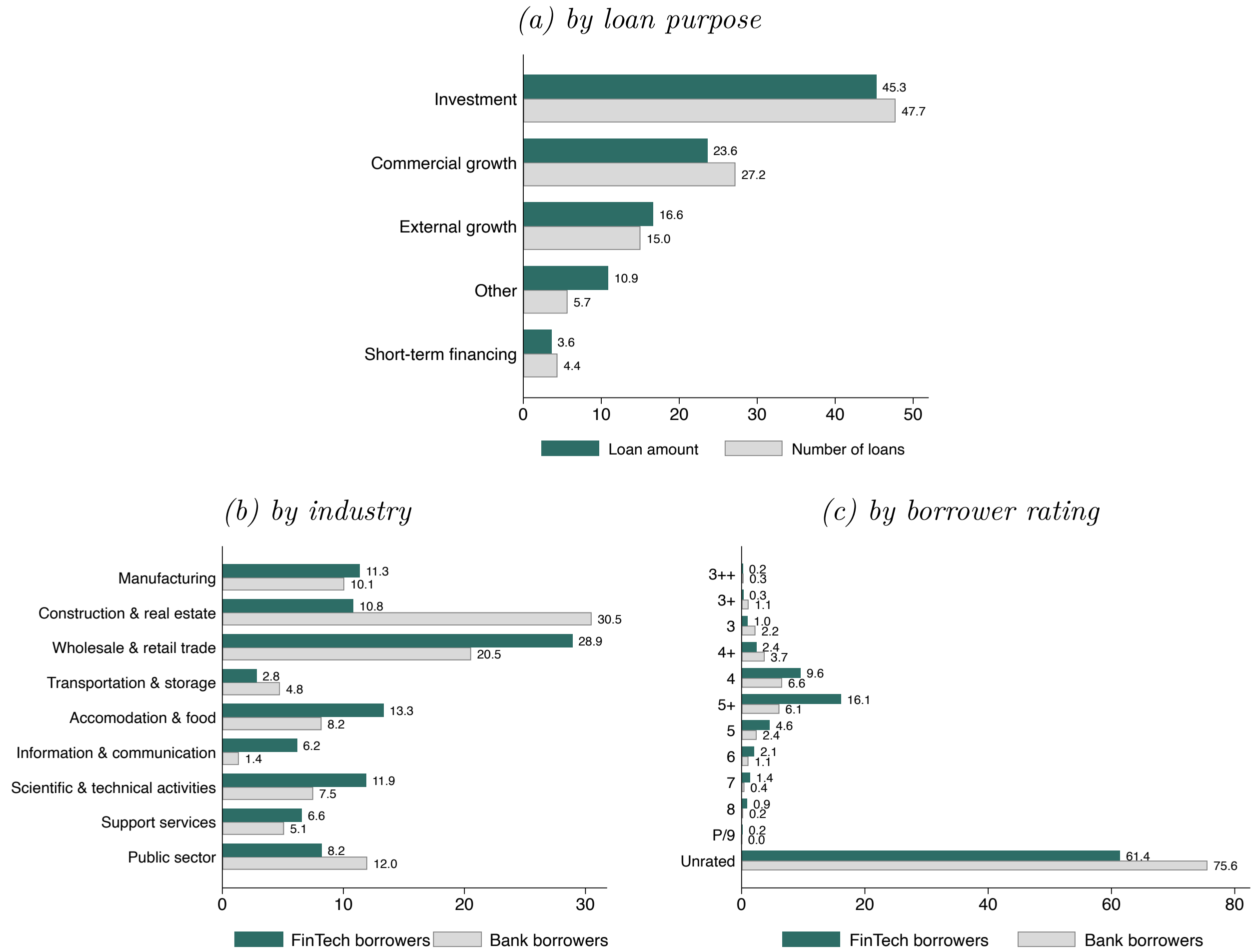
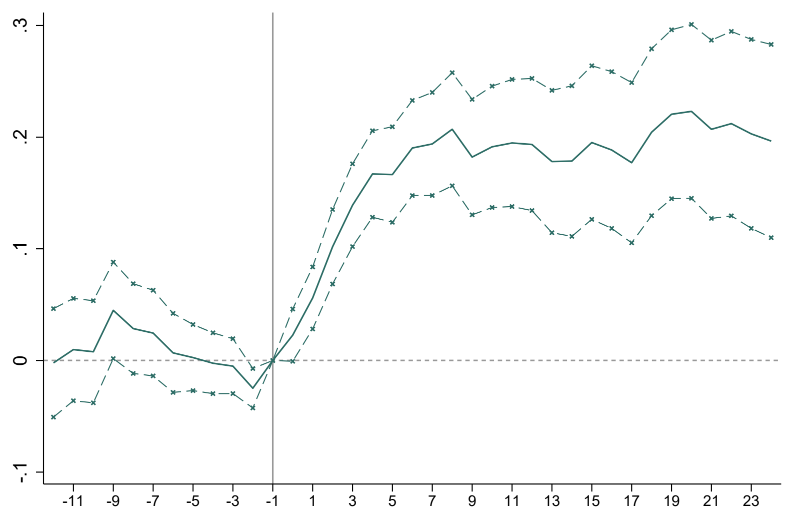
FIGURE 1
FinTech and bank borrower composition




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

FIGURE 2
Credit dynamics of FinTech borrowers




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

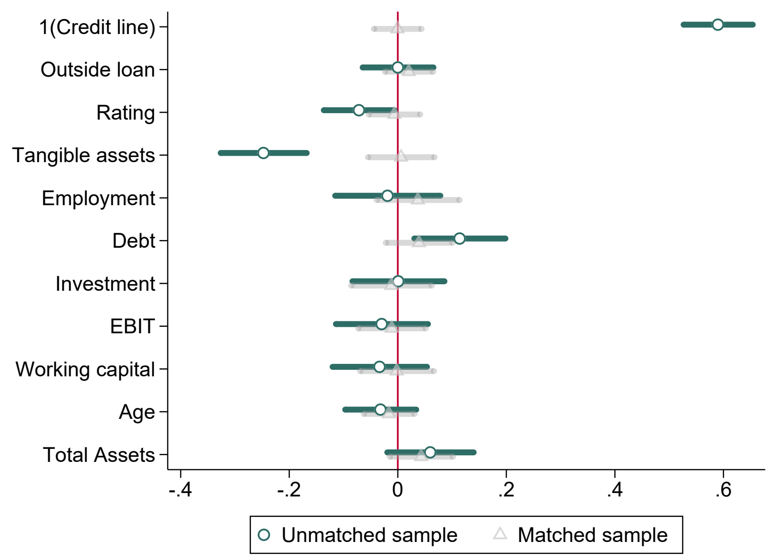
$$log(1 + y_{i,t}) = \sum_{t \in [-12,24]} \beta_t \times D_t + \gamma_{i,year} + \varepsilon_{i,t},$$

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

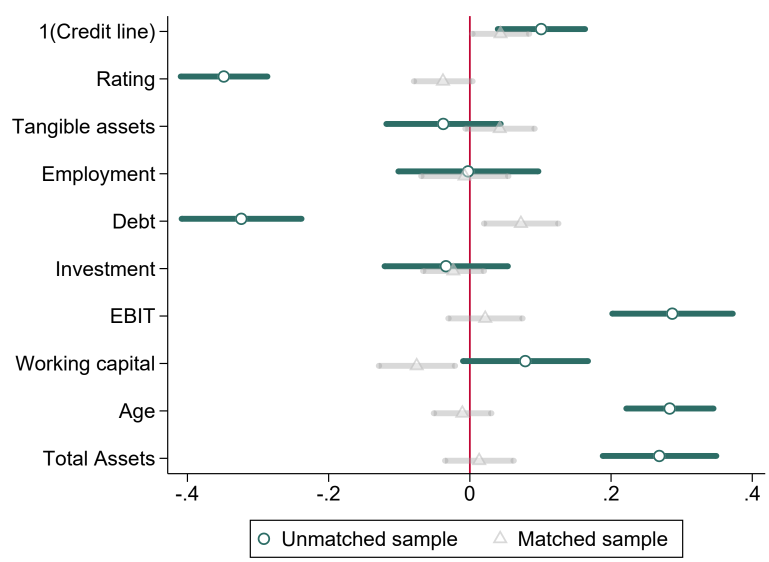
FIGURE 3

Testing covariates balance

*(a) FinTech borrowers vs. Bank borrowers*




*(b) FinTech borrowers vs. Rejected borrowers*

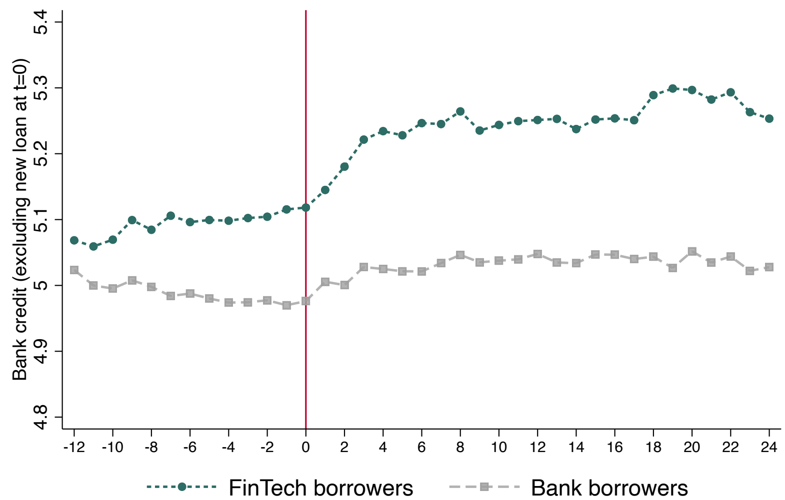



NOTE.—This figure shows estimates and 95% confidence intervals of the differences in various characteristics of FinTech borrowers and bank borrowers in Panel a and of FinTech borrowers and rejected borrowers in Panel b. All variables are normalized to have a mean of zero and a standard deviation of one and are taken the year before the outside loan origination. A positive coefficient means the variable has a higher mean for FinTech borrowers. *Rating* is the numerical equivalent of the Bank of France rating (1 for the best rating, 12 for the worst rating, 13 if the firm is unrated - see Table C.2). *Total Assets* and *Employment* are measured in logarithm. *Tangible assets*, *Debt*, *EBIT*, *Investment*, *Working capital* are normalized by total assets. *Age* is measured in years. $\mathbb{1}$(*Credit line*) indicates whether the firm has a line of credit before the outside loan origination. *Outside loan* is the log amount of the outside loan. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. We retain outside loans that originated between January 2014 and June 2019.

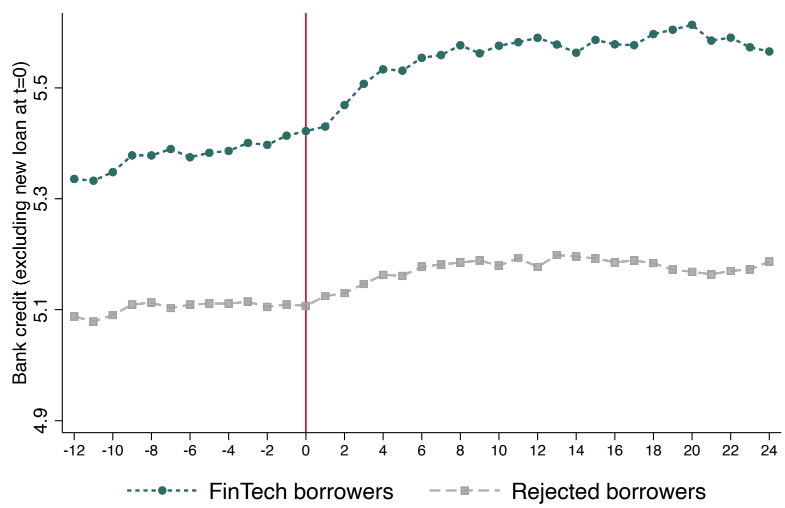
FIGURE 4

Evolution of bank loan amount for the matched firms

*(a) FinTech borrowers vs. Bank borrowers*




*(b) FinTech borrowers vs. Rejected borrowers*

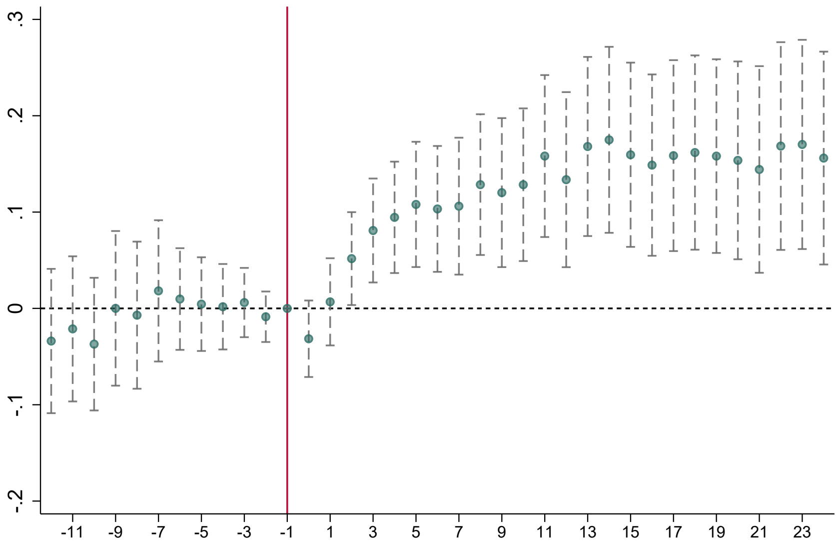



NOTE.—This figure presents the average log amount of bank credit by borrower type in the 36-month window around the origination of the outside loan at $t = 0$. Panel a (b) is based on the matched sample of FinTech and bank borrowers (resp. FinTech and rejected firms). An outside loan is a loan originated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

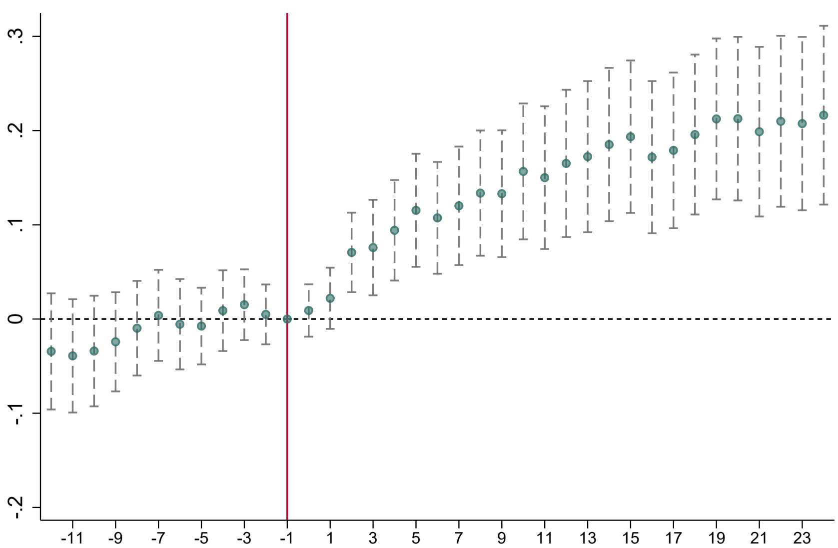
FIGURE 5

Credit dynamics: FinTech borrowers vs. benchmark firms

*(a) FinTech borrowers vs. Bank borrowers*




*(b) FinTech borrowers vs. Rejected borrowers*




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

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

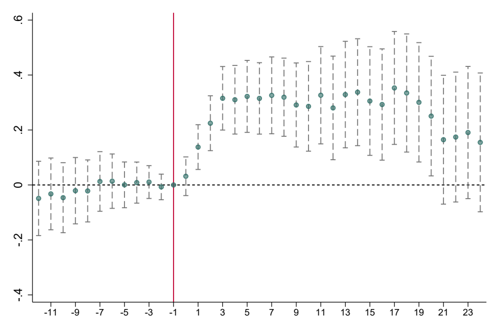
where $y_{i,t}$ is the total amount of outstanding bank credit of firm $i$ at time $t$. The graphs plot the $\beta_t$ coefficients. The outside loan can either be a FinTech loan or a bank loan. We exclude the outside loan from the calculation of firm credit balance. In Panel a, the benchmark group is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

FIGURE 6

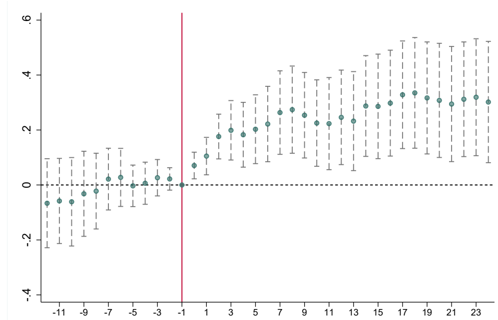
Firm credit dynamics by bank loan category

*(a) Long-term loans*

FinTech vs. Bank

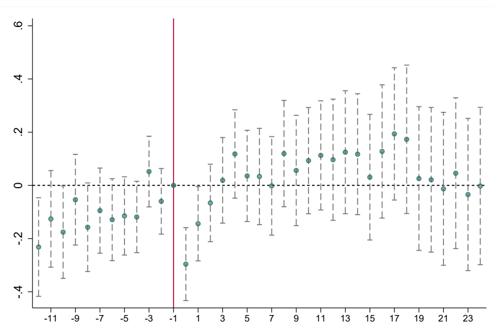


FinTech vs. Rejected

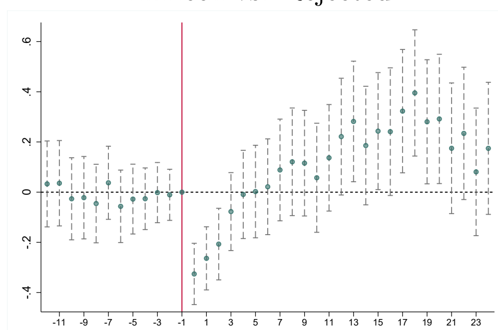


*(b) Used line of credit*

FinTech vs. Bank

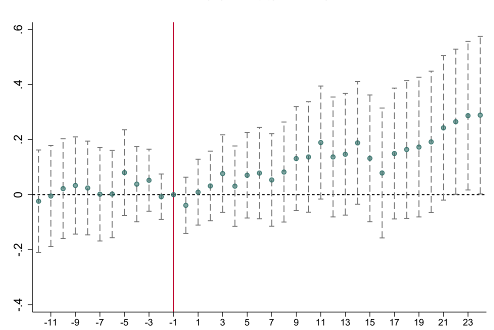


FinTech vs. Rejected

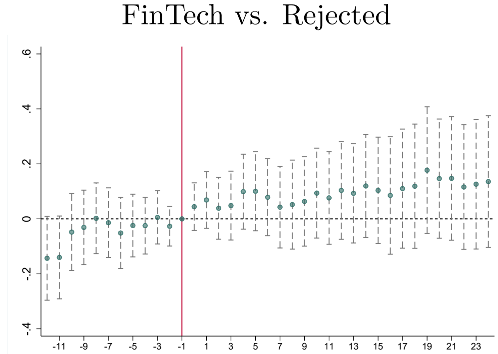


*(c) Other loans*

FinTech vs. Bank



FinTech vs. Rejected



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

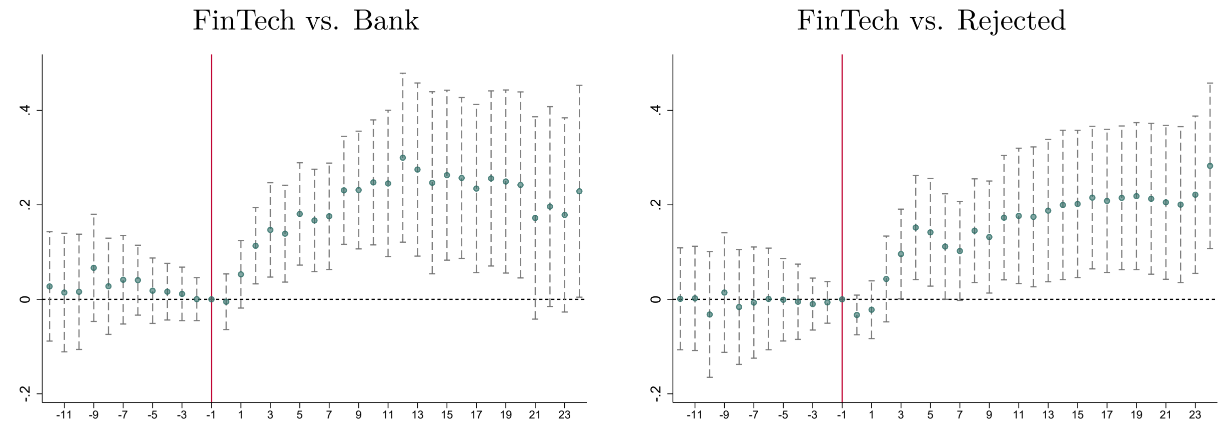
$$log(1 + y_{i,t}) = \sum_{t\in[-12,24]} (\alpha_t + \beta_t FinTech_i) \times D_t + \gamma_{i,year} + \rho_{month} + \varepsilon_{i,t},$$

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

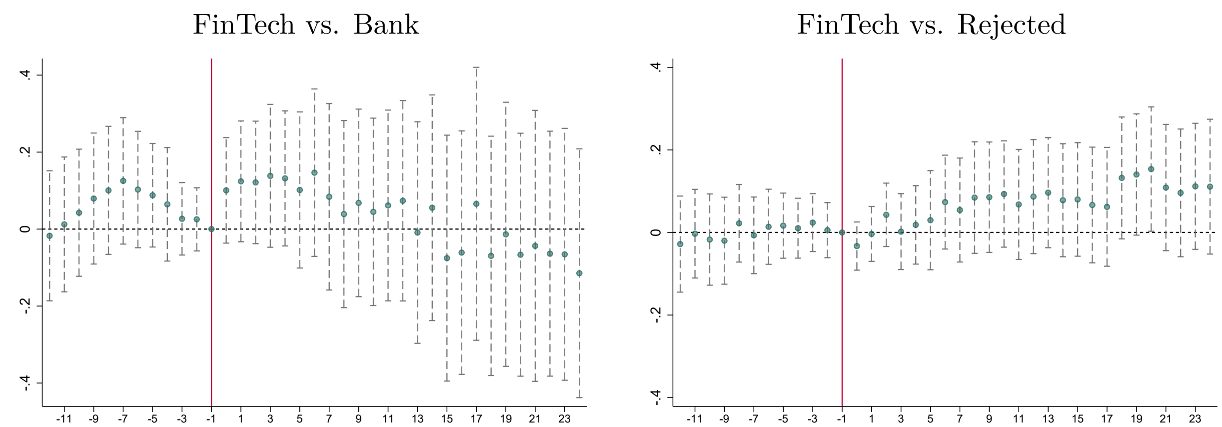
FIGURE 7

Firm credit dynamics by outside loan purpose

*(a) Loan purpose: Investments*




*(b) Loan purposes: Others*



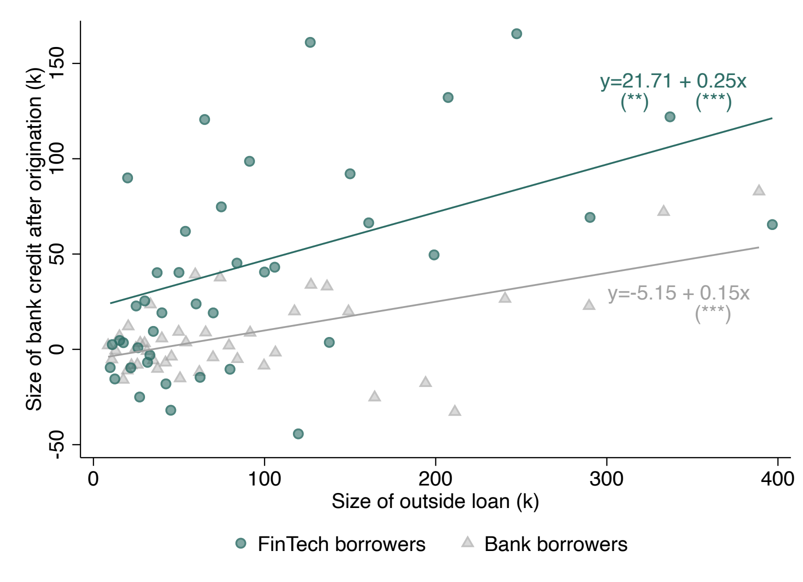

NOTE.— The figure presents the estimation results of the following equation, using the 36-month window around the origination of the outside loan at $t = 0$:

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

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

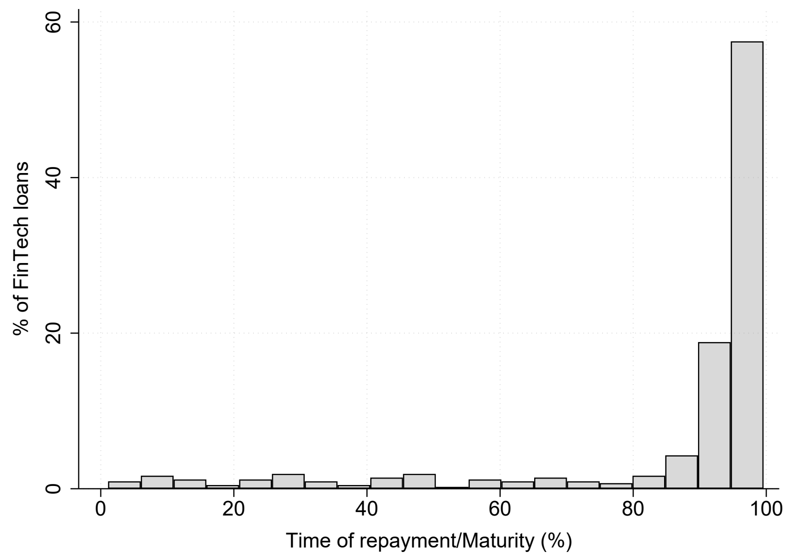
FIGURE 8

Relationship between outside loan size and subsequent bank loan size




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

FIGURE 9
Timing of repayment of FinTech loans




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

TABLE 1
Characteristics of FinTech loans

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

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

TABLE 2
Comparing FinTech and bank loans

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

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

TABLE 3
Exploiting variations in banks' collateral requirements

| | FinTech | log(1+bank credit) | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | first stage | reduced form | second stage | placebo | placebo |
| Secured ratio × Post | 0.188*** | 0.633*** | | | |
| | (3.55) | (3.35) | | | |
| FinTech × Post | | | 3.363*** | 0.0454 | 0.770 |
| | | | (2.75) | (0.02) | (0.32) |
| Post | 0.124 | 0.469 | 0.0529 | 0.370 | -0.754 |
| | (1.01) | (0.91) | (0.09) | (0.54) | (-1.03) |
| Credit supply | 0.000310 | -0.0607** | -0.0617* | -0.0495** | 0.0102 |
| | (0.04) | (-2.03) | (-1.81) | (-2.20) | (0.41) |
| Industry × Year-quarter | Y | Y | Y | Y | Y |
| Size × Year-quarter | Y | Y | Y | Y | Y |
| Region × Year-quarter | Y | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y | Y |
| Observations | 45,107 | 45,107 | 45,107 | 45,107 | 45,107 |
| F-stat | | | 12.602 | 3.385 | 2.853 |
| R-sq | 0.674 | 0.819 | | | |

NOTE.—This table presents the results of the 2SLS estimation of:

$$log(1 + Credit_{i,t}) = (\beta FinTech_i + \gamma Credit\ Supply_i + \delta) \times Post_t + \alpha_i$$
$$+ \text{Interacted Fixed effects} + \varepsilon_{i,t}$$

where $Post_t$ is equal to one after the origination of the outside loan; $\alpha_i$ denotes firm fixed effects, and $Credit_{i,t}$is the total amount of long-term loans of firm $i$ in quarter $t$. Interacted fixed effects include industry × quarter, region × quarter, and size × quarter fixed effects. $FinTech_i \times Post_t$ is instrumented by $Secured\ ratio_i \times Post_t$. $Secured\ ratio_i$ is the weighted average of the share of secured loans to SMEs issued by all the existing banks of firm $i$. The weights are calculated using the firm's credit exposure to the banks two quarters before the outside loan. The share of secured loans is computed in the same quarter as the outside loan. Column 1 provides the first-stage estimation results, column 2 the reduced form, and columns 3 to 5 the second-stage results. In Columns 4-5, we perform placebo tests by changing the share of secured loans in a bank's loan portfolio from relative quarter $t = 0$ to $t = -1$ and to the average of that from all quarters before $t - 2$. $Credit\ supply_i$ controls for the overall credit supply by a firm's relationship banks in relative quarter 0 and is computed as a weighted average of the logarithm of the volume of new loans to SMEs from the existing banks of firm $i$ at $t = 0$. We retain outside loans that originated between January 2016 and June 2019. Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

TABLE 4

The propensity to post collateral post FinTech loan origination

| | $\mathbb{1}(Secured)$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| FinTech × Post | 0.045*** | 0.067** | 0.003 |
| | (0.010) | (0.028) | (0.020) |
| Post | -0.076*** | -0.103*** | -0.015 |
| | (0.005) | (0.010) | (0.025) |
| Firm FE | Y | Y | Y |
| Industry-Quarter FE | Y | Y | Y |
| N | 74,404 | 17,928 | 20,252 |
| R-sq | 0.11 | 0.18 | 0.15 |

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

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

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

TABLE 5
Testing the collateral channel

*(a) Benchmark: Bank borrowers*

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

*(b) Benchmark: Rejected borrowers*

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

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

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

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

TABLE 6

Testing the information channel

*(a) Benchmark: Bank borrowers*

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

*(b) Benchmark: Rejected borrowers*

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

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

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

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

TABLE 7
Other firm outcomes

*(a) Benchmark: Bank borrowers*

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

*(b) Benchmark: Rejected borrowers*

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

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

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

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

TABLE 8

Firm defaults

| | $\mathbb{1}$(Default) | | |
|---|---|---|---|
| *Benchmark:* | *Bank borrowers* | | *Rejected borrowers* |
| | (1) | (2) | (3) |
| FinTech × Post | 0.048*** | 0.029** | -0.062*** |
| | (0.010) | (0.012) | (0.011) |
| FinTech × Post × High rate | | 0.041** | |
| | | (0.020) | |
| High rate × Post | | 0.021* | |
| | | (0.011) | |
| Post | -0.014** | -0.025*** | 0.060*** |
| | (0.006) | (0.008) | (0.007) |
| Firm FE | Y | Y | Y |
| Industry-Quarter FE | Y | Y | Y |
| N | 147,336 | 147,336 | 203,216 |
| R-sq | 0.49 | 0.49 | 0.54 |

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

$$\mathbb{1}(Default)_{i,t} = \beta FinTech_i \times Post_t + \delta Post_t + \alpha_i + \mu_{s,t} + \varepsilon_{i,t}$$

where $\mathbb{1}(Default)$ is a dummy variable indicating whether firm $i$ enters a liquidation or bankruptcy procedure at time $t$. *High rate* is equal to one when the FinTech (bank) loan rate is higher than the median FinTech (bank) loan rate. $Post_t$ is equal to one when $t \geq 0$. Columns 1-2 present the results on the matched sample of FinTech and bank borrowers, and in column 3, the benchmark group is rejected FinTech applications. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We include annual firm-level observations in the nine-year window around loan origination (four years before, four years after). Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

# Collateral Effects: The Role of FinTech in Small Business Lending

## Online Appendix

Paul Beaumont Huan Tang Eric Vansteenberghe

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# A Pretup versus other platforms

In this Appendix Section, we first compare the characteristics of loans across the ten platforms covered by our sample and then compare the characteristics of the successful FinTech applicants to the rejected ones using data provided by Pretup.

Figure A.1 presents the market share, average loan amount, interest rates, and maturity of loans of the 10 FinTech platforms in our sample. We only include Fintech and bank loans that originated between January 2016 and June 2019.

FIGURE A.1
Loan characteristics

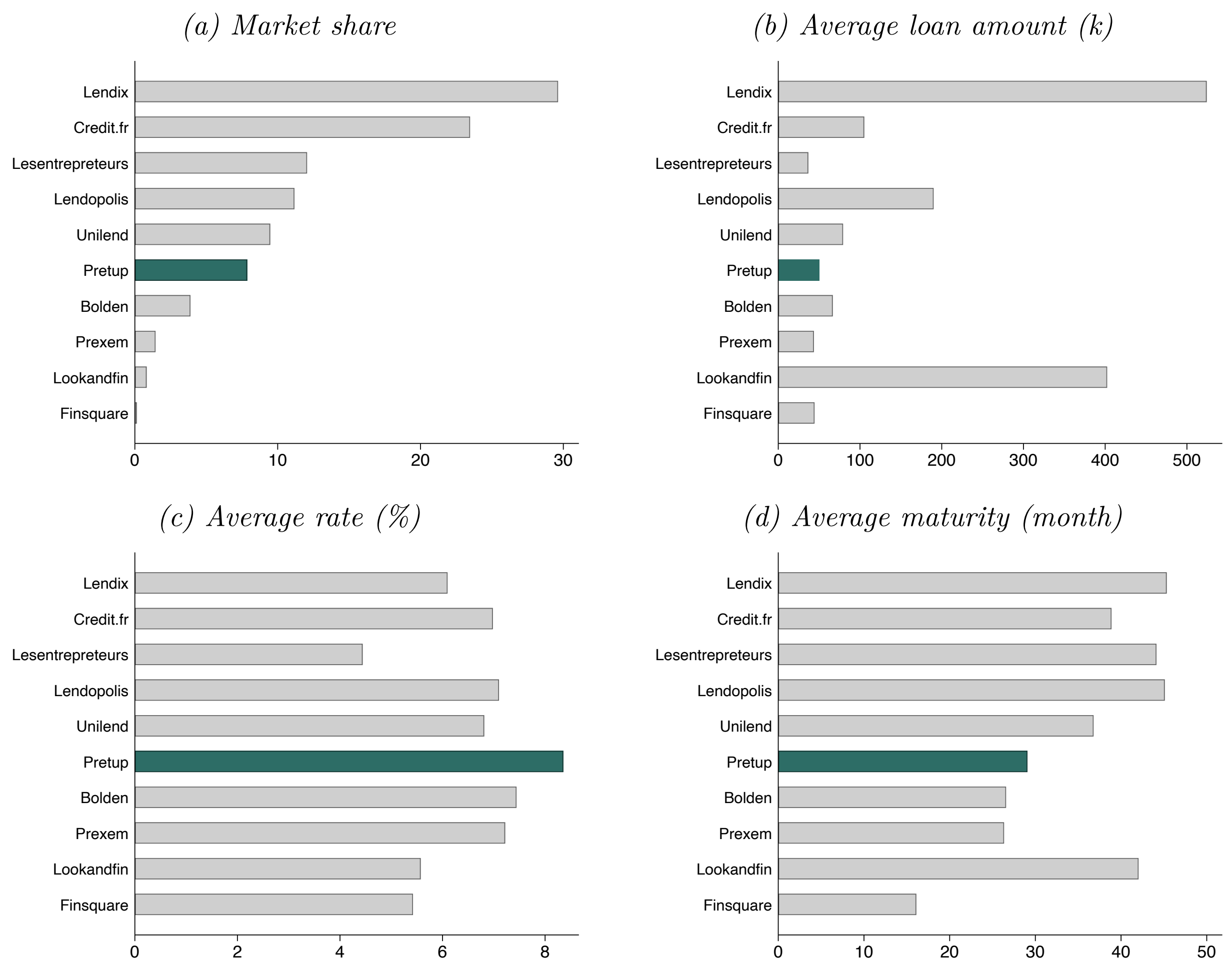
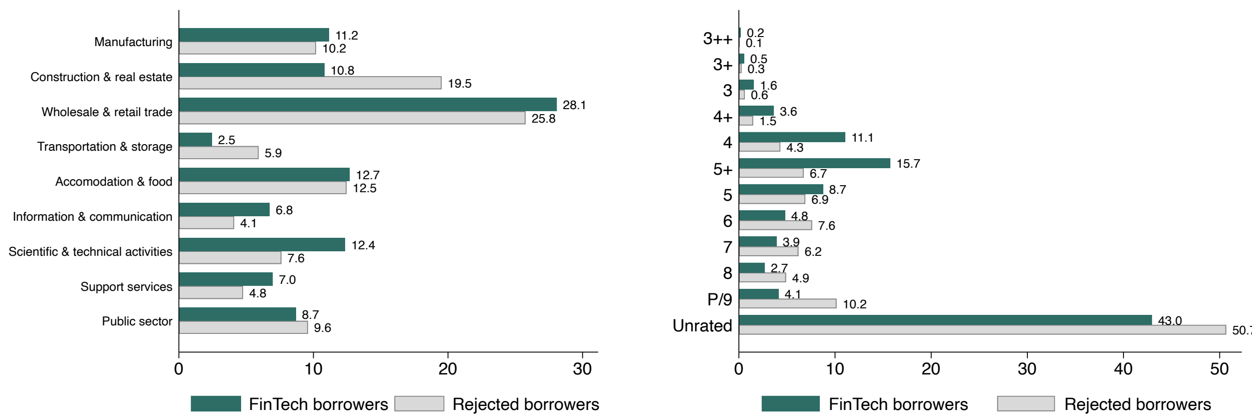



Figure A.2 presents the breakdown (%) of loans by firm industry (Panel a) and firm credit rating (Panel b). In both panels, green (white) bars represent the breakdown for FinTech (rejected) borrowers. The list of rejected firms is provided by PretUp. Data on firm characteristics come from FIBEN and Orbis. We only keep FinTech and bank loans that originated between January 2016 and June 2019.

FIGURE A.2
FinTech and rejected borrowers on Pretup

*(a) by industry* *(b) by borrower rating*



# B Summary Statistics on the Unmatched and Matched Samples

This section presents summary statistics on FinTech borrowers and the two benchmark groups of firms in both the unmatched and matched samples.

TABLE B.1

Comparing FinTech borrowers and benchmark firms - Before matching

*(a) Benchmark: Bank borrowers*

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

*(b) Benchmark: Rejected FinTech applicants*

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

NOTE.—This table compares the characteristics of FinTech borrowers and two benchmark groups of borrowers before the matching. Panel a (resp., panel b) presents the *t*-test result of the differences in various variables between FinTech and bank borrowers (resp., between FinTech borrowers and rejected borrowers). *Rating* is the numerical equivalent of the Bank of France rating (1 for the best rating, 12 for the worse rating, 13 if the firm is unrated - see Table C.2). *Total Assets* and *Employment* are measured in logarithm. *Tangible assets*, *Debt*, *EBIT*, *Investment*, *Working capital* are normalized by total assets. *Age* is measured in years. $\mathbb{1}$(*Credit line*) indicates whether the firm has a line of credit before the outside loan origination. *Outside loan* is the log amount of the outside loan. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. We only keep outside loans that originated between January 2016 and June 2019.

## TABLE B.2

Comparing FinTech borrowers and benchmark firms - After matching

*(a) Benchmark: Bank borrowers*

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

*(b) Benchmark: Rejected FinTech applicants*

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

NOTE.—This table compares the characteristics of FinTech borrowers and two benchmark groups of borrowers after the matching. Panel a (resp., panel b) presents the $t$-test result of the differences in various variables between FinTech and bank borrowers (resp., between FinTech borrowers and rejected borrowers). *Rating* is the numerical equivalent of the Bank of France rating (1 for the best rating, 12 for the worse rating, 13 if the firm is unrated - see Table C.2). *Total Assets* and *Employment* are measured in logarithm. *Tangible assets*, *Debt*, *EBIT*, *Investment*, *Working capital* are normalized by total assets. *Age* is measured in years. $\mathbb{1}$(*Credit line*) indicates whether the firm has a line of credit before the outside loan origination. *Outside loan* is the log amount of the outside loan. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. We only keep outside loans that originated between January 2016 and June 2019.

# C Definition of variables

This section provides the definition of credit rating and firm size categories, both from the FIBEN dataset, as well as all other variables used in the analysis.

TABLE C.1

Description of variables

| Variables | Description |
|---|---|
| **Main explanatory variables:** | |
| $FinTech_i$ | Dummy variable that is equal to one if the outside loan taken by firm $i$ is issued by a FinTech platform, 0 if it is issued by a bank. |
| $Post_t$ | Dummy variable that is equal to one for any period $t$ (month, quarter, or year) after the origination of the outside loan. |
| **Credit variables:** | |
| $Total\ loans_{i,t}$ | Total amount of bank credit firm $i$ has at time $t$ (excluding the outside loan). |
| $Line\ of\ Credit_{i,t}$ | Drawn overdraft facilities (excluding the outside loan). |
| $Long\text{-}term\ loans_{i,t}$ | Long-term loans, with a maturity longer than one year (excluding the outside loan). |
| $Other\ loans_{i,t}$ | Loans other than drawn credit lines or long-term loans (excluding the outside loan). |
| $\mathbb{1}(Secured)_{i,t}$ | Dummy variable that equals to one if the bank loan $i$ obtained in quarter $t$ is secured. |
| $Investment\ loan_i$ | Dummy variable that equals to one if the bank or FinTech loan obtained by firm $i$ at time $t = 0$ is used to finance the acquisition of new assets. |
| $Total\ loans\ from\ new\ lenders_{i,t}$ | Total loans granted to firm $i$ observed at time $t$ from banks that have a shorter-than-median length of relationship with firm $i$. |
| $Total\ loans\ from\ existing\ lenders_{i,t}$ | Total loans granted to firm $i$ observed at time $t$ from banks that have a longer-than-median length of relationship with firm $i$. |
| $Total\ loans\ from\ local\ lenders_{i,t}$ | Total loans granted to firm $i$ observed at time $t$ from banks that are located in the same county (département) as firm $i$. |
| $Total\ loans\ from\ distant\ lenders_{i,t}$ | Total loans granted to firm $i$ observed at time $t$ from banks that are located in a different county (département) as firm $i$. |
| $\mathbb{1}(Credit\ line)_{i,t}$ | Dummy variable that equals to one if firm $i$ has an open bank line of credit at time $t$. |
| **Shift-share instrument and controls:** | |
| $Secured\ ratio_i$ | The weighted average of the share of secured loans to SMEs issued by all the existing banks of firm $i$. The weights are calculated using the firm's credit exposure to the banks two quarters before the outside loan. The share of secured loans is computed in the same quarter of the outside loan. |
| $Credit\ supply_i$ | The weighted average of the logarithm of the volume of new loans to SMEs from the existing banks of firm i at t = 0 |
| **Balance sheet, profit & loss statements:** | |
| $Total\ assets_{i,t}$ | Logarithm of the total assets of the firm $i$ at time $t$. |
| $Age_{i,t}$ | Age in months of the firm $i$ at time $t$. |
| $Working\ capital_{i,t}$ | Ratio of working capital to lagged total assets of the firm $i$ at time $t$. |
| $Accounts\ payable_{i,t}$ | Ratio of account payable to lagged total assets of the firm $i$ at time $t$. |
| $Other\ working\ capital_{i,t}$ | Ratio of the sum of working capital and account payable to lagged total assets of the firm $i$ at time $t$. |
| $EBIT_{i,t}$ | Ratio of earnings before interests and taxes to lagged total assets of the firm $i$ at time $t$. |
| $Investment_{i,t}$ | Growth of fixed assets of the firm $i$ between time $t$ and $t-1$, normalized by lagged total assets. |
| $Leverage_{i,t}$ | Ratio of total assets less equity to lagged total assets of the firm $i$ at time $t$. |
| $Employment_{i,t}$ | Logarithm of number of employees of the firm $i$ at time $t$. |
| $Tangible\ assets_{i,t}$ | Ratio of fixed assets to lagged total assets of the firm $i$ at time $t$. |

*Continued next page*

**Description of Variables (continued)**

| Variables | Description |
|---|---|
| **Defaults and rating:** | |
| $Default_{i,q}$ | Dummy variable that indicates whether firm $i$ has entered a liquidation or bankruptcy procedure in quarter $q$. |
| $Rating_{i,t}$ | Credit rating of the firm $i$ at time $t$ issued by Banque de France. |
| $\mathbb{1}(Rated)_{i,t}$ | Dummy variable that equals to one if the Banque de France is rating the firm $i$ at time $t$. |
| **Customer defaults:** | |
| $Customer\ default_{i,q}$ | Dummy variable that indicates that firm $i$ experiences at least one customer defaults at quarter $q$, when the outside loan is originated. |
| $Customer\ default_{i,q-1}$ | Dummy variable that indicates that firm $i$ experiences at least one customer defaults at quarter $q-1$, one quarter before the outside loan is originated. |
| $Customer\ default_{i,Before\ q-2}$ | Dummy variable that takes the value one if firm $i$ has experienced at least one customer default more than two quarters ago before the origination of the outside loan, but no customer defaults in the two quarters preceding the loan origination. |

TABLE C.2
FIBEN credit rating and firm size categories

*(a) Firm size*

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

*(b) Credit rating*

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

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

# D Alternative Propensity Score Matching Procedures

In this Appendix section, we assess the robustness of our results. We estimating Equation D.1 using the unmatched sample and samples obtained with different matching procedures:

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

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

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

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

TABLE D.1
Matching Procedure - Robustness Checks

*(a) Benchmark: Bank borrowers*

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

*(b) Benchmark: Rejected borrowers*

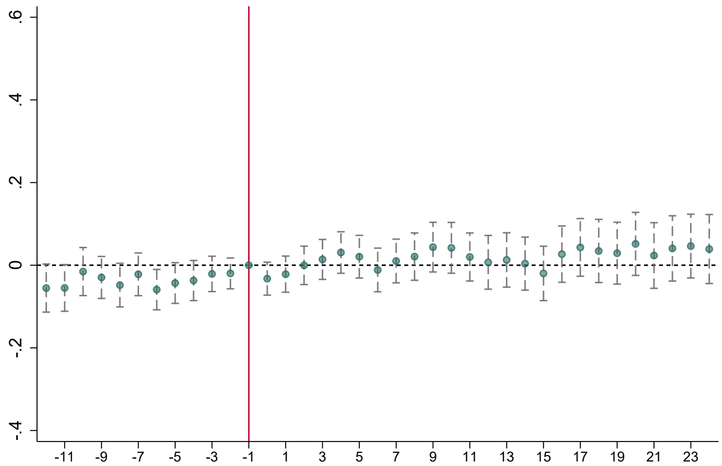
| | Unmatched | PSM no rep. | PSM with rep. | Five-nearest neighbor matching | | | Excl. Lendix & Lookandfin |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| FinTech × Post | 0.10*** | 0.07*** | 0.06** | 0.07*** | 0.16*** | 0.13*** | 0.07*** |
| | (0.02) | (0.02) |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

NOTE.—This table shows the results of the baseline DiD regressions on different samples. Column 1 is based on the unmatched sample. In columns 2 to 5, results are based on the matched samples using alternative propensity score matching specifications: PSM without replacement, PSM with replacement, and PSM with $k$-nearest neighbor ($k = 5$). In columns 5 and 6, we replace firm×year fixed effects with firm fixed effects and industry-, location-, rating- × year fixed effects, respectively. In column 7, we exclude FinTech loans from two platforms, Lendix and Lookandfin and repeat the matching. Column 4 is our baseline specification. The number of unique firms is reported at the bottom of the table. Data on bank loans come from the M-Contran survey. Data on Fintech loans come from the Banque de France Fintech and Crowdlending.fr datasets. Data on firms come from FIBEN and Orbis. We only include bank and Fintech loans that originated between January 2016 and June 2019. Significance levels 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

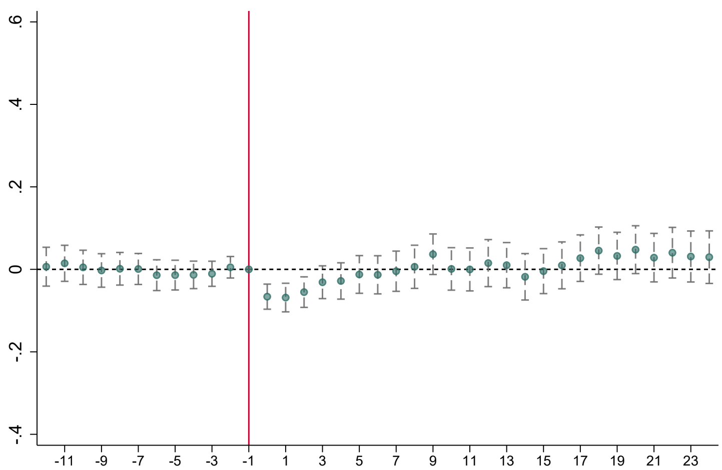
# E Credit line utilization rates

FIGURE E.1
Credit line utilization rates

*(a) FinTech borrowers vs. Bank borrowers*




*(b) FinTech borrowers vs. Rejected borrowers*




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

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

where $Credit\ Utilization_{i,t}$ is the credit line utilization rate of firm $i$ in relative month $t$. It is defined as the amount of used credit over the total credit line limit. The graphs plot the $\beta_t$ coefficients. $t - 0$ is the month when firms take an outside loan, which is a loan originated by a lender that has not previously extended credit to firm $i$. Firm $i$ can either be a FinTech borrower (i.e., the outside loan is a FinTech loan) or a bank borrower. In panel (a), the benchmark group is bank borrowers, and in panel (b), it is rejected applicants. Coefficients are reported along with the 95% confidence intervals. Standard errors are clustered at the firm level. The baseline is set at $t = -1$.

# F Alternative Specifications of the Shift-share Instrument

As mentioned in Section 4.4, the shift-share instrument in our main specification is constant for a given firm. One may be concerned that variations in $\textit{Secured ratio}_i$ are primarily from the endogenous credit exposure component $\omega_{b,i,t=\text{-}2}$, instead of the exogenous change in banks' collateral requirements.

To mitigate this concern, we show in this Appendix Section that our results are not sensitive to the number of lagged periods for the credit exposure, suggesting that it is the shifts rather than the share in $\textit{Secured ratio}_i$ that contributes to the identification of the IV estimates. Moreover, allowing both the shift and share to vary in the shift-share instrument, we find qualitatively similar results.

Specifically, we consider the following alternative specifications and report the results from the second stage in Table F.1. In column 1, relative to the main specification, we additionally control firm characteristics. The set of control variables includes a dummy indicating whether the firm has a line of credit with any bank at the time of the outside loan origination, the firm's age, credit rating, total assets in logarithm, total debt, tangible assets, and EBIT, all taken at the last year-end before the outside loan is originated. Total debt, tangible assets, and EBIT are divided by total assets. In columns 2 and 3, we construct the shift-share instrument using the firm's credit exposure to a bank three and four quarters prior to the quarter of the outside loan, respectively. In column 4, we use time-varying version of the shift-share instrument, $\textit{Secured ratio}_{i,t}$. $\textit{Credit supply}_i$ controls for the overall credit supply by a firm's relationship banks in relative quarter 0. It is constructed in a similar fashion as $\textit{Secured ratio}_i \times \textit{Post}_t$, except that it is a weighted average of the logarithm of the total SME lending volume from the relationship banks in a given quarter.

TABLE F.1

Exploiting variations in banks' collateral requirements - Robustness Checks

| | log(1+bank credit) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| FinTech×Post | 3.339*** | 3.057** | 3.409** | 9.220*** |
| | (2.76) | (2.38) | (2.32) | (3.50) |
| Post | 0.0647 | 0.534 | 0.411 | -1.924*** |
| | (0.11) | (0.79) | (0.54) | (-4.60) |
| Credit supply | -0.0629* | -0.0865** | -0.0824** | -0.0315 |
| | (-1.85) | (-2.39) | (-2.03) | (-1.13) |
| Industry × Year-quarter | Y | Y | Y | Y |
| Size × Year-quarter | Y | Y | Y | Y |
| Region × Year-quarter | Y | Y | Y | Y |
| Firm FE | Y | Y | Y | Y |
| Firm controls | Y | | | |
| Shares | -2 | -3 | -4 | $t-2$ |
| Shifts | 0 | 0 | 0 | $t$ |
| Observations | 45,107 | 38,602 | 32,060 | 45,017 |
| F-stat | 12.758 | 10.520 | 9.099 | 18.504 |

This table presents the results of the 2SLS estimation of:

$$\begin{aligned} log(1 + Credit_{i,t}) &= \beta FinTech_i \times Post_t + \delta Post_t + \alpha_i \\ &+ \gamma Credit\ Supply_i \times Post_t + \text{Interacted Fixed effects} + \mu X'_{i,t} + \varepsilon_{i,t}, \end{aligned}$$

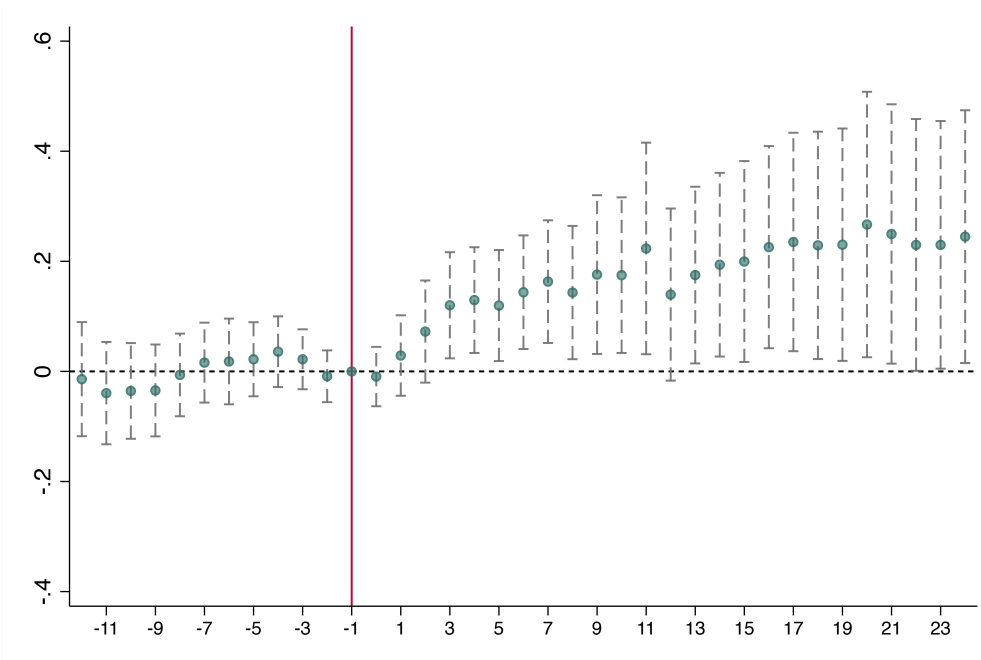
where $Post_t$ is equal to one when $t \geq 0$, $\alpha_i$ denotes firm fixed effects, and $Credit_{i,t}$ is the total amount of long-term loans of firm $i$ in quarter $t$. Interacted fixed effects include industry × quarter, region × quarter, and size × quarter fixed effects. We vary the specification in each column to show that our results are robust to various specifications. In column 1, we additionally control for firm characteristics. The set of control variables includes a dummy indicating whether the firm has a line of credit with any bank at the time of the outside loan origination, the firm's age, credit rating, total assets in logarithm, total debt, tangible assets, and EBIT, all taken at the last year-end before the outside loan is originated. Total debt, tangible assets, and EBIT are divided by total assets. In columns 2 and 3, we construct the shift-share instrument using firm's credit exposure to a bank three and four quarters prior to the quarter of the outside loan, respectively. In column 4, we use the time-varying version of the shift-share instrument, *Secured ratio*$_{i,t}$. *Credit supply*$_i$ controls for the overall credit supply by a firm's relationship banks in relative quarter 0 and is computed as a weighted average of the logarithm of the volume of new loans to SMEs from the existing banks of firm $i$ at $t = 0$. We retain outside loans that originated between January 2016 and June 2019. Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

## G Restricting outside bank loans to unsecured loans

FIGURE G.1

Restricting outside bank loan to unsecured loans

(a) Total bank credit




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

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

where $y_{i,t}$ is the amount of total bank credi of firm $i$ in relative month $t$. The graphs plot the $\beta_t$ coefficients. In this set of results, we impose that the outside loan is an unsecured loan from a lender that has not previously extended credit to firm $i$. Note that unsecured loans can still be secured against cash collateral (e.g., personal guarantees). Firm $i$ can either be a FinTech borrower (i.e., the outside loan is a FinTech loan) or a bank borrower. Coefficients are reported along with the 95% confidence intervals. Standard errors are clustered at the firm level. The baseline is set at $t = -1$.

# H Fraction of loans secured by assets

Table H.1 shows the repartition of loan volume by credit category and the fraction of loans secured by specific assets (in terms of loan volume) within each category. Loans backed by personal guarantees are not observed in the dataset. All numbers are calculated based on the loans originated between 2014-2019 in the M-Contran database.

TABLE H.1
Fraction of loans secured by assets

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

In Table H.2, we analyze firms' propensity to post collateral after the FinTech loan origination, using rejected FinTech applicants as the benchmark group. The first three columns show the results based on the unmatched sample, and the last three columns on the matched sample. Based on the unmatched sample, FinTech borrowers are 1.9-p.p more likely to pledge specific assets to reporting banks compared to rejected FinTech applicants after the FinTech loan origination. This effect is entirely driven by borrowers that use the outside loan to invest, with the estimated coefficient of $FinTech \times Post$ being 0.034 in column 2, or 3.4 percentage points. In contrast, there is no significant difference in the propensity to pledge assets between the two groups of firms when the FinTech loan is not used for investment. In columns 4-6, when we focus on the matched sample, none of the estimated coefficients is statistically significant. This is because matching our baseline dataset to the M-Contran reduces the sample size substantially. Recall that while all benchmark bank borrowers, by construction, take up at least one bank loan that is included in M- Contran, this is not the case for FinTech and rejected borrowers. Hence, the number of firms and observations in the regression sample is significantly lower when the benchmark group is rejected borrowers.

With that caveat in mind, we interpret the results based on the magnitude of the point estimate. The coefficient is positive and larger when the FinTech loan is used for investment (column 5) than when it is not (column 6).

TABLE H.2

The propensity to post collateral post FinTech loan origination

| | $\mathbb{1}(Secured)$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| FinTech × Post | 0.019** | 0.034** | 0.011 | -0.001 | 0.009 | -0.005 |
| | (0.008) | (0.014) | (0.008) | (0.017) | (0.020) | (0.018) |
| Post | -0.006 | -0.005 | -0.006 | 0.001 | -0.001 | -0.001 |
| | (0.005) | (0.005) | (0.005) | (0.014) | (0.012) | (0.014) |
| Firm FE | Y | Y | Y | Y | Y | Y |
| Industry-Quarter FE | Y | Y | Y | Y | Y | Y |
| With PSM | N | N | N | Y | Y | Y |
| N | 12,292 | 10,120 | 11,240 | 23,148 | 13,908 | 18,408 |
| R-sq | 0.11 | 0.11 | 0.11 | 0.15 | 0.19 | 0.17 |

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

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

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

# I Firm rating change around FinTech loan origination

TABLE I.1
Firm ratings

| | Rating | | |
|---|---|---|---|
| *Benchmark:* | *Bank borrowers* | | *Rejected borrowers* |
| | (1) | (2) | (3) |
| FinTech × Post | 0.414*** | 0.389** | -0.358*** |
| | (0.129) | (0.161) | (0.108) |
| FinTech × Post × High rate | | 0.057 | |
| | | (0.269) | |
| High rate × Post | | 0.160 | |
| | | (0.159) | |
| Post | -0.103 | -0.167 | 0.447*** |
| | (0.082) | (0.105) | (0.078) |
| Firm FE | Y | Y | Y |
| Industry-Quarter FE | Y | Y | Y |
| N | 56,582 | 56,582 | 94,545 |
| R-sq | 0.71 | 0.71 | 0.71 |

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

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

where *Rating* is a categorical variable measured at time $t$. *High rate* is equal to one when the FinTech (bank) loan rate is higher than the median FinTech (bank) loan rate. $Post_t$ is equal to one when $t \geq 0$. Columns 1-2 present the results on the matched sample of FinTech and bank borrowers, and in column 3, the benchmark group is rejected FinTech applications. Data on bank loans come from the French Credit Registry and the M-Contran survey. Data on FinTech loans come from the Banque de France FinTech dataset and the Crowdlending.fr dataset. Data on firms come from FIBEN and Orbis. We include annual firm-level observations in the nine-year window around loan origination (four years before, four years after). Coefficients are reported along with the standard errors (in parentheses). Standard errors are clustered at the firm level. Significance levels of 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

# J Speed channel

In this Appendix Section, we examine another potential advantage of FinTech lenders: their faster online application and funding process. This could allow them to have a competitive edge in meeting firms' urgent liquidity needs. We show this is indeed the case. However, the faster speed cannot explain the subsequent increase in bank credit following the FinTech origination.

First, we examine whether, compared to similar firms that take a new bank loan, FinTech borrowers are systematically more likely to have recently experienced a negative liquidity shock. If FinTech lenders are indeed faster at meeting firms' liquidity needs, we should observe that liquidity shocks are more likely to be followed by the origination of FinTech loans than bank loans.

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

Before proceeding to the empirical specification, we provide detailed information on the CIPE dataset. This dataset reports all firms' payment defaults related to trade bills. Defaults are recorded on a daily basis and are defined as any trade bill between two firms not paid in full and/or on time. For each payment default record, the following information is reported: the SIREN number of the defaulter, the due date of the payment, the default amount, the name of the firm that has been defaulted upon, and the reason for the default. Defaults are sorted into four categories: disagreement, omission, illiquidity, or insolvency.[1]

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 the 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. We retain the best-ranked match when there is more than one potential match. We discard matches for which the runner-up score is too close to the best-ranked match (i.e., the distance between the two is less than 0.01). This allows us to identify 4,862 payment incidents in which P2P borrowing firms are the party being defaulted upon (359 firms). We aggregate the daily payment incident records at a quarterly frequency.

Following Boissay and Gropp (2013), we define a dummy *Customer default*$_{i,q}$ equal to one if at least one customer of firm $i$ defaulted on trade credit in quarter $q$. We define variables at the quarter level instead of the month level because we only observe the origination of individual bank

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

loans at the quarter level, as described in Section 3. Since we are interested in what motivates firms to choose between FinTech lenders and banks, we do not apply the propensity matching procedure and perform this test on the unmatched sample that includes bank and FinTech borrowers in the same two-digit industry and size category (see Section 4 for the sample construction). We estimate the following equation:

$$\mathbb{1}(Outside\ loan)_{i,q} = \beta Customer\ default_{i,q} + \delta FinTech_i \times Customer\ default_{i,q} + \alpha_i + \mu_{s,q} + \varepsilon_{i,q}, \quad \text{(J.2)}$$

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

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

TABLE J.1
Liquidity shocks and demand for FinTech loans

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

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

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

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

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

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

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

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

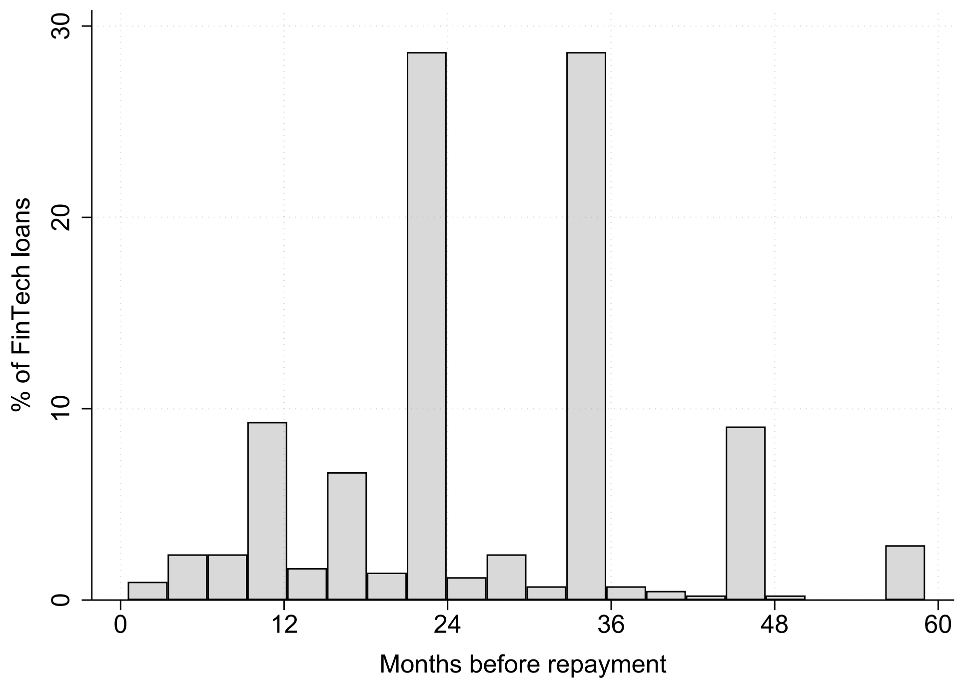
Our results show that liquidity shocks and the origination of new loans tend to be more synchronized for FinTech borrowers. We interpret this finding as evidence that FinTech platforms are faster at originating loans and, therefore, better equipped to meet firms' liquidity needs.

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

FinTech loan over the maturity of the FinTech loan. The evidence suggests that the vast majority of FinTech borrowers repay their loan around the maturity date. For 82% of FinTech borrowers, the loan is repaid after a period corresponding to more than 80% of the loan's maturity. This suggests that the increase in bank credit in the first 6 months following the new loan observed in Figure 6 is unlikely to be driven by FinTech firms refinancing their loans. Figure J.1 plots the distribution of the realized maturity of FinTech loans, that is, the number of months for the loan to be fully repaid. Approximately 96% of the loans are fully repaid after six months. Hence, it cannot explain the gradual increase in bank credit observed in the first six months after loan origination (Figure 5). In untabulated tests, we also verify that removing firms that repay their loans fully within six months does not change our results.

Overall, our results lead us to conclude that while FinTech platforms may be faster than banks at processing loan applications, differences in speed are unlikely to explain the increase in bank credit experienced by FinTech borrowers.

FIGURE J.1
Realized maturity of FinTech loans




Note.—This figure shows the distribution of FinTech loans by the number of months it takes for the loan to be fully repaid. We exclude loans that are defaulted upon. We only include loans that originated after 2016 and matured before 2019 (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.