北京大学中国经济研究中心
China Center for Economic Research
讨论稿系列
Working Paper Series

E2022009 2022-07-28

Big techs, QR code payments and financial inclusion

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Abstract

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Keywords: big tech, big data, QR code, banks, asymmetric information, financial inclusion, credit markets.

JEL classification: D22, G31, R30.

Big techs, QR code payments and financial inclusion[*]

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Using a unique dataset of around half a million Chinese firms that use a QR code-based mobile payment system, we find that (i) the creation of a digital payment footprint allows firms to access credit provided by the same big tech company; (ii) transaction data generated via QR code generate spillover effects on access to bank credit; and (iii) there are positive effects of access to big tech credit on sales, including during the Covid-19 shock. The findings suggest that access to innovative payment methods helps micro firms build up credit history, and that using big tech credit can ease access to bank credit.

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[*] We thank an anonymous referee for very constructive comments. We also thank participants at seminars held at the Bank of Italy and BIS for useful comments and suggestions. The views in this paper are those of the authors only and do not necessarily reflect those of the Bank for International Settlements or Ant Group. The authors highlight that the data and analysis reported in this paper may contain errors and are not suited for the purpose of company valuation or to deduce conclusions about the business success and/or commercial strategy of Ant Group or other firms. All statements made reflect the private opinions of the authors and do not express any official position of Ant Group and its management. The analysis was undertaken in strict observance of the Chinese law on privacy. Yiping Huang acknowledge financial support by the National Social Science Foundation of China (project number 18ZDA091). The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. Zhenhua Li discloses an employment relationship in Ant Group. Ant Group did not exercise any influence on the content of this paper but has ensured confidentiality of the (raw) data.

1. Introduction

The presence of information asymmetries between small firms and credit intermediaries is a serious problem that may reduce financing of good investment opportunities and the development of promising entrepreneurs' projects (Petersen and Rajan, 1994; Berger and Udell, 1995, 2006). Possible solutions to mitigate this problem for small enterprises are posting collateral or relying on credit history (techniques often referred to as transaction-based lending) or building close and long-term relationships with specific lenders (often referred to as relationship lending). Big data and machine learning, however, have provided a new solution, allowing large technology firms (also referred to as big techs) to use credit-scoring techniques to provide lending for clients operating in their business platforms (BIS, 2019).

This paper gauges the example of Ant Group, which started providing payment services through QR codes, thus giving offline merchants access to digital payment services, and uses the information collected through these services to decide on credit provision to merchants. We find that the use of QR codes for payment services allows such offline merchants to gain not only access to credit from the big tech company but also (by being included in the credit registry after having received big tech loans) access to unsecured bank credit. We also document positive real effects of the use of big tech credit, including during the Covid-19 pandemic, when recovery in transactions was 20% more pronounced for users of big tech credit than for non-users.

Theory and evidence have provided contrasting evidence on the role of new providers of financial services, such as fintech and big tech companies as substitutes or complements for incumbent banks. Our findings point to the potential of big tech companies to provide credit services to previously unbanked small firms, and to the positive spillover effects that the use of big tech loans can have for access to bank credit.

Big techs are large companies that operate platforms enabling direct interaction among a large number of users over a range of businesses, including e-commerce, social media, internet search, mobile phone hardware and software, ride hailing and telecommunications (Frost et al, 2019; Stulz, 2019). Increasingly, big techs have become substantial players in payments in several advanced and emerging market economies (FSB, 2019a, 2019b). They account for 94% of mobile payments in China

(Carstens et al, 2021). Globally, big tech credit grew by 40% in 2020 alone, to a total of over $700 billion. In some jurisdictions, big techs have participated in government credit schemes during the Covid-19 pandemic period (Cornelli et al, 2021).

The use of Quick Response (QR) codes, as used by Ant Group, can have positive effects for financial inclusion beyond the simple efficient processing of transaction payments. Small businesses not equipped with point of sale (POS) machines are now able to collect payment through a simple QR code that they can easily print. A QR scan code system allows small vendors to improve the processing of payments and provide, at the same time, relevant information to payment companies that operate the platforms. For example, in China firms that are active on e-commerce platforms (e.g., online merchants operating on Taobao and Tmall, two Alibaba e-commerce platforms) are integrated into the big tech's platform ecosystem. The big tech firm is thus able to collect large amounts of information not only on clients' payment transactions but also on their input-output production chain and their client networks. Big tech companies can use these data to very precisely assess firms' behaviour and characteristics. Importantly, data can also be collected for offline merchants (e.g., shops or restaurants) that do not trade on the e-commerce platform.

In addition to more effective payment services, the use of QR payment services generates a vast amount of data that can be used to better assess the risk profile of customers and provide them with other financial services. For example, the application of machine learning techniques on big data is widely used for credit scoring, which mitigates asymmetric information problems between lenders and borrowers. As mentioned above, payment data are collected not only for firms that operate on the e-commerce platform (online firms) and are perfectly integrated in the big tech ecosystem, but also for firms that operate on other more traditional business channels (offline). Payment data are typically merged with other non-traditional data derived from the use of apps or social media.

This paper explores whether (i) the use of QR codes in payments allows firms to have access to big tech credit; (ii) access/use of big tech credit allows firms to have access to more traditional bank credit; and (iii) there are real effects of the use of QR codes in payment and the subsequent provision of credit on firms' business volume.

To answer these questions, we use a unique dataset that compares the characteristics of loans provided by MYbank, one of the brands under Ant Group (an important big tech company in China) with loans supplied by traditional financial institutions. In particular, we analyse a random sample of around 500,000 Chinese firms that received credit from a big tech company and/or traditional financial institutions in the period 2017:01-2020:07. We consider the period 2017:01-2019:12 for our baseline results and use part of the Covid pandemic period (2020:01-2020:06) for a specific test on the real effects of the use of big tech credit as a cushion against the shock. We have access to detailed information on credit supplied by MYBank and firm characteristics at monthly frequency.[1] In particular, we have access to credit data and specific information used to model firms' creditworthiness, such as vendor transaction volumes and their network score. The latter measures users' centrality in the network and is based on a firm's payments history and social interactions of the entrepreneur in the Alipay ecosystem.

We find that the creation of a digital payment footprint allows firms to access other financial services and products offered by big techs. We also find that the use of big tech financial services and transaction data generated via QR codes generates spillover effects on bank credit. Specifically, the inclusion of big tech credit exposure in the credit registry acts as a signalling device and allows SMEs to also access more traditional banking services. Further, the use of credit lines offered to firms has positive effects on firms' business volume. These effects are quantitatively small in normal times, reflecting the use of credit lines mainly for liquidity management, not to expand the business, but significantly larger during the Covid-19 period, when credit lines are used to insulate the effects of an unexpected shock.

Related literature. We contribute mostly to four broad strands of literature. First, we provide new supportive evidence on the real effect of fintech credit (especially for big tech credit) and the way it can contribute to financial inclusion (BIS, 2019). Barrot and Nanda (2020) find strong direct effects of quick pay, a reform that permanently accelerated payments to small business contractors, on employment growth at the firm level. Using data from Alibaba's online retail platform, Hau et al. (2021) show that fintech credit approval and credit use boost a vendor's sales and transaction growth.

[1] All the data remained located at the Ant Group headquarters, and the regression analysis was conducted onsite by employees of MYbank, without the need to export the raw data.

Suri et al. (2021) study the Kenyan case and find that fintech credit can improve households' resilience: households are 6.3 percentage points less likely to forgo expenses due to negative shocks. Similarly, Ji et al. (2021) find that individuals' consumption significantly increases after being extended fintech consumer credit. Our paper contributes by complementing these results and finding that use of QR payments increases the probability of credit access/use for small and micro businesses and that this has positive effects on firms' business volumes, including during the pandemic. Unlike previous studies, our sample of firms contains not only firms operating on the e-commerce platforms (online firms) but also those that use more traditional business channels (offline firms).

Second, our paper is related to the literature that studies the interaction between fintech and traditional banking. Tang (2019) shows for the US that peer-to-peer (P2P) lending is a substitute for bank lending in terms of serving infra-marginal bank borrowers, yet complements bank lending with respect to small loans, while Cornaggia et al. (2018) find that high-risk fintech loans tend to substitute bank loans, while low-risk loans complement them and tend to expand the overall mass of credit provided to the economy. Chava et al. (2021) find that borrowers of marketplace lenders (MPL) reduce their traditional credit card balances after MPL origination, which increases their credit scores and ultimately enables additional lending from banks, thus higher aggregate indebtedness and ultimately higher default rates. Di Maggio and Yao (2021) show that fintech lenders in the US acquire market share by lending first to higher-risk borrowers and then to safer ones, and rely mainly on hard information to make credit decisions. We show that the use of big tech financial services and transaction data generated via QR codes produces spillover effects on bank credit; the inclusion of big tech loans in the credit registry allows small and medium-sized enterprises (SMEs) to be better screened/monitored by banks. With this, we also connect to a small literature focusing specifically on spillover effects from one segment of the financial system to another; Agarwal et al. (2021), for example, examine the impact of a large-scale microcredit expansion programme in Rwanda on financial access and show that a sizable share of first-time borrowers switched to banks, which cream-skim less risky borrowers and grant them larger, cheaper, and longer-maturity loans. Our paper is also closely related to that of Balyuk (2022), who finds that US banks expand credit access for consumers who obtain fintech loans. This effect is stronger for more creditconstrained consumers, consistent with the idea that fintech activity could help to solve information frictions. Our paper complements these findings, looking at the case of SMEs in China and how use of a QR code-based mobile payment system could contribute to financial inclusion.

Third, we contribute to the empirical literature that studies asymmetric information problems in credit markets. In this stream of the literature, collateral plays a key role in mitigating the financial constraints for the development of economic activity (Stiglitz and Weiss, 1981; Besanko and Thakor, 1987; Cerqueiro et al, 2016). Schmalz et al (2016) find that an increase in collateral value (proxied by house prices) leads to a higher probability of becoming an entrepreneur.[2] Our paper investigates how the use of massive data by big techs to assess firms' creditworthiness could reduce the need for collateral in solving asymmetric information problems.

Fourth, the paper contributes to the recent literature that looks at the informational content of digital soft information and credit performance. Dorfleitner et al. (2016) study the relationship between soft factors in P2P loan applications and financing and default outcomes. Using data on the two leading European P2P lending platforms, Smava and Auxmoney, they find that soft factors influence the funding probability but not the default probability. Jagtiani and Lemieux (2018a) find that the rating grades assigned on the basis of alternative data perform well in predicting loan performance over the two years after origination. The use of alternative data has allowed some borrowers who would have been classified as subprime by traditional criteria to be slotted into "better" loan grades, enabling them to benefit from lower-priced credit. Berg et al. (2020) show that digital footprints are a good predictor of the default rate and equal to or better than the information from credit bureau scores. Iyer et al. (2016) analyse the performance of new online lending markets that rely on nonexpert individuals to screen their peers' creditworthiness and find that these peer lenders predict an individual's likelihood of defaulting on a loan with 45% greater accuracy than the borrower's exact credit score (unobserved by the lenders, who only see a credit category). Gambacorta et al. (2019) find that the credit scoring models based on

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[2] Another important way to mitigate asymmetric information problems is the creation of a long-term credit relationship between a bank and a firm (Berger and Udell, 1992; Petersen and Rajan, 1994). Several studies have shown that banking relationships continue to smooth credit supply to firms when banks themselves face external liquidity shocks in a downturn (Bolton et al, 2016; Beck et al, 2018).

machine learning and non-traditional data are better able to predict losses and defaults than traditional models in the presence of a negative shock to the aggregate credit supply. Huang et al. (2020) show that fintech risk management could benefit small business relatively more. Our paper provides new evidence showing that use of transaction data generated via QR code payments improves big tech credit scoring techniques and that this allows SMEs to be better screened/monitored.

The rest of the paper is organised as follows. Section 2 presents the data and describes some stylised facts. Section 3 explains our empirical strategy and how we tackle identification issues. Section 4 presents the main results and robustness tests. The last section summarises the main conclusions. The Appendix reports stylised facts on Ant Group and some supplementary material.

2. Data and stylized facts

The empirical analysis in this paper focuses on Chinese micro and small enterprises that obtained credit from Ant Group.[3] For these firms, we can also observe their credit history and we can distinguish between collateralised and unsecured bank credit. All credit by Ant Group is unsecured and is provided by MYbank.

The database is constructed at the firm-month level over the period 2017:01 to 2020:07. The sample includes around 500,000 firms that have been randomly selected from a larger sample of more than 80 million firms that recorded transaction records every month and obtained bank credit since January 2017.[4] We use two different samples in our estimations, one on a monthly basis from 2017 to 2019 and one on a weekly basis from the end of October 2019 to June 2020.

Table 1a presents the summary statistics on our monthly database for normal times (2017:01-2019:12) and is divided into four panels: (i) Credit information; (ii) Firms' characteristics; (iii) Entrepreneurs' characteristics; (iv) Economic and financial

[3] The *Alibaba Group* is one of the biggest tech companies in the world. It was publicly listed on the New York Stock Exchange in September 2014 and on the Hong Kong Stock Exchange in November 2019. Alibaba has a market capitalisation of around USD 305 billion USD in NYSE and HKD 2.4 trillion in SEHK as of 28th January 2022. *Alipay* is a third-party mobile and online payment platform, established by the Alibaba Group that was subsequently rebranded as *Ant Financial Services Group* in October 2014 and *Ant Group* in June 2020. Additional information on Ant Group is provided in the Appendix.

[4] The initial sample of 500,000 firms have been reduced to 475,000 firms, excluding the top 5% of firms by transaction size. This allows us to exclude very large enterprises (i.e., supermarkets, good producers) that use the QR code payment system with a completely different business model.

conditions. Panel B reports weekly data that focus on the pre-pandemic period (2019.10.1-2020.1.25) and the pandemic period (2020.1.26-2020.6.30). The Appendix includes summary statistics separately for firms that had access to big tech credit, firms that used it and bank borrowers.

For big tech credit, we have more than 9 million firm-month observations. Over the sample period 58.2% of the observations refer to QR Code merchants that had access to big tech credit and 4.8% to merchants who also used it. The use of bank credit is much more limited: less than 1% of the QR Code merchants use bank credit (0.5% use unsecured bank credit and 0.2% use secured bank credit).

To give a sense of the evolution of financial inclusion over the sample period, Table 1a reports information also in two specific points in time: i) when firms have access to the QR code based mobile payment system for the first time; ii) at the end of the sample period.

When firms start to use QR code applications, 16% of them have already access to big tech credit, but only 0.2% use it. Most of the firms that have access to big tech credit have access to specific big tech credit products tailored for firms on e-commerce platforms. Interestingly, only 0.1% of firms when they start to use QR code payment system uses bank credit, mostly in the form of credit lines. Overall, the use of big tech credit and bank credit is very limited and concentrated to firms that operate online.

At the end of the sample (December 2019, before the Covid-19 pandemic), 69.8% of firms in our database have access to big tech credit and 7.8% use it. The percentage of firms that use bank credit increase to 1.2%, again mostly in the form of credit lines. The increase from 0.1% to 1.2% is economically relevant for such a short period of time, also considering that it involves 15% of the firms that use big tech credit.

Looking only at those firms that use bank credit (i.e., “banked firms”), we find that only 11% of these firms use also big tech credit (Figure 1). Among firms with bank credit, only very few have no access to MYbank credit (only 0.2% of the cases) or have access to but do not use MYbank credit (0.5%). The separation of bank and MYbank client is even more stringent in the case of secured bank credit borrowers, where fewer than 2% also use MYbank credit.

The median credit volume for big tech borrowers is RMB 10,000 (USD 1500), reflecting the micro nature of MYbank credit and the short maturity of the contract. Big tech credit is typically granted for short periods and in the form of a credit line (mainly 1 month; see Figure 2) and then rolled over, as long as the credit approval remains in place. The median bank credit is of RMB 80,773 (USD 12,100); the larger size of the loan also comes with longer loan maturity (1 to 3 years). By contrast, the difference in firm size between big tech and bank credit users is not large. The median monthly transaction volume of firms that use big tech credit is RMB 3,388 (USD 510), while that for firms that use bank credit is RMB 4,485 (USD 705). Interestingly, the median firm that uses big tech credit is less connected in the big tech ecosystem than firms that use bank credit (the network scores - that measures users' centrality in the ecosystem - are 49 and 54, respectively).[5] There is a positive correlation between firms' size and access to MYbank credit, as well as between MYbank credit use and bank credit use. Borrowers who access big tech credit are slightly younger (the median age is 34 years) than the owners of firms that use bank credit (36 years). More female entrepreneurs have access to MYbank credit.[6] Despite the larger access to MYbank credit, female entrepreneurs tend to use less MYbank credit and bank credit.

In the period under investigation big tech credit has lower default rates than bank credit. Table A1 in the Appendix taken from Gambacorta et al (2022) compares non-performing loans (NPLs) for Chinese banks and for MYbank, focusing on credit to small and medium-sized enterprises. As reported in the first two rows of the table, NPLs for the Chinese banking industry have been substantially higher on average than for MYbank in the period under investigation in this paper (2017-2019) and also during the Covid-19 pandemic (2020). These results are consistent with Huang et al. (2020), who find that big tech credit scoring yields better prediction of loan defaults during normal times and periods of large exogenous shocks, reflecting information and modelling advantages.[7]

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5 The network score is obtained as a rank calculated using a PageRank algorithm. This algorithm was introduced by Larry Page, one of the founders of Google, to evaluate the importance of a particular website page. The calculation is done by means of webgraphs, where webpages are nodes and hyperlinks are edges. Each hyperlink to a page counts as a vote of support for that webpage. In the case of the Ant Group network score, customers and QR code merchants can be considered as interconnected nodes (webpages) and payment funding flows can be considered as edges (hyperlinks).

6 This fact is very interesting because, in general, female entrepreneurs tend to be less financial included when considering traditional banks. In particular, data from the SME Finance Forum indicate that China's 74 million SMEs face a share of financially excluded entrepreneurs of 43 per cent, rising to almost 63 per cent for women-owned SMEs. See 202008_D2E_MyBank.pdf (ifc.org).

7 The results contrast with the evidence in Brailovskaya et al. (2021) who show in the context of digital loans in Malawi that the majority of borrowers fail to repay on time and incur high late fees.

3. Empirical strategy

We use duration models to gauge the time period that elapses between when a firm starts to use the QR code for payments and a given event (e.g., access to big tech credit, use of big tech credit or use of bank credit) referring to this time as *QR Code duration*. Duration models are applied in many economic fields, include the modelling of the length of time for a firm to go into default (e.g., Baele et al., 2014) or for individuals to remain unemployed (e.g., Kiefer, 1988).

We estimate a duration model with exponential distribution as a baseline hazard function. The sign of coefficients on the regressors indicate if they contribute to increasing or decreasing the time that elapses between when a firm starts to use the QR code for payments and a given event. The model has the hazard rate as dependent variable that can be interpreted as a convolution of the probability for the given event to occur. Therefore, a positive sign of the coefficient indicates that the specific regressor shorten such time (increase the probability for the given event), whereas a negative sign of the coefficient indicates that the regressor tend to increase this time (reduces the probability for the given event). The hazard rate $h_i(t)$ (probability that a given event happens at time *t*) for firm *i* is given by:

$$h_i(t) = \lambda(t) \exp(\sum_{j=1}^{m} (\beta_j x_{ij})) \tag{1}$$

where, independent variables (x_{ij}) include firms' financial and business conditions, macroeconomic variables, time and province fixed effects.$\lambda(t)$ is the baseline hazard function. Different kinds of proportional hazard models may be obtained by making different assumptions about the baseline hazard function. In our paper, we assume that the baseline risk is constant over time, so $\lambda(t) = \lambda$, therefore the model is given by:

$$h_i(t) = \lambda \exp(\sum_{j=1}^{m} (\beta_j x_{ij})) \tag{2}$$

Therefore, the probability a given event happens before time *t* (where *t* is the time that elapses between a firm starts to use the QR code) is given by:

$$S_i(t) = \int_0^t h_i(t)dt = \int_0^t \lambda \exp\left(\sum_{j=1}^{m} (\beta_j x_{ij})\right) dt \tag{3}$$

We consider three main events in our paper: (i) the time that elapses between the date a firm starts to use the QR code and the date the firm **gets access to big tech credit**, (ii) the time that elapses between when a firm starts to use the QR code and when the firm starts to **use big tech credit**, and (iii) the time that elapses between when a firm starts to use the QR code and when the firm **obtains a loan from a traditional bank**.

4. Results

4.1 Does the use of QR code in payment allow firm to have access to big tech credit?

Figure 3 shows a rapid increase in the likelihood of gaining access to big tech credit the longer a firm uses the QR code in payments. We start our analysis with the duration model that describes the amount of time that elapses between when a firm starts to use the QR code and when she receives the offer of a credit line from MYbank. The analysis is based on the Kaplan-Meier survival estimate, with the Y-axis reporting the probability of having access to big tech credit and the X-axis reporting *QR Code Duration*.[8] The figure shows that after one year from starting use QR code payments, the probability to have access to a big tech credit line is almost 60 per cent. This probability increases to 80 per cent after two years.

The first column of Table 2 reports the regression results of the duration model with time-invariant borrower characteristics (gender, age, house property, distance to bank branch), together with transaction volumes and network score. The probability to get big tech access increases by 64% if transaction volume increases by 10% at a specific point of time.[9] The amount of time that it takes between when a firm starts to use the QR code and when she receives the offer of a credit line from the big tech is faster for entrepreneurs who own a house (even if big tech credit is not collateralised) and who are younger. Specifically, the probability to get big tech access is 1.76 times higher for entrepreneurs who own a house than for entrepreneurs who do not own a house (exp(0.566)=1.76). Interestingly, access is faster for female entrepreneurs even though they are typically less likely to have a bank account. In particular, the probability for a male entrepreneur to have access to big tech credit is only 0.86 times that of a female

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8 For ease of representation, we show our results in graphical format computing the Kaplan and Meier (1958) estimators that indicate the probability that a given event occurs before *t*. The graphs report a non-parametric estimate of the failure probability (1-survival probability) as a function of time *t*.

9 The coefficient is 0.0497. This means that if transaction volume increases by 10%, the probability increase by 64% (exp(0.0497*10)-1).

entrepreneur (exp(-0.153)=0.86). The speed of access to big tech credit is also negatively correlated with the distance of the firm's location to bank branches. This could be explained by the fact that most firms are located in metropolitan areas where distance to bank branches is minimal and the fact that most micro-enterprises are located in commercial centres where also bank branches are located.

4.2 Does the use of QR code in payment allow firm to use bank credit?

The time a firm uses the QR code for payments does not seem to increase the probability of use of bank credit. Figure 4 reports the results based on the Kaplan-Meier survival estimate (green line). The Y-axis reports the probability of using bank credit, while the X-axis reports QR code duration. After one year from starting to use the QR code, the probability to use bank credit line is less than 1 per cent. This probability reaches only 2.5 per cent in 3 years.[10] When focusing on unsecured (red) or secured (blue) bank credit, we find that for unsecured bank credit the probability reach 1.5 per cent after three years, while it reaches less than 0.5 per cent for secured bank credit. In summary, it seems that for a firm having a simple documentation of transaction volumes (obtained by using QR Code payments) does not alter significantly the probability for the firm to use bank credit. This reflects the fact that big tech credit is more similar to unsecured bank credit and that secured bank credit requires a collateral asset to pledge that in many cases it is not available to small entrepreneurs. Indeed, the use of the QR code payment does not increase the speed of access to secured credit. After three years from starting use the QR code, the probability to use secured credit is very close to zero. It is interesting to note that, also the spillover effects for use of unsecured bank credit, while statistically significant, remain very small.

The second column of Table 2 reports the corresponding regressions results. The time that elapses between when a firm starts to use the QR code and when she uses bank credit is strongly correlated with firm-specific variables (transaction volumes and network score). The other control variables have similar sign as in column I, with the notable exception of the gender variable. Male entrepreneurs tend to have a quicker use of bank credit. Columns III to V of Table 2 additionally control for (i) big tech credit

[10] The results do not change dramatically if we use a duration model to test directly how much it takes for a firm from having access to the big tech credit line to using the bank credit, restricting the sample only to firms that that have access to big tech credit. After three years from the offer of the credit line, only 2.8 per cent of firms use bank credit.

access, (ii) big tech credit use and (iii) both. The inclusion of these variables allows us to test in a nested model how the use of the QR payment technology affects the use of bank credit for firms with no access to or no use of big tech credit and those with access or use. The results are very similar to those already discussed above. Both access to and use of big tech credit increases the speed with which firms can access bank credit, when included separately. When included together, the use of big tech credit increases the speed with which firms get access to bank credit while access reduces it. The probability to use bank credit for those firms who use big tech credit is 8.9 times that for firms which do not use it at that point of time (exp(2.188)=8.92). Controlling for the effects of big tech credit use, the probability to use bank credit for firms who have only access to big tech credit (but did not use it) is 0.7 that of other firms (exp(-0.344=0.71). This is probably due to a demand effect as firms that had the opportunity to use big tech credit and did not use it have probably less need for bank credit as well.

Figures 5 and 6 show that there are substantial differences in the economic effect of access to or use of big tech credit for the use of bank credit. After three years from the use of the QR code, the probability to use bank credit is only 3% for firms with access to MYBank credit, while it is 1.5% for those with no access to big tech credit (Figure 5, left hand panel). Also in this case, spillover effects remain very low considering separately unsecured bank credit (centre panel) or secured bank credit (right hand panel).[11] Figure 6, on the other hand, shows that the use the big tech credit line increases significantly the probability of using of bank credit. After one year from starting use the QR codes, the probability to use bank credit line is around 8 per cent. This probability reaches 17 per cent after 3 years (left hand panel). By contrast, the probability for firms that do not use the credit line is always close to zero over the three years. Qualitatively the results remain similar when considering separately unsecured bank credit (centre panel) or secured bank credit (right hand panel).[12]

Why is the spillover effect so different for a firm that uses the big tech credit line rather than for one that has simple access to it? One possible explanation for this difference is the positive signal given by the presence of the firm in the credit bureau. When a

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[11] The specific regressions for the two different bank credit types are reported in columns II of Table 3 (unsecured bank credit) and Table 4 (secured bank credit).

[12] The specific regressions for the two different bank credit types are reported in columns III of Tables 3 (unsecured bank credit) and Table 4 (secured bank credit).

firm uses the big tech credit line it does enter the PBC credit bureau system and starts to have a footprint in the financial system.[13] This footprint is visible also for banks and represents a positive signal on firm's quality, a result consistent with Agarwal et al (2021), though in a very different setting.[14]

Figures 4, 5 and 6 have already pointed to important differences between secured and unsecured bank credit. Tables 3 and 4 report the corresponding duration models.

The first columns of Tables 3 and 4 report the results of models that evaluate how QR code duration affects use of unsecured and secured bank credit, respectively and are equivalent to column (2) of Table 2. We find that firms with higher transaction volume and network scores, male and younger entrepreneurs and with house property access and use both unsecured and secured bank credit more rapidly. While a shorter distance to the nearest bank branch accelerates use of secured bank credit it does not accelerate use of unsecured bank credit. As in Table 2, we then add subsequently, a dummy indicating (i) access to and (ii) use of big tech credit, before (iii) including both.

4.3 Disentangling demand and supply effects

Our results could be driven by credit demand rather than information spillover effects. A firm who borrows from a big tech may simply have a higher credit demand compared to other firms that would not use such credit even if offered. Given their higher credit demand, these firms (that use big tech credit) are more likely to ask for more credit also from traditional banks.

To tackle this issue, we focus our attention only on firms that have used big tech credit, distinguishing their behaviour prior and after the use of big tech credit. In Table 5, we report the results of the duration model that describes the amount of time that elapses between when a firm starts to use the QR code and when she uses bank credit. We run

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13 Differently from credit registries in other countries, in China a credit line that is granted but not used by the firm is not registered. At the same time, there is no minimum threshold and all credit used – also of very limited amount – is reported in the credit registry system.

14 A similar positive signalling effect is provided by mutual guarantee institutions (MGIs) in Italy. Mutual guarantee institution (MGI) members contribute to a guarantee fund which is then used as collateral to back loans granted to the members themselves. In this scheme, joint responsibility derives from firms' contribution to the mutual fund. Columba et al. (2010) show that small firms affiliated to MGIs pay less for bank credit compared with similar firms. The reason is that each member of the MGI is better informed than banks about other members' characteristics and behaviour and grant access to the fund only if members are financially resilient. Be part of a MGI creates a sort of certification effects on banks.

the duration models for the three different types of bank credit (total, secured and unsecured) but only for the subset of firms that have used big tech credit in our sample period and therefore should have more similar demand needs.[15] We also include in the model directly the Big tech use dummy that allows us to consider the impact of the *QR Code Duration* on the event (use of bank credit) prior and after the use of big tech credit.

The results in Table 5 show that the use of big tech credit is associated with firms more quickly gaining access to unsecured but not secured bank credit. Figure 7 reports, for each month that passes from the start of the use of QR code payment, the probability of having access to different form of bank credit. The results clearly show that even within the group of firms that use big tech credit at some point, the probability of bank credit use increases significantly after using big tech credit.[16]

The spillover effects caused by the use of big tech credit could be heterogeneous for different characteristics of QR Code merchants. To test for such differences, in Table 6 we include interaction terms between firm-specific characteristics and the big tech use dummy. The results indicate that the spillover effects from big tech use to bank credit use are larger for firms with female entrepreneurs, without house property and with lower network score. Other things being equal, these firms have more difficulties to have access to bank credit so the positive effects from using the QR code payments seems more helpful compared to other firms. Figure 8 reports the different probabilities for a spillover effect from big tech credit use to bank credit use for firms with different firm/entrepreneur's characteristics.

4.4 Real effects of big tech credit

Next, we test whether the introduction of QR code payments and the use of big tech credit produces real effects for firms' activity. The first test uses the period around the introduction of the big tech loan product, while the second test considers the whole pre-Covid period (2017-2019); finally, we focus on the Covid-19 shock and compare the pre-pandemic to the pandemic period, considering firms with and without big tech credit.

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15 For comparison, we also run similar models for the subset of firms that had access to MYbank credit (see Table 6).

16 In robustness tests not reported here for the sake of brevity, results are confirmed also expanding our sample to all firms that gained access to MYbank credit even if they did not use it.

4.4.1 Introduction of MYbank credit

The first test focuses on the initial offering of big tech loans. Ant Group introduced the possibility of MYBank credit products to QR Code merchants at the end of June 2017 and started to supply loans in August 2017. We can use this exogenous shock to analyse the real effects of the provision of MYbank credit on firms' transactions volumes, comparing firms with and without credit. We exclude August 2017 from the analysis and compare 3 months before (2017.5-2017.7) and 3 months afterwards (2017.9-2017.11) the introduction of MYbank credit.

To rule out the possibility that a selection in the treatment of different firms may influence our results, we use a propensity score matching combined with a difference-in-differences type of analysis.

We first average selected firms' characteristics in the period before the launch of the new big tech loan product (pre-treatment period) and use log(transaction volume) for the pre-treatment period and average transaction volumes and growth rate of transaction volumes to predict the probability of being treated. Finally, we match each firm in the control group with one or more firm in the treatment group that has the closest score, that is the same probability of being treated. We estimate the following logit regression:

$$Treat_i = \alpha + \beta_1 \ln(trans\ volume)_{i,average} + \beta_2 \ln(trans\ volume)_{i,May\ 2017} + \beta_3 \ln(trans\ volume)_{i,Jun\ 2017} + \beta_4 \ln(trans\ volume)_{i,Jul\ 2017} + \beta_5 \text{growth rate}(trans\ volume)_{i,Jul-Jun\ 2017} + \beta_5 \text{growth rate}(trans\ volume)_{i,Jun-May\ 2017} + \varepsilon_i \quad (4)$$

where Treat_i is a dummy that equals 1 if firm *i* is in the treatment group (obtain the big tech credit access in August 2017) and 0 otherwise. Matching is done using a Nearest Neighbor approach with a conservative Caliper equal to 0.0001. Finally, the matching is done with replacement, so that there is more than one match between a firm in the treatment with a firm in the control group.

We then use the following difference-in-differences model.

$$\ln(transaction\ volume)_{it} = \alpha + \beta * Post_t * Treat_i + u_i + s_t + \varepsilon_{it} \quad (5)$$

where the dependent variables is the logarithm of transaction volume for firm *i* and time *t*. The dummy *Treat* takes the value of 1 for those QR Code merchants who received MYbank credit approval in August 2017 (only in this initial month) and zero otherwise. The variable *Post* takes the value of 1 after August 2017 and zero before. We control for firm fixed effect u_i and time fixed effect s_t. ε_{it} is an error term. Standard errors are clustered at the firm level.[17]

The results in Column 1 of Table 7 show that the transaction volume increases 9.6 per cent more for firms that had access to big tech credit (treated group) with respect to firms with similar characteristics which did not have access (control group). The left-hand panel of Figure 9 visualizes the behaviour of the logarithm of transaction volumes of the two groups prior and after the launch of the offer of credit products by MYbank. The right-hand panel report the difference between the two firms' type and 95% confidence bands. While there is no difference between the treated and the control group until August 2017, the treatment group achieves higher levels of transactions thereafter.

The second test evaluates the effects of the provision of big tech credit over the period 2017.2-2019.12, i.e., beyond the initial period of introduction. Similarly to the test above, we use a propensity score matching combined with a diff-in-diff type of analysis:

$$ln(transaction\ volume)_{i,T+k} = \alpha + \beta * post_k * Treat_{i,T} + u_{iT} + s_k + \varepsilon_{it} \qquad (6)$$

Where the dependent variables is the logarithm of transaction volume for firm *i* and time T+k, while u_{iT} is Firm*Time fixed effect, and s_k is the fixed effect to control period k.[18] The range of k is from -3 to 3 and ε_{it} is an error term.

The dummy $Treat_{i,T}$ takes the value of 1 for a firm *i* who received MYbank credit approval in T (only in this initial month). Those firms with $Treat_{i,T}$ equal to zero represent our control group, composed of QR Code merchants who did not get MYbank credit approval before T+3 (but maybe later). The variable *Post* takes the value of 1 after T and zero elsewhere. We analyse the three months before the supply of credit in

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17 The results are robust to the use of alternative cluster procedures, such as city*time level.

18 It is worth noting that for test 2 we use a different set of fixed effects with respect to test 1. While in test 1 we evaluate a one-off shock, in test 2 we consider the effects over a time span of 36 months. For each group (control and treated) we evaluate seven periods (T-3, T-2, T-1, T, T+1, T+2, T+3) and therefore in regression (6), the level of observation is Firm (i) * Time (T) * Period (k). Following Brown and Earle (2017), we include in equation (6) both Firm*Time fixed effect and period k fixed effects.

T and the three months afterwards. For each time T, we have a subsample which includes one control group and one treatment group.

The left-hand panel of Figure 10 shows that the treatment group of firms grows their transaction volume at a higher rate once it receives loans from MYbank. The results reported in column II or Table 7 and in the right hand panel of Figure 10 show that the transaction volume (significantly) increases (by around 3.5 per cent more) for the treated group than for the control variable over the whole period.

4.4.2 Real effects during the Covid19 pandemic

The Covid-19 pandemic has hit the Chinese economy hard, with some sectors affected particularly badly. Lockdown measures have reduced activity in transport, leisure and retail industries have collapsed. We now test if access to big tech credit provided a way to insulate the effects of the shock for SMEs.

Different from above, we use weekly data to capture the effect during the Covid-19 pandemic. Our sample period is from 30th Sep 2019 to 28th June 2020. In particular we compare the pre-Covid period (30th Sep 2019 to 19th Jan 2020) with the Covid period (26th Jan 2020 to 28th June 2020).

We consider an approach that is similar to that described above, using a propensity score matching approach and a difference in difference model (see equation 5). The dependent variables is the logarithm of transaction volume for firm *i* and time *t*. The treatment dummy *Treat* takes the value of 1 for those QR Code merchants who received MYbank credit approval before 1st Oct 2019 and 0 otherwise. The variable *Post* takes the value of 1 after 26th Jan 2019 and zero elsewhere. Lock down policies in Chinese cities are captured by City*time fixed effect to control for geographically different effects of the pandemic. Time-invariant variables (eg pre-pandemic use of bank credit and other merchant-specific information) are captured by firm fixed effect.

The results in Column III of Table 8 and illustrated in Figure 11 show that the transaction volume growth is around 20 per cent higher for the treated group than for the control group during the pandemic, suggesting that the real effect duration Covid-19 are significantly large than that in normal time. It probably reflects the insulation value of big tech credit for firms to cope with the unexpected consequences of the shock. Figure 11 visualizes the behaviour of the logarithm of transaction volumes (at the weekly level) of the two groups prior and after the Covid-19 shock.

5. Conclusions

The use of apps for mobile payments, through so-called QR codes, simplifies the collection of payments for firms at a reduced cost. This can help firms to increase transaction volumes and to disclose their characteristics via payment data. Big tech firms can process these data – together with other non-traditional information collected on social media, search engines and e-commerce platforms – to generate a credit score. Firms that are typically unbanked and lack financial statements can have access to small loans that are not collateralised and typically used to adjust their liquidity needs. Overall, the use of QR codes could have positive effects for financial inclusion that go well beyond the simple efficient processing of transaction payments.

Using a unique dataset of around 500,000 Chinese firms that received credit from both an important big tech firm (Ant Group) and traditional commercial banks, this paper finds the following. First, the creation of a digital payment footprint allows firms to access other financial services and products offered by big techs. Second, the use of big tech financial services and transaction data generated via QR codes generates spillover effects on bank credit. The inclusion of big tech credit in the credit registry allows SMEs to be better screened/monitored by banks. This alleviates SMEs' asymmetric information problems with banks and allows SMEs to also access more traditional banking services. And third, the real effects of QR code credit are economically relevant, especially in the case of the Covid-19 shock.

While this evidence is encouraging and sheds some additional light on the effects of big techs' entry into finance, much remains to be done to address the larger economic questions. First, it would be interesting to compare the results obtained for China with other countries. For example, in many African countries digital lending through mobile network operators is captured in the credit registry, only because the loans are done in partnership with a commercial bank. Second, an important question is what the implications of big techs are for relationship lending. A bank acquires soft information from its clients by developing long-term relationships. By contrast, credit scoring with advanced analytics does not necessarily rely on long-term, one-to-one relationships, but exploits patterns of consumer preferences and behaviour using big data. Third, another set of questions relates to possible cases of discrimination and privacy concerns. The algorithms used to process data may develop biases, leading to unethical discrimination (based e.g., on race or religion) and greater inequality (O'Neil, 2016). For instance, one study of the US mortgage market found that black and Hispanic borrowers were less likely to benefit from lower interest rates from machine learning-based credit scoring models than non-Hispanic white and Asian borrowers (Fuster et al., 2022). Finally, the use of large amounts of personal data from non-traditional sources (e.g., social media, browser history, telephone calls) can infringe on privacy. All these are relevant aspects for future research in this area.

References

Agarwal, S., T. Kigabo, C. Minoiu, A. F. Presbitero, and A. F. Silva (2021), “Serving the Unnderserved: Microcredit as a Pathway to Commercial banks”, *Review of Economics and Statistics*, forthcoming.

Baele, L., Farooq, M., and Ongena, S. (2014), “Of religion and redemption: Evidence from default on Islamic loans”, *Journal of Banking and Finance*, 44, 141-159.

Banerjee, A., Karlan, D., and Zinman, J. (2015), “Six randomized evaluations of microcredit: Introduction and further steps”, *American Economic Journal: Applied Economics*, 7(1), 1-21.

Bank for International Settlements (2019). “Big tech in finance: opportunities and risks”, BIS Annual Economic Report, Ch. III, June.

Balyuk, T. (2022), “FinTech lending and bank credit access for consumers”, *Management Science*, forthcoming.

Barrot, J. N., and Nanda, R. (2020), “The employment effects of faster payment: evidence from the federal quickpay reform”, The Journal of Finance, 75(6), 3139-3173.

Beck, T., Degryse, H., De Haas, R., van Horen, N. (2018), “When arm’s length is too far. Relationship banking over the credit cycle”, *Journal of Financial Economics*, 127(1), 174-196.

Berg, T., Burg, V., Gombović, A., and Puri, M. (2020), “On the rise of fintechs: Credit scoring using digital footprints”, *The Review of Financial Studies*, 33(7), 2845-2897.

Berger A.N. and Udell G.F. (1995), “Relationship Lending and Lines of Credit in Small Firms Finance”, *Journal of Business*, 68, 351-381.

Berger A.N. and Udell G.F. (2006), “A More Complete Conceptual Framework for SME Finance”, *Journal of Banking and Finance*, 30 (11), 2945-66.

Berger, A.N., and Udell, G.F. (1992), “Some evidence on the empirical significance of credit rationing”, *Journal of Political Economy*, 100, 1047-77.

Besanko, D., and Thakor, A.V. (1987), “Competitive equilibrium in the credit market under asymmetric information”, *Journal of Economic Theory*, 42(1), 167-182.

Bolton, P., Freixas X., Gambacorta L., and Mistrulli P.E. (2016), “Relationship and transaction lending in a crisis”, *Review of Financial Studies*, 29(10), 2643-2676.

Brailovskaya, V., Dupas, P., and Robinson, J. (2021), “Is Digital Credit Filling a Hole or Digging a Hole? Evidence from Malawi”. NBER WP 29573.

Brown J.D. and J. S. Earle (2017), Finance and growth at the firm level: Evidence from SBA loans, The Journal of Finance, 72(3),1039-1080.

Carstens A. (2021), “Public policy toward big techs in finance”, speech, 27 January.

Carstens A., Claessens S., Restoy F., and Shin H.S. (2021), "Regulating big techs in finance", *BIS Bulletin*, no 45, 2021.

Cerqueiro, G., Ongena, S., and Roszbach, K. (2016), “Collateralization, bank loan rates, and monitoring”, The Journal of Finance, 71(3), 1295-1322.

Chava, S., Ganduri, R., Paradkar, N., and Zhang, Y. (2021), “Impact of Marketplace Lending on Consumers’ Future Borrowing Capacities and Borrowing Outcomes”, *Journal of Financial Economics* (forthcoming).

Columba, F., Gambacorta L., and Mistrulli P.E. (2010), “Mutual Guarantee Institutions and Small Business Finance”, *Journal of Financial Stability*, 6, 45-54.

Cornaggia, J., Wolfe, B., and Yoo, W. (2018), "Crowding out banks: Credit substitution by peer-to-peer lending". Available at SSRN 3000593.

Cornelli G., Frost J., Gambacorta L., Mu C. and Ziegler T. (2021), "Big tech credit during the Covid-19 pandemic", mimeo.

Cornelli G., Frost J., Gambacorta L., Rau R., Wardrop R. and Ziegler T. (2020), "Fintech and big tech credit: a new database", BIS Working Papers, 887.

Degryse, H., Kim, M., and Ongena, S. (2009), *Microeconometrics of Banking*. Oxford University Press.

Di Maggio, M, and Yao V. (2021), "Fintech Borrowers: Lax Screening or Cream-Skimming?", *The Review of Financial Studies*, 34(10), 4565–4618.

Dorfleitner, G., Priberny C., Schuster S., Stoiber J., Weber M., de Castro I., and Kammler J. (2016), "Description-text related soft information in peer-to-peer lending – Evidence from two leading European platforms", *Journal of Banking and Finance*, 64, 169–-87.

Financial Stability Board (2019a), "FinTech and market structure in financial services: Market developments and potential financial stability implications", February.

Financial Stability Board (2019b), "BigTech in finance: Market developments and potential financial stability implications", December.

Frost J., Gambacorta L., Huang Y., Shin H.S., and Zbinden P. (2019), "BigTech and the changing structure of financial intermediation", *Economic Policy*, 34(100), 761–99.

Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., and Walther, A. (2022), "Predictably unequal? The effects of machine learning on credit markets". *The Journal of Finance*, 77(1), 5-47.

Gambacorta, L., Huang Y., Qiu H., and Wang, J. (2019), "How do machine learning and non-traditional data affect credit scoring? New evidence from a Chinese fintech firm", BIS Working Papers, 834.

Gambacorta, L., Huang Y., Li Z., Qiu H., and Chen S. (2022), "Data vs collateral", *Review of Finance*, forthcoming.

Hau, H., Y. Huang, H. Shan, Z. Sheng (2021), "Fintech credit, financial inclusion and entrepreneurial growth", Swiss Finance Institute Research Paper, 21-47.

Huang, Y., Zhang, L., Li, Z., Qiu, H., Sun, T., and Wang, X. (2020), "Fintech Credit Risk Assessment for SMEs: Evidence from China", IMF Working Papers, 2020.193.

Iyer, R., Khwaya A. J., Luttmer E.F.P. and Shue K. (2016), "Screening Peers Softly: Inferring the Quality of Small Borrowers", *Management Science*, 62(6), 1554–1577

Jagtiani, J. and Lemieux C. (2018), "The roles of alternative data and machine learning in fintech lending: evidence from the LendingClub consumer platform", Federal Reserve Bank of Philadelphia Working Papers, 18–15, April.

Ji, Y., Wang, X., Huang, Y., Chen, S., and Wang, F. (2021), "An experiment of Fintech consumer credit in China: A mixed story of liquidity constraint and liquidity insurance", mimeo

Kiefer, N.M. (1988), "Economic duration data and hazard functions", *Journal of economic literature*, 26(2), 646-679.

Lian, C., and Y. Ma, (2019), Anatomy of corporate borrowing constraints. mimeo.

O'Neil, C. (2016), Weapons of math destruction: how big data increases inequality and threatens democracy, Broadway Books.

Petersen M. A. and Rajan R.G. (1994), “The Benefit of Firm-Creditor Relationships: Evidence from Small Business Data”, *Journal of Finance*, 1, 3-37.

Petersen, M., and Rajan, R. (1994), “The benefits of lending relationships: Evidence from small business data”, *Journal of Finance*, 49, 3–37.

Philippon, T. (2019), “On fintech and financial inclusion”, NBER working paper 26330.

Restoy F. (2021), “Fintech regulation: how to achieve a level playing field”, FSI Occasional Papers, 17, February.

Schmalz, M.C., Sraer D.A., and Thesmar D. (2017), “Housing collateral and entrepreneurship”, *The Journal of Finance*, 72(1), 99-132.

Stiglitz, J.E., and Weiss, A. (1981), “Credit rationing in markets with imperfect information”, *The American Economic Review*, 71(3), 393-410.

Stulz R. (2019), “FinTech, BigTech, and the Future of Banks”, *Journal of Applied Corporate Finance*, 31(4), 86–97.

Suri, T., Bharadwaj, P., and Jack, W. (2021), “Fintech and household resilience to shocks: Evidence from digital loans in Kenya”, *Journal of Development Economics*, 102697.

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

Thakor, A. V. (2020), “Fintech and banking: What do we know?”. *Journal of Financial Intermediation*, 41, issue C.

Tables and figures

Table 1a. Summary statistics （normal time: 2017:01-2019:12）

	N	Mean	St. Dev.	P25	Median	P75
i) Credit information						
All sample period						
Big tech credit access (0/1)	9,277,205	0.582	0.493	0	1	1
Big tech credit use (0/1)	9,277,205	0.048	0.214	0	0	0
Bank credit use (0/1)	9,277,205	0.01	0.098	0	0	0
Bank unsecured credit use (0/1)	9,277,205	0.005	0.067	0	0	0
Bank secured credit use (0/1)	9,277,205	0.002	0.042	0	0	0
Big tech credit used (RMB)	160,670	18,295	28,292	3,200	10,000	21,200
Bank credit used (RMB)	13,649	166,749	321,175	30,000	80,773	190,000
Bank unsecured credit used (RMB)	7,131	83,451	112,326	17,425	50,000	100,000
Bank secured credit used (RMB)	2,003	451,339	546,996	120,000	300,000	520,000
Beginning of access to QR code						
Big tech credit access (0/1)	475,000	0.163	0.37	0	0	0
Big tech credit use (0/1)	475,000	0.002	0.049	0	0	0
Bank credit use (0/1)	475,000	0.001	0.032	0	0	0
Bank unsecured credit use (0/1)	475,000	0.0005	0.022	0	0	0
Bank secured credit use (0/1)	475,000	0.0002	0.013	0	0	0
End of sample						
Big tech credit access (0/1)	475,000	0.698	0.459	0	1	1
Big tech credit use (0/1)	475,000	0.078	0.268	0	0	0
Bank credit use (0/1)	475,000	0.012	0.111	0	0	0
Bank unsecured credit use (0/1)	475,000	0.007	0.081	0	0	0
Bank secured credit use (0/1)	475,000	0.002	0.046	0	0	0
ii) Firms' characteristics						
Transaction volume monthly (RMB)	927,7205	5709	8886	801	2,458	6,643
Network Score	911,7297	35.04	20.07	20.51	31.85	45.84
iii) Entrepreneurs' characteristics						
Age	9,272,528	38.918	9.497	31	38	46
Male (0/1)	9,277,205	0.509	0.5	0	1	1
House property (0/1)	9,277,205	0.566	0.496	0	1	1
iv) Economic and financial conditions						
GDP (billion RMB)	8,973,458	723.891	792.310	215.350	403.960	944.340
Distance to Bank (KM)	9,275,309	0.96	1.65	0.16	0.33	0.80

Table 1b. Summary statistics （weekly data 2019.10.1-2020.1.25）

	N	Mean	St. Dev.	P25	Median	P75
i) Before Covid-19 (2019.10.1-2020.1.25)						
Transaction volume monthly (RMB)	1,417,664	1,636	3,110	152	577	1,721
Network Score	1,409,600	32.504	18.950	18.649	28.916	42.504
Age	1,417,104	39.775	10.163	32	40	47
Male (0/1)	1,417,664	0.504	0.5	0	1	1
House property (0/1)	1,417,664	0.484	0.5	0	0	1
ii) After Covid-19 (2020.1.26-2020.6.30)						
Transaction volume monthly (RMB)	2,037,892	1,084	2,552	0	215	1,020
Network Score	2,026,300	32.504	18.950	18.649	28.916	42.504
Age	2,035,669	40.131	10.169	32	40	48
Male (0/1)	2,037 ,892	0.504	0.5	0	1	1
House property (0/1)	2,037,892	0.518	0.5	0	1	1

Table 2. Duration models

Explanatory variables	I	II	III	IV	V
	Hazard rate: Probability that the firm …				
	has access to big tech credit	uses bank credit	uses bank credit (controlling for big tech credit access)	uses bank credit (controlling for big tech credit use)	uses bank credit (controlling for big tech credit access and use)
Log Transaction volume	0.0497***	0.0369***	0.0346***	0.0278***	0.0320***
	(0.00114)	(0.00943)	(0.00944)	(0.00922)	(0.00927)
Network score (1)	0.0022***	0.0237***	0.0235***	0.0178***	0.0183***
	(0.00014)	(0.00062)	(0.00062)	(0.00067)	(0.00067)
Male (0/1)	-0.152***	0.492***	0.497***	0.387***	0.376***
	(0.00402)	(0.0292)	(0.0293)	(0.0297)	(0.0297)
Age	-0.003***	-0.0158***	-0.0159***	-0.00236	-0.00264
	(0.00022)	(0.00168)	(0.00169)	(0.00172)	(0.00170)
House property (0/1)	0.566***	0.864***	0.823***	0.687***	0.781***
	(0.005104	(0.0429)	(0.0445)	(0.0434)	(0.0460)
Distance to bank branch	0.0088***	-0.0257**	-0.0251**	-0.0247**	-0.0262**
	(0.00156)	(0.0109)	(0.0109)	(0.0108)	(0.0109)
Big tech credit access (0/1)			0.135***		-0.344***
			(0.0342)		(0.0394)
Big tech use (0/1)				2.092***	2.188***
				(0.0330)	(0.0348)
Time fixed effects	Y	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y	Y
Macroeconomic controls	Y	Y	Y	Y	Y
Observations	3,498,246	8,319,705	8,319,705	8,319,705	8,319,705

Notes: (1) Network score measures users' centrality in the network and is based on users' payment and funds information and social interactions. The user who has more connections gets a higher network score. Standard errors in brackets are clustered at the firm level. Significance level: *p<0.1; ** p<0.05; *** p<0.01.

Table 3. Duration models: Unsecured bank credit

Explanatory variables	I	II	III	IV
	Hazard rate: Probability that the firm … .			
	uses unsecured bank credit	uses unsecured bank credit (controlling for big tech credit access)	uses unsecured bank credit (controlling for big tech credit use)	uses unsecured bank credit (controlling for big tech credit access and use)
Log Transaction volume	0.0248**	0.0226*	0.0126	0.0179
	(0.0127)	(0.0127)	(0.0122)	(0.0123)
Network score (1)	0.0258***	0.0257***	0.0185***	0.0190***
	(0.000826)	(0.000828)	(0.000917)	(0.000916)
Male (0/1)	0.452***	0.457***	0.311***	0.295***
	(0.0400)	(0.0400)	(0.0407)	(0.0407)
Age	-0.0276***	-0.0278***	-0.0117***	-0.0117***
	(0.00237)	(0.00238)	(0.00242)	(0.00238)
House property (0/1)	0.980***	0.937***	0.739***	0.878***
	(0.0608)	(0.0629)	(0.0616)	(0.0655)
Distance to bank branch	-0.0156	-0.0151	-0.0151	-0.0171
	(0.0146)	(0.0146)	(0.0145)	(0.0145)
Big tech credit access (0/1)		0.146***		-0.531***
		(0.0471)		(0.0561)
Big tech use (0/1)			2.286***	2.441***
			(0.0437)	(0.0472)
Time fixed effects	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y
Macroeconomic controls	Y	Y	Y	Y
Observations	8,363,872	8,363,872	8,363,872	8,363,872

Notes: (1) Network score measures users' centrality in the network and is based on users' payment and funds information and social interactions. The user who has more connections gets a higher network score. Standard errors in brackets are clustered at the firm level. Significance level: *p<0.1; ** p<0.05; *** p<0.01.

Table 4. Duration models: Secured bank credit

Explanatory variables	I	II	III	IV
	Hazard rate: Probability that the firm …			
	uses secured bank credit	uses secured bank credit (controlling for big tech credit access)	uses secured bank credit (controlling for big tech credit use)	uses secured bank credit (controlling for big tech credit access and use)
Log Transaction volume	0.0320***	0.103***	0.0985***	0.101***
	(0.00927)	(0.0257)	(0.0253)	(0.0254)
Network score (1)	0.0183***	0.0268***	0.0226***	0.0227***
	(0.000674)	(0.00151)	(0.00159)	(0.00159)
Male (0/1)	0.376***	0.406***	0.314***	0.310***
	(0.0299)	(0.0705)	(0.0711)	(0.0712)
Age	-0.00264*	0.0275***	0.0383***	0.0380***
	(0.00170)	(0.00376)	(0.00383)	(0.00382)
House property (0/1)	0.781***	1.201***	1.128***	1.183***
	(0.0460)	(0.131)	(0.129)	(0.134)
Distance to bank branch	-0.0262**	-0.166***	-0.165***	-0.166***
	(0.0109)	(0.0266)	(0.0264)	(0.0264)
Big tech credit access (0/1)		0.157*		-0.169*
		(0.0854)		(0.0947)
Big tech use (0/1)			1.862***	1.901***
			(0.0831)	(0.0859)
Time fixed effects	Y	Y	Y	Y
Province fixed effects	Y	Y	Y	Y
Macroeconomic controls	Y	Y	Y	Y
Observations	8,319,705	8,386,574	8,386,574	8,386,574

Notes: (1) Network score measures users' centrality in the network and is based on users' payment and funds information and social interactions. The user who has more connections gets a higher network score. Standard errors in brackets are clustered at the firm level. Significance level: *p<0.1; ** p<0.05; *** p<0.01.

Table 5. Duration models: Only firms that had used MYbank credit

Explanatory variables	I	II	III
	Hazard rate: Probability that the firm …		
	uses bank credit	uses unsecured bank credit	uses secured bank credit
Transaction volume	0.0230**	0.00335	0.0845***
	(0.0110)	(0.0140)	(0.0311)
Network score (1)	0.0111***	0.0116***	0.0181***
	(0.000860)	(0.00112)	(0.00213)
Male (0/1)	0.173***	0.114**	0.122
	(0.0354)	(0.0467)	(0.0899)
Age	0.0318***	0.0151***	0.0782***
	(0.00216)	(0.00294)	(0.00500)
House property (0/1)	0.159***	0.290***	0.328*
	(0.0543)	(0.0760)	(0.169)
Distance to bank branch	-0.0376***	-0.0325*	-0.155***
	(0.0130)	(0.0167)	(0.0328)
Big tech use (0/1)	0.144***	0.254***	0.124
	(0.0408)	(0.0538)	(0.104)
Time fixed effects	Y	Y	Y
Province fixed effects	Y	Y	Y
Macroeconomic controls	Y	Y	Y
Observations	815,207	844,544	861,784

Notes: (1) Network score measures users' centrality in the network and is based on users' payment and funds information and social interactions. The user who has more connections gets a higher network score. Standard errors in brackets are clustered at the firm level. Significance level: *p<0.1; ** p<0.05; *** p<0.01.

Table 6: Duration models: different characteristics of QR code merchants

Explanatory variables	I	II	III
	Hazard rate: Probability that the firm uses bank credit at a certain time		
Transaction volume	0.0255***	0.0279***	0.0277***
	(0.00915)	(0.00921)	(0.00922)
Network score (1)	0.0225***	0.0179***	0.0177***
	(0.000750)	(0.000671)	(0.000675)
Male (0/1)	0.390***	0.596***	0.387***
	(0.0298)	(0.0370)	(0.0299)
Age	-0.000699	-0.00267	-0.00168
	(0.00171)	(0.00171)	(0.00174)
House property (0/1)	0.610***	0.681***	0.758***
	(0.0438)	(0.0433)	(0.0484)
Distance to bank branch	-0.0251**	-0.0246**	-0.0245**
	(0.0108)	(0.0108)	(0.0108)
Big tech use (0/1)	2.888***	2.493***	2.417***
	(0.0807)	(0.0511)	(0.0977)
Network score*Big tech use	-0.0140***		
	(0.00132)		
Male*Big tech use		-0.600***	
		(0.0606)	
House property* Big tech use			-0.353***
			(0.0998)
Time fixed effects	Y	Y	Y
Province fixed effects	Y	Y	Y
Macroeconomic controls	Y	Y	Y
Observations	8,319,705	8,319,705	8,319,705

Notes: (1) Network score measures users' centrality in the network and is based on users' payment and funds information and social interactions. The user who has more connections gets a higher network score. Standard errors in brackets are clustered at the firm level. Significance level: *p<0.1; ** p<0.05; *** p<0.01.

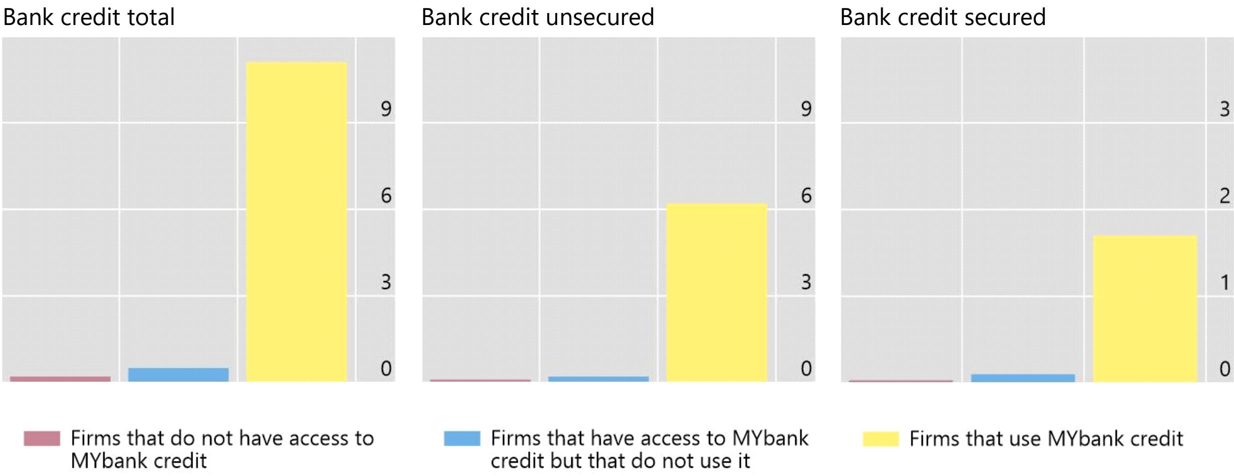
Table 7. Real effects of access to MYbank credit

Explanatory variables	I	II	III
	Dependent variable: Log Transaction volume		
	Test 1 Exogenous shock of credit supply	Test 2 Effect in normal times	Test 3 Effect Covid-19 shock
$Post * Treat$	0.096***	0.032***	0.200***
	(0.000)	(0.000)	(0.008)
Time fixed effect	Y	N	N
Firm fixed effects	Y	N	Y
Firm*Time fixed effects	N	Y	N
Period fixed effect	N	Y	N
City*Time fixed effects	N	N	Y
Observations	117,012	2,297,540	6,715,578

Notes: Standard errors in brackets are clustered by treated firm-control groups. For test 1 and test 3, the level of observation is Firm (i) * Time (T). For test 2, the level of observation is Firm (i) * Time (T) * Period (K). Significance level: *p<0.1; ** p<0.05; *** p<0.01.

Percentage of firms that use bank credit in the sample

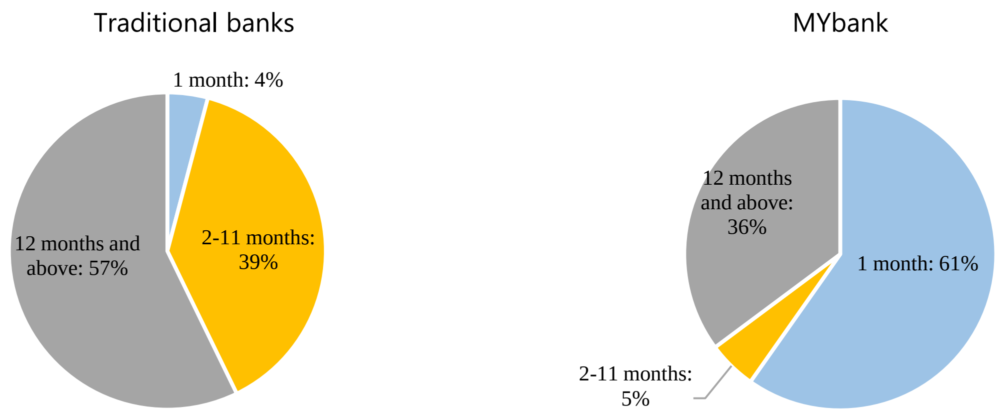
In per cent | Figure 1



Source: Ant Group.

Distribution of loan duration: Traditional banks vs MYBank

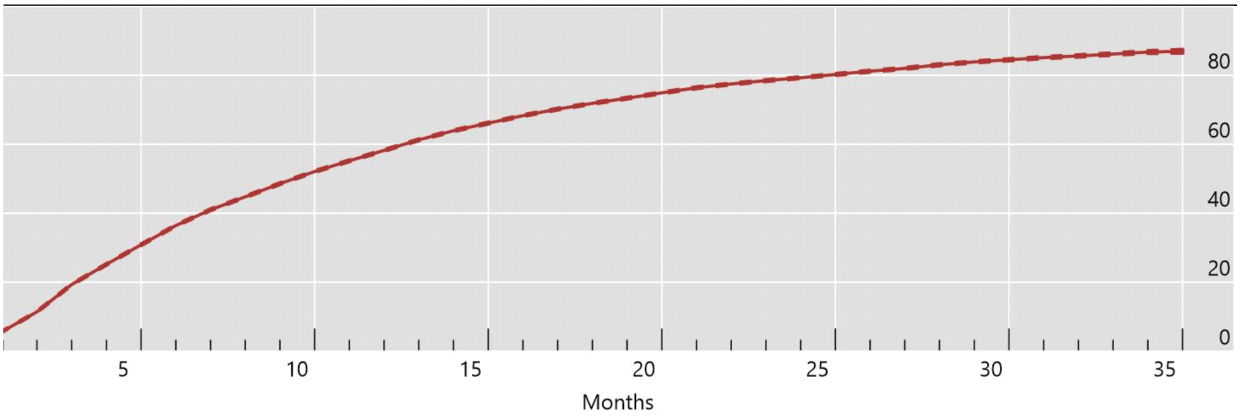
In per cent | Figure 2



Source: MYbank. Huang et al. (2020)

Does the use of QR code in payment allows firms to have access to big tech credit?

In per cent Figure 3

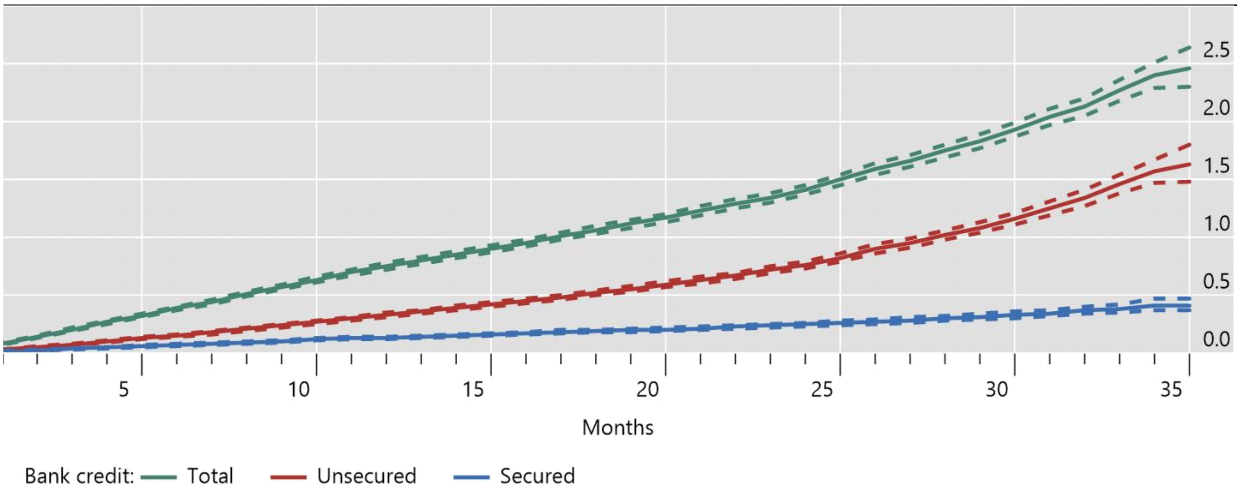


Dashed lines indicate 5th/95th percentiles. The x-axis reports the QR code duration, that is the number of months after the firm started to use the QR code payment system. The y-axis reports the probability for a firm of having access to big tech credit.

Source: Authors' calculations.

QR code payments do not increase too much the probability of bank credit use

In per cent Figure 4



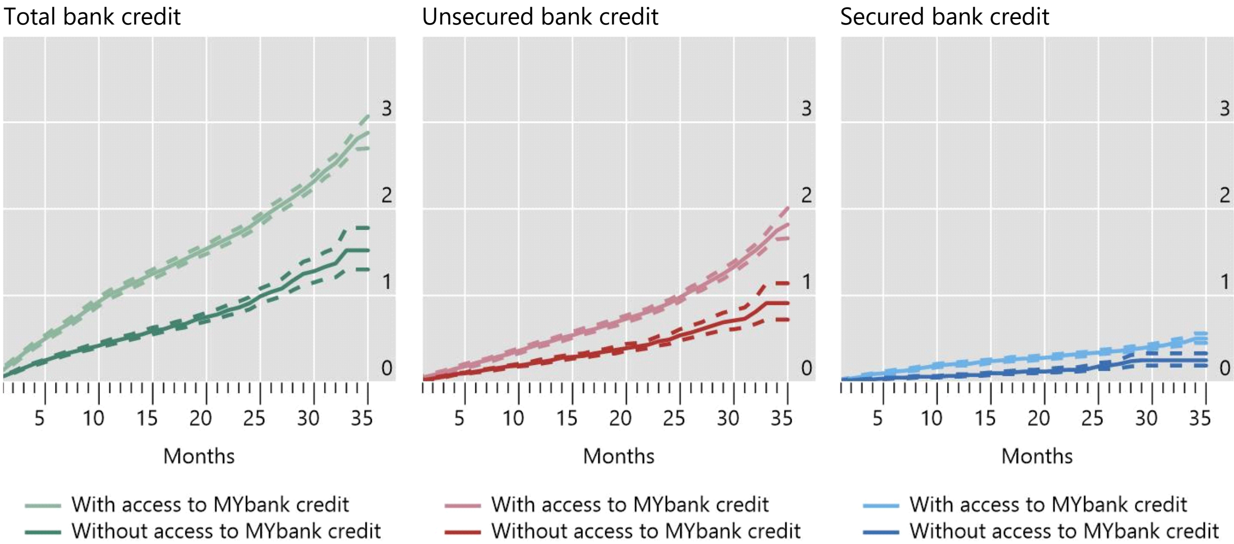
Dashed lines indicate 5th/95th percentiles. The x-axis reports the QR code duration, the number of months after the firm started to use the QR code payment system. The y-axis reports the probability for a firm of using bank credit.

Source: Authors' calculations.

Spillover effect from big tech credit access to bank credit use

In per cent

Figure 5



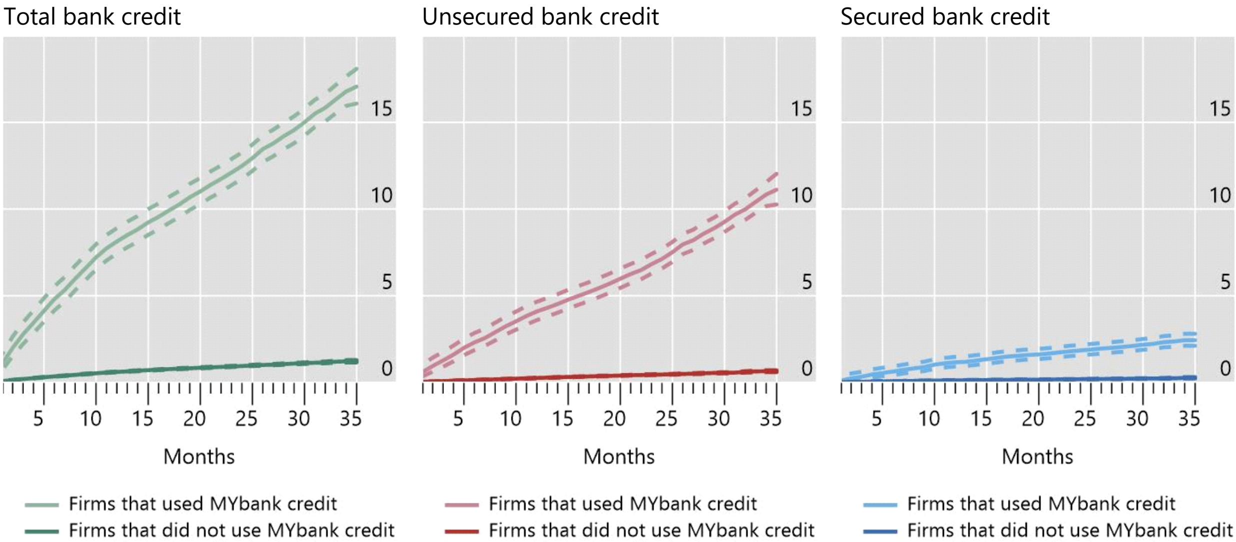
Dashed lines indicate 5th/95th percentiles. The x-axis reports the QR code duration, the number of months after the firm started to use the QR code payment system. The y-axis reports the probability for a firm of using bank credit.

Source: Authors' calculations.

Spillover effect from big tech credit use to bank credit use

In per cent

Figure 6

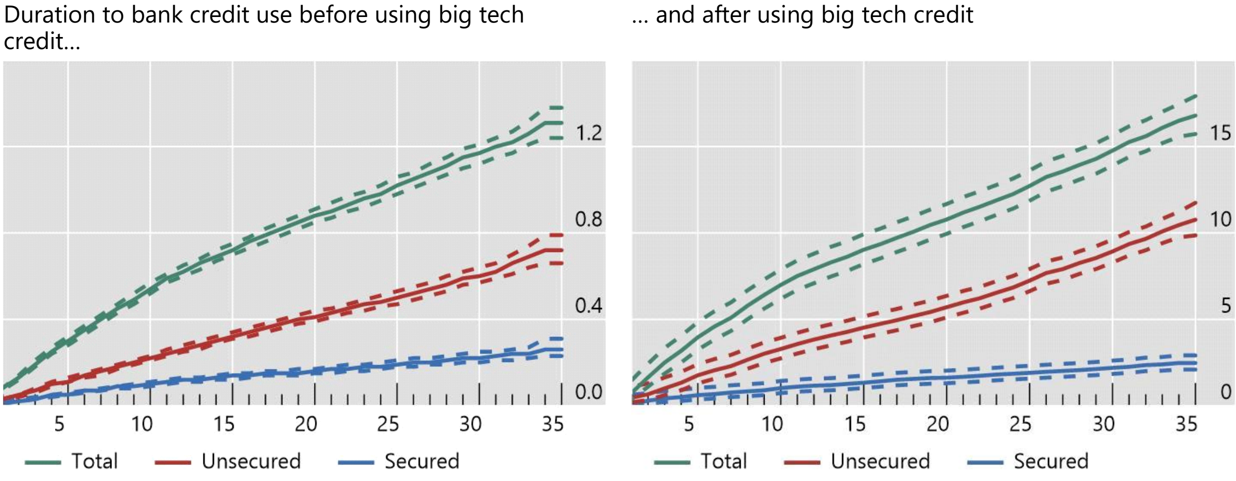


Dashed lines indicate 5th/95th percentiles. The x-axis reports the QR code duration, the number of months after the firm started to use the QR code payment system. The y-axis reports the probability for a firm of using bank credit.

Source: Authors' calculations.

Controlling for demand effects: only firms which used big tech credit

In per cent Figure 7

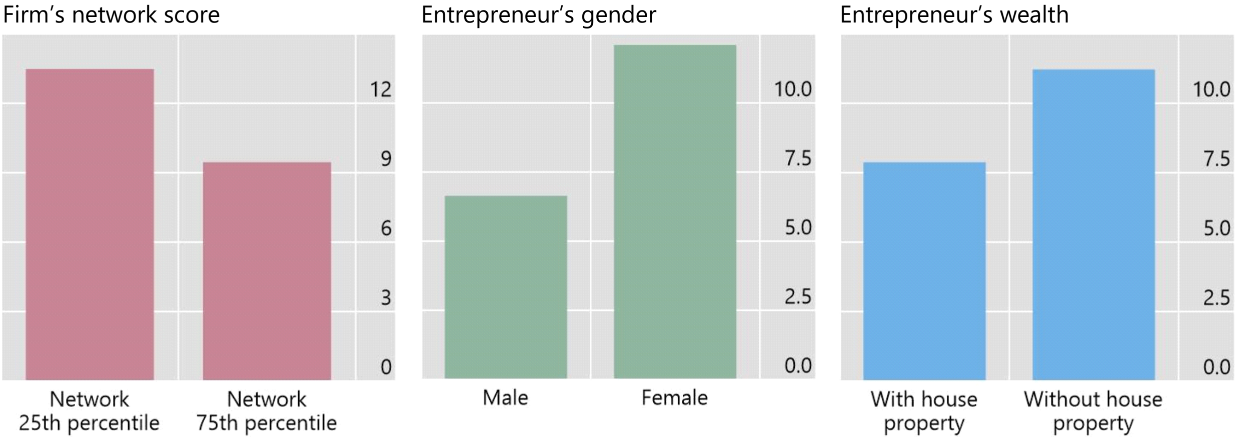


Dashed lines indicate 5th/95th percentiles. The x-axis reports the QR code duration, the number of months after the firm started to use the QR code payment system. The y-axis reports the probability for a firm of using bank credit.

Source: Authors' calculations.

Probability for a spillover effect from big tech credit use to bank credit use

In per cent Figure 8

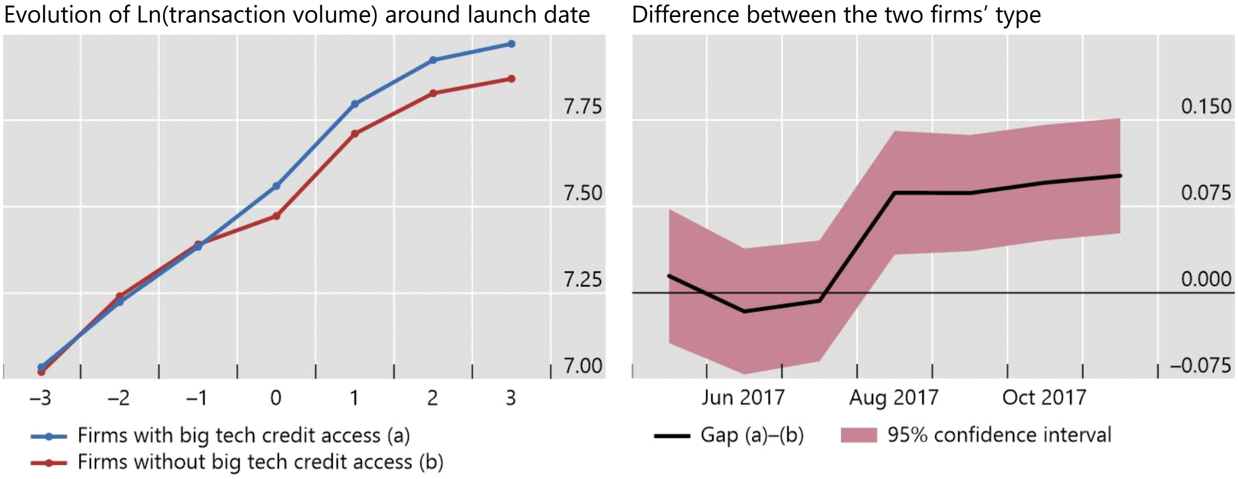


The bars show the different probability to get bank credit for firms who used big tech compared those that do not use it.

Source: Authors' calculations.

Effect of the launch of big tech loan products on firms' transaction volumes

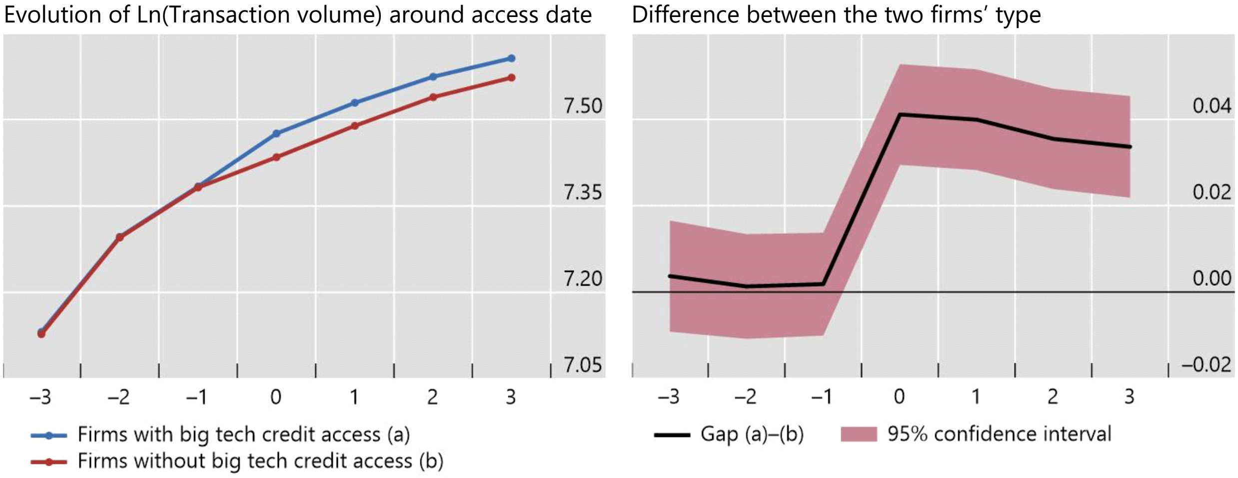
Log(transaction volumes in RMB, monthly data) Figure 9



Source: Authors' calculations.

Effect of big tech credit access on firms' transaction volumes in normal times

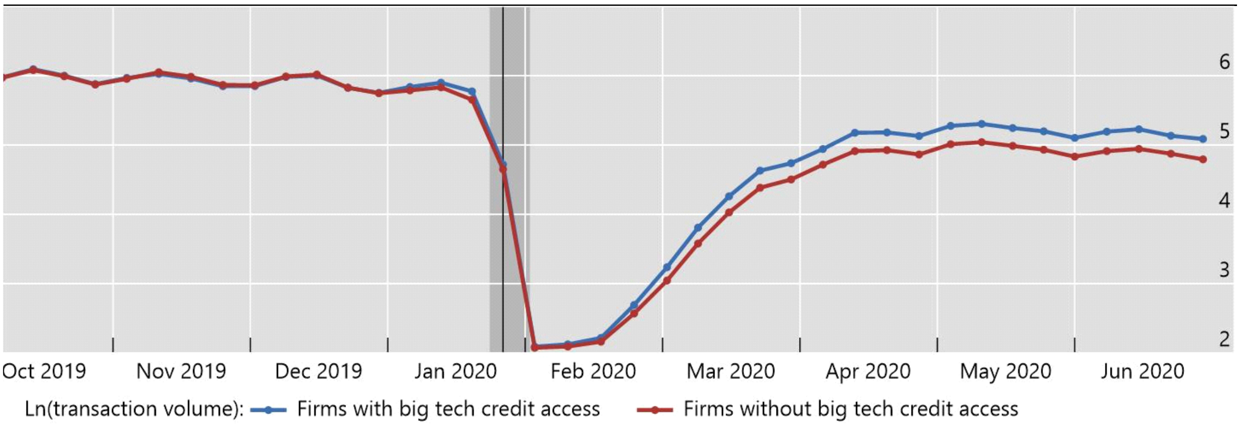
Log(Transaction volumes in RMB, monthly data) Figure 10



Source: Authors' calculations.

Chinese firms with QR code and access to big tech credit suffered less Covid-19 pandemic

Log(Transaction volumes in RMB, weekly data) Figure 11



The vertical line indicates 26 Jan 2020 (Covid-19 measures were effective from this date onwards). The shaded area indicates 24 Jan–2 Feb 2020 (Chinese Spring Festival). The sample includes 8,800 randomly selected QR codes of merchants which are used to construct weekly-firm level panel data. 4,400 QR code merchants have access to big tech credit and others don't.

Source: Authors' calculations.

Appendix. Some facts about Ant Group

The *Alibaba Group* is one of the biggest tech companies in the world. It was publicly listed on the New York Stock Exchange in September 2014, and has a market capitalisation of USD 640 billion as of July 2020. *Alipay* is a third-party mobile and online payment platform, established by the Alibaba Group that was subsequently rebranded as *Ant Financial Services Group* in October 2014 and *Ant Group* in June 2020. Initially, Alipay provided financial service to online business on Alibaba Group's e-commerce platforms. Today, the business of Ant Group includes Alipay, Ant Fortune, MYbank, ZHIMA Credit and Ant Group Cloud, serving millions of small and micro-sized enterprises (SMEs), both online and offline, and retail customers. Our paper focuses on the credit to SMEs, so our data is obtained from Alipay and MYbank.

Operated by Ant Group, Alipay is a payment and lifestyle platform. Launched in 2004, Alipay currently serves over 1 billion users with its local e-wallets partners. Alipay is thus the world's largest mobile and online payments platform with a market share of over 50 per cent in China. Ant Group has detailed information on enterprises and customers based on Alipay. MYbank is a private online bank established on June 25, 2015 by Ant Group with a mission to serve SMEs, to support the real economy and to practice inclusive finance. MYbank provides online, unsecured loan to SMEs based on a credit-scoring algorithm. The provision of credit is very fast and completely automated based on the so-called "310 model": 3 minutes to apply for credit, 1 second to approve and 0 people involved in the decision.

Alibaba Group owns three major trading e-commerce platforms, Alibaba (B2B), Tmall (B2C) and Taobao (C2C). Tmall and Taobao have the largest market shares in China at more than 50 per cent. It is easier for firms fully integrated into the Alipay/Ant Group ecosystem to obtain financial services. This is for the following three reasons. First, the information on these firms is very rich. The big tech company can collect and process the data of these companies more comprehensively, such as those on business operations and scoring. Second, as discussed above, for firms in the ecosystem it is strategically more difficult to default, as big techs can use the receivables of these companies in their accounts to repay their debts. Third, given network effects and high switching costs, big techs could also enforce loan repayments by the simple threat of a downgrade or exclusion from their ecosystem if in default. Overall, the provision of credit to online borrower can be done with a careful credit scoring assessment and the credit was (at least initially) less risky that that provided to offline borrowers, operating out of the platform.

The use of QR code and offline vendors. In the second half of 2017, Ant Group promoted a campaign to offer to offline vendors a QR code technology for payments. Many small stores only needed to place a QR code sticker for their customers to scan and complete their payments.

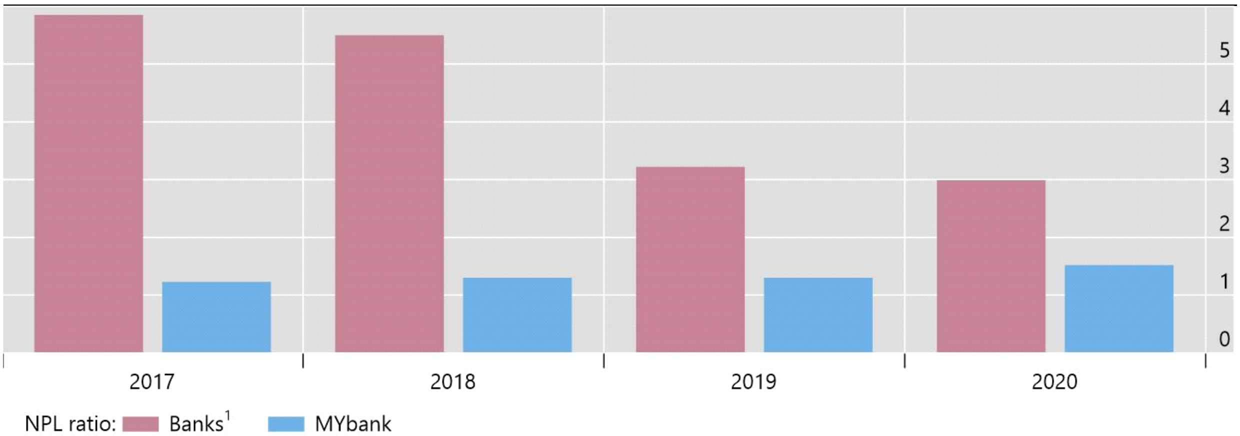
Larger stores also installed scanners of Ant Group to directly scan the QR code of the customer in Alipay. The QR code expanded the services of MYbank from the online firms to offline stores, which greatly expanded their business. As payments were done by means of Alipay, the data could be collected and used to analyse the evolution of the vendor's activity. Most of the offline stores are small (micro enterprises) and could therefore receive a credit score evaluation for the first time. The data were also used to calculate a network score to evaluate the position of the offline vendor in the big tech ecosystem and their connection with other vendors.

Ant Group Credit Scoring technique. The risk control model of MYbank is implemented through a credit scoring that use machine learning techniques and big data. The latter include transaction information, entrepreneur information, credit information and third-party information (client reviews and network score).

Credit quality SMEs: Non-performing loans

In per cent

Graph A1



Non-Performing Loans (NPLs) indicate loans that are typically overdue from 90 days and more. See "Interim Measures for the Risk Classification of Financial Assets of Commercial Banks 商业银行金融资产风险分类暂行办法".

[1] Credit lines below 10 million Yuan (5 million in 2017 and 2018). For 2020, January–August 2020.

Sources: CBIRC, Annual reports of MYbank.

Credit quality and interest rates. Figure A1compares non-performing loans (NPLs) for Chinese banks and for MYbank, focusing on credit to small and medium-sized enterprises. NPLs for the Chinese banking industry have been substantially higher on average than for MYbank in the period under investigation in this paper (2017-2019) and also during the Covid-19 pandemic (2020).

The ex-post measure of credit risk is not mirrored in the interest rates that are higher for big tech credit.[19] Three reasons may cause interest rates for big tech credit to be higher than those for bank credit. First, the funding costs of MYbank are substantially higher than those of traditional banks. This reflects the fact that MYbank cannot accept retail deposits. In China big techs can establish an online bank, but regulation prevents them from opening remote (online) bank accounts. MYbank relies mostly on interbank market funding and certificates of deposit that are typically more costly than retail deposits (BIS, 2019). Second, firms that borrow from MYbank are smaller than the customers of traditional banks, so the ex-ante potential risk for MYbank is also higher than that of traditional banks. Third, data processing for credit scoring could have high fixed costs to set up the necessary IT infrastructure and create a highly specialised team. These costs could be particularly high at the beginning, when the number of borrowers is low, and then decline with time, when the market share increases.

Table A2-A4 provide summary statistics for firms that have access to big tech credit, big tech borrowers and bank borrowers.

[19] For example in May 2020, the average interest rate of MYbank was around 11% while that of bank loans for SMEs was slightly higher than 6%. 民营银行利润增速何以能逆势上涨_聚焦_中国金融新闻网 (financialnews.com.cn).

Table A2. Summary statistics – Firms that can access big tech credit

	N	Mean	St. Dev.	P25	Median	P75
i) Normal Time						
Transaction volume monthly (RMB)	7,302,135	5884	8946	870	2,625	6,943
Network Score	7,271,773	37.44	19.67	23.42	34.25	47.77
Age	7,302,072	38.52	8.68	31	38	45
Male (0/1)	7,302,135	0.5	0.5	0	1	1
House property (0/1)	7,302,135	0.65	0.47	0	1	1
GDP (billion RMB)	7,167,890	725.497	791.300	216.330	406.200	944.340
Distance to Bank (KM)	7,300,613	0.94	1.64	0.16	0.32	0.78
ii) Before Covid-19 (30th Sep 2019 to 28th June 2020)						
Transaction volume monthly (RMB)	708,832	1,678	3,129	159	620	1,810
Network Score	708,384	38.43	18.49	25.30	35.24	47.91
Age	708,832	39.85	8.64	33	40	48
Male (0/1)	708,832	0.505	0.5	0	1	1
House property (0/1)	708,832	0.718	0.45	0	1	1
iii) After Covid-19 (26th Jan 2020 to 30th June 2020)						
Transaction volume monthly (RMB)	1,018,946	1,160	2,663	0	244	1,120
Network Score	1,018,302	38.43	18.49	25.30	35.24	47.91
Age	1,018,795	40.21	8.65	33	40	47
Male (0/1)	1,018,946	0.505	0.5	0	1	1
House property (0/1)	1,018,946	0.756	0.43	1	1	1

Table A3. Summary statistics – Big tech borrowers

	N	Mean	St. Dev.	P25	Median	P75
i) Normal Time						
Transaction volume monthly (RMB)	935,378	7,094	10,112	1,110	3,388	8,719
Network Score	934,682	49.01	19.94	35.00	46.44	60.21
Age	935378	34.355	7.71	29	33	39
Male (0/1)	935,378	0.616	0.49	0	1	1
House property (0/1)	935,378	0.81	0.40	1	1	1
GDP (billion RMB)	915,695	708.533	779.357	211.100	384.780	940.940
Distance to Bank (KM)	935,208	1.01	1.76	0.16	0.34	0.82
ii) Before Covid-19 (30th Sep 2019 to 28th June 2020)						
Transaction volume monthly (RMB)	82,464	2,140	3,780	215	912	2,672
Network Score	82,464	50.63	18.46	37.82	47.89	60.68
Age	82,464	35.53	7.84	30	34	40
Male (0/1)	82,464	0.63	0.48	0	1	1
House property (0/1)	82,464	0.89	0.32	1	1	1
iii) After Covid-19 (26th Jan 2020 to 30th June 2020)						
Transaction volume monthly (RMB)	118,542	1,609	3,440	0	350	1,602
Network Score	118,542	51.55	18.92	38.09	48.75	62.07
Age	118,542	35.71	7.76	30	34	40
Male (0/1)	118,542	0.605	0.489	0	1	1
House property (0/1)	118,542	0.91	0.293	1	1	1

Table A4. Summary statistics – Bank borrowers

	N	Mean	St. Dev.	P25	Median	P75
i) Normal Time						
Transaction volume monthly (RMB)	157,483	8,691	11,436	1,493	4,485	11,202
Network Score	157,349	54.03	21.05	38.97	51.91	67.4
Age	157,478	36.60	7.8	30	36	42
Male (0/1)	157,483	0.66	0.47	0	1	1
House property (0/1)	157,483	0.87	0.33	1	1	1
GDP (billion RMB)	153,344	596.867	673.465	208.540	345.460	689.700
Distance to Bank (KM)	157,483	0.94	1.68	0.15	0.30	0.74
ii) Before Covid-19 (30th Sep 2019 to 28th June 2020)						
Transaction volume monthly (RMB)	14,384	2,743	4,389	292	1,189	3,267
Network Score	14,384	54.61	20.31	40.39	52.61	69.97
Age	14,384	37.90	8.13	32	37	43
Male (0/1)	14,384	0.69	0.46	0	1	1
House property (0/1)	14,384	0.92	0.27	1	1	1
iii) After Covid-19 (26th Jan 2020 to 30th June 2020)						
Transaction volume monthly (RMB)	20,677	2,041	3,196	0	562	2,215
Network Score	20,677	54.61	20.31	40.39	52.62	66.69
Age	20,677	38.25	8.14	32	37	44
Male (0/1)	20,677	0.69	0.46	0	1	1
House property (0/1)	20,677	0.93	0.25	1	1	1