The Big Tech Lending Model*

Lei Liu†, Guangli Lu‡, Wei Xiong§

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Abstract

By comparing a sample of big tech business loans with a sample of conventional bank loans in China, we find that big tech lending facilitates credit to borrowers unserved or underserved by traditional banks, without experiencing more severe adverse selection and incurring greater risks (even after COVID-19). Additionally, we provide a sharp characterization of the big tech lending model: big tech loans tend to be smaller in size and have substantially higher interest rates, and borrowers tend to repay their big tech loans far before the debt matures and borrow more frequently. These characteristics remain even for the big tech loans made to borrowers with access to cheaper alternative credit. Our findings highlight the restrained advantages of the big tech lender in serving the short-term liquidity needs of borrowers in its ecosystem rather than competing with traditional banks to finance borrowers' activities outside its ecosystem.

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† Institute of Economics, Chinese Academy of Social Sciences. Email: liu_lei@cass.org.cn.

‡ The Chinese University of Hong Kong, Shenzhen. Email: luguangli@cuhk.edu.cn.

§ Princeton University. E-mail: wxiong@princeton.edu.

Big tech lending refers to lending services made by big tech companies either directly or in partnership with financial institutions. Big tech companies across the world have started to offer lending services in recent years. For example, in China, Alibaba's Ant Group offers credit services to small businesses through its subsidiary MyBank, Tencent offers credit services through its subsidiary WeBank, and Baidu offers credit services through Du Xiaoman, while in the United States, Apple, Google, and Amazon have also started to offer credit services. Aided with advantages in information, distribution, technology, and monitoring embedded in these big tech companies' ecosystems, the global credit volume of big tech lending grew rapidly from $10.6 billion in 2013 to $572 billion in 2019, more than twice the volume of fintech lending, which mainly consists of decentralized online platforms that match lenders with borrowers and use unconventional data to assist lenders with credit assessments (Cornelli, Frost, Gambacorta, Rau, Wardrop and Ziegler, 2020). The rapid expansion of big tech lending has raised many questions about its lending model and its potential disruptions to the banking industry.

There have been extensive studies of fintech lending, which are reviewed recently by Allen, Gu and Jagtiani (2021) and Berg, Fuster and Puri (2021). This literature has accumulated important understandings about fintech lending. First, unconventional data such as digital footprints can be highly useful for credit risk assessment, especially for borrowers with low credit scores and short credit histories.[1] Yet, fintech lenders may not have an information advantage compared to traditional banks who use soft information in lending.[2] Second, fintech lending mainly substitutes for bank lending, especially when banks are constrained, rather than targeting borrowers without access to regular bank credit.[3] Third, although technology may not necessarily allow fintech

[1] By using data from an e-commerce company in Germany, Berg, Burg, Gombović and Puri (2020) show that digital footprints that users leave online when accessing or registering on a website complement the information content of credit scores and can thus improve the prediction of consumer default. By analyzing data from a major fintech platform that provides consumer loans, Upstart Network, Di Maggio, Ratnadiwakara and Carmichael (2021) show that alternative data can be particularly useful in screening "invisible primes"—borrowers with low credit scores and short credit histories.

[2] Chava, Ganduri, Paradkar and Zhang (2021) show that U.S. borrowers in marketplace lending platforms have higher default rates in the long run relative to observably similar applicants of bank loans, suggesting that marketplace lenders face more severe adverse selection relative to traditional banks.

[3] Tang (2019) shows that peer-to-peer (P2P) lending in the United States is a substitute for bank lending in that it serves inframarginal bank borrowers after a negative shock to bank credit supply induced by regulations. De Roure, Pelizzon and Thakor (2021) provide both theoretical and empirical analysis to reinforce the notion that P2P lenders are bottom-fishing, i.e., they compete with banks for the lower spectrum of borrowers with access to bank credit. Di Maggio and Yao (2021) find that the quality of fintech borrowers improves over time, and on average, fintech borrowers have higher incomes, better education, higher credit scores, and more access to credit than bank borrowers. By comparing borrowers of consumer credit from three fintech firms with credit card borrowers of a leading state-owned bank in China, Bao and Huang (2021) find that fintech borrowers have more car loans, more mortgages, and more credit access than the bank borrowers, though they have less income, lower education, and are less likely to be

lenders to better screen borrowers excluded by banks, technology facilitates fast and convenient application processes, which is a key advantage of fintech lenders. Furthermore, as fintech lenders do not take deposits, they face less stringent regulatory requirements, which is another key advantage fintech lenders have relative to banks.[4] Fourth, fintech lending may worsen, rather than improve, the borrowers' financial health.[5] Fifth, fintech lending may not be robust to severe economic shocks such as COVID-19.[6]

Even though big tech lending also relies on the use of unconventional data, such as mobile payment flows and other digital records left by customers on digital platforms, to access credit risk, big tech lenders have substantial advantages relative to fintech lenders due to their access to the big techs' platforms and ecosystems, such as extensive customer bases, powerful brands, superior data about borrower preferences and behaviors, and capacities to monitor and even control customer activities inside the ecosystems. These advantages may make the nature and consequences of big tech lending different from fintech lending.

There are only a few studies of big tech lending. The Luohan Academy Report (2019) and Frost, Gambacorta, Huang, Shin and Zbinden (2019) both argue that big tech lending promotes financial inclusion by providing credit coverage to unbanked borrowers. By using cross-country data, Cornelli et al. (2020) find that countries with more competitive banking sectors have less big

employed than the latter. Gopal and Schnabl (2021) document that fintech lenders increased lending to small businesses after the 2008 financial crisis to substitute for the reduction in lending by banks. Beaumont, Tang and Vansteenberghe (2021) use French data to show a nuanced complementarity among fintech lending and bank lending: Small and medium-sized enterprises may use uncollateralized fintech loans to acquire tangible assets that they can then pledge to obtain bank loans.

[4] Fuster, Plosser, Schnabl and Vickery (2019) show that fintech lenders in the U.S. mortgage market process mortgage applications 20% faster than other lenders, and faster processing does not come with higher defaults. They also find no evidence of fintech lenders targeting borrowers with low access to finance. Buchak, Matvos, Piskorski and Seru (2018) find that in the United States, mortgage market regulation accounts for roughly 60% of the growth of fintech lending, while technology accounts for roughly 30%. Interestingly, they also show that convenience allows fintech lenders to charge a premium of 14–16 basis points.

[5] Di Maggio and Yao (2021) show that in the U.S. consumer lending market, fintech lenders may target present-biased borrowers, whose default rates increase after taking fintech loans. Relatedly, Wang and Overby (2021) conduct a difference-in-difference analysis by exploiting variations in the timing that state regulators granted approval for the fintech lender Lending Club and find an increase in bankruptcy filings following the approval. Brailovskaya, Dupas, and Robinson (2020) find that in Malawi, digital lenders offer loans without disclosing late fees, and a majority of borrowers fail to repay on time and, as a result, pay high late fees. Burlando, Kuhn and Prina (2021) find that reducing loan speed significantly decreases the likelihood of default for loans made by a Mexican digital lender, suggesting that fast processing time might reduce borrowers' deliberation and induce them to overborrow.

[6] Ben-David, Johnson and Stulz (2021) find that during the COVID-19 crisis in March 2020, fintech lending to small businesses in the United States collapsed due to the drying up of loan supply with fintech lenders becoming financially constrained and losing their ability to fund more loans. Bao and Huang (2021) show that in China, fintech lenders expanded credit to new and financially constrained borrowers after the start of the pandemic, but the delinquency rate of fintech loans tripled, even though there was no significant change in the delinquency of bank loans.

tech lending. By using loan data from MyBank, a leading big tech lender in China, Huang, Zhang, Li, Qiu, Sun, Wang and Berger (2020) show that unconventional data from Alibaba's e-commerce platform and the Alipay payment system can substantially improve the predictive power for default risks over a model that is only based on information from credit reports, especially for small firms in small cities, which tend to be underserved by traditional banks. Ghosh, Vallee and Zeng (2021) and Ouyang (2021) highlight the roles of mobile payments in facilitating credit inclusion using data from India and China. Gambacorta, Huang, Li, Qiu and Chen (2020) highlight that by relying on massive user data flows in digital platforms rather than physical collaterals, big tech credit does not correlate with local business conditions and house prices, in sharp contrast to cyclical bank credit. By also analyzing credit provided by MyBank to small vendors on Alibaba's online retail platform, Hau, Huang, Shan and Sheng (2019, 2021) highlight that the use of big tech credit is positively correlated with a vendor's physical distance to the five largest state banks, suggesting that big tech helps mitigate financial frictions of online vendors close to such banks. In addition, they show that big tech loans help to boost a vendor's sales growth in the short run. Chen, Huang, Lin and Sheng (2021) show that big tech credit from MyBank reduces firm daily sales volatility in the three months following the credit approval by allowing vendors to increase advertisement expenses and to sell new products.

While these studies highlight a contrast in the capacity of big tech lenders to provide credit and assist business development of borrowers underserved and unserved by traditional banks, several key questions remain. First, is big tech lending riskier than bank lending? Is big tech lending robust to severe economic shocks that create structural breaks to the risk assessment models used by big tech lenders? The evidence of fintech lending exacerbating borrower risk and drying up during the COVID-19 crisis makes these concerns particularly relevant to big tech lending. Second, despite the evidence of big tech lenders expanding credit to underserved and unserved borrowers, we still know very little about how big tech lenders structure loans to help these likely risky borrowers and what these borrowers use big tech loans for. Third, how do big tech lenders compete with traditional banks? De la Mano and Padilla (2018) and Vives (2019) argue that big tech lenders may disrupt the banking industry because their massive advantages in data and technology may allow them to eventually monopolize the origination and distribution of loans to consumers and small and medium-sized enterprises (SMEs) and force banks to merely fund the loans intermediated by big techs.

We aim to address these issues by analyzing big tech business loans made by the syndication of MyBank with a large retail bank in China, which we refer to as Bank X hereafter for security

reasons. MyBank is the leading big tech lender to small businesses in China, the country with the most active big tech lending—$516 billion in 2019—which is about 90% of the global volume. MyBank is embedded in Alibaba's ecosystem and its borrowers are mostly users of Alibaba's digital payment system or e-commerce platforms. Founded only in 2015, it had lent to a cumulative of 35.07 million SMEs by 2020. Furthermore, MyBank's lending is primarily funded by syndication with traditional banks. In its syndication with Bank X, MyBank is responsible for acquiring borrowers, assessing risk, processing loan applications, determining interest rates and credit limits, and managing the loans after origination, while Bank X provides the majority of the funding for the loans it accepts. Bank X is one of MyBank's top syndication partners, and its syndicated loans with MyBank are representative of MyBank's syndication loan portfolio. Thus, this syndication setting is highly relevant for studying how big tech firms may compete or collaborate with traditional banks.

Our data come from Bank X and cover loans from three business lending programs: big tech loans made through the syndication program of MyBank and Bank X, and regular and online loans from Bank X's two conventional lending programs, which are both independently managed by Bank X. We obtain a 10% random sample of borrowers in each of the three lending programs and all loans made to these borrowers from August 2019 to December 2020.

Our summary statistics of borrower characteristics show that the big tech lending program serves borrowers who tend to be much younger, better educated, and more likely from rural areas, and who have substantially more limited access to credit from other sources than the borrowers of Bank X's regular and online lending programs. These differences in borrower characteristics show that big tech lending is more than just regulatory arbitrage and instead confirm the argument that big tech lending expands credit to borrowers underserved and unserved by traditional banks.

Our summary statistics of loan characteristics further show that the big tech loans in our sample are sharply different from Bank X's regular loans and online loans in many aspects. More than 98% of the big tech loans are uncollateralized, which is substantially higher than the fraction among Bank X's conventional loans, and thus motivates us to focus our analysis on uncollateralized loans. Uncollateralized big tech loans have an average, *annualized* interest rate of 14.6%, substantially higher than the average interest rate of Bank X's uncollateralized online and regular loans, which are 8.6% and 8.5%, respectively. The uncollateralized credit limit offered by the big tech lending program is less than half of that offered by Bank X's online and regular lending programs.

To examine whether the big tech loans are riskier than Bank X's regular and online loans, we measure repayment risk by the likelihood of a loan payment being overdue for at least 30 days. The overall delinquency rate is 2.6% for the big tech loans, which is higher than the rate of 1.1% for the online loans and 1.6% for the regular loans. Interestingly, nearly half of the big tech loans in our sample are made to first-time borrowers of the big tech lending program. Among the borrowers that have paid off at least one loan from the same lending program, the delinquency rate of the big tech loans is only 1.2%, very similar to that of Bank X's online and regular loans. Our regression analysis also formally confirms there is no difference in repayment risk after controlling for borrower and loan characteristics. Our analysis of the delinquency rate of loans originated before and after the start of the COVID-19 crisis in China in February 2020 further shows that the risk in the big tech loans remained stable, even slightly reduced, relative to Bank X's conventional loans after the onset of the COVID-19. These findings are in sharp contrast to the aforementioned evidence of fintech loans exacerbating borrower default risk and becoming more fragile after the COVID-19 as discussed in footnotes 5 and 6.

Each of the three lending programs that we analyze allows an authorized borrower to take a loan within a credit limit at a specified interest rate. This setting permits us to adopt the correlation test proposed by Chiappori and Salanié (2000) to examine the presence of adverse selection in these lending programs—that is, whether borrowers who choose to use up their credit limits are more likely to become delinquent later. Interestingly, we find no evidence of such adverse selection among the big tech loans, even though it is present among Bank X's regular loans. The absence of adverse selection thus validates the capacity of the big tech lender to screen borrowers, which is again in contrast to the finding of Chava et al. (2021) that fintech lenders in the U.S. lending market face more severe adverse selection than traditional banks.

Our analysis of repayment speed uncovers even sharper findings about what the borrowers might have used the big tech loans for. Even though the big tech loans have short maturities of either 6 or 12 months, similar to Banks X's regular and online loans, the big tech loans tend to be repaid far before the loan matures and substantially earlier than the other types of loans. The average repayment time is only 46% of the loan maturity for the big tech loans, while it is 74% and 77% for Bank X's online and regular loans, respectively. Interestingly, the 25th percentile of the ratio of repayment time to loan maturity is only 4% for the big tech loans, sharply lower than that of 48% for the online loans and 61% for the regular loans. We also confirm this sharp difference in regression analysis after controlling for loan and borrower characteristics. To the

extent that borrowers repay the big tech loans so quickly, they are unlikely to use these loans to finance long-term business expansions or to borrow beyond their means.

Thus, while the big tech lender extends credit to a set of borrowers underserved or unserved by traditional banks, the credit does not finance all activities of these borrowers, but mainly their short-term liquidity needs, which motivates us to propose a nuanced view of restrained advantages of big tech lending. That is, big tech lenders may have unique advantages relative to traditional banks, but such advantages are limited to the financing of specific activities of borrowers inside their ecosystems. This restrained advantage view implies that big tech lenders may not be able to compete with traditional banks for the full spectrum of lending businesses, which contrasts with the view that big tech lenders might eventually monopolize the banking industry.

Interestingly, a small set of big tech borrowers also had access to Bank X's conventional loans. This sample of marginal borrowers allows us to examine how big tech lenders may compete with traditional banks. So far, there have been many conjectures by commentators about this important issue, but very few facts. As these marginal borrowers have both better credit quality and outside options, one would expect them to get better terms from the big tech lender. To our surprise, we find similarly high interest rates and similarly low credit limits between the big tech loans made to these marginal borrowers and the borrowers in the main sample. Furthermore, these marginal borrowers repay their big tech loans quickly, far before the loan matures and substantially faster than they repay their conventional bank loans.

These patterns offer a nuanced picture of the segmentation between big tech lending and conventional bank lending. By revealed preferences, the marginal borrowers' willingness to take these big tech loans despite substantially higher interest rates than their outside options confirms the convenience provided by the big tech loans. More importantly, their fast repayments of the big tech loans suggest that they also use the big tech loans only to meet their short-term liquidity needs, which is a natural consequence of the high interest rates. This in turn reflects that the big tech lender is either unwilling or unable to compete for the broad financing needs of the marginal borrowers. Taken together, this nuanced picture does not lend support to the view that big techs are on track to monopolize the banking industry. Instead, it highlights big tech lenders' restrained advantages in meeting certain financing needs of borrowers inside their own ecosystem.

It should be clear that our analysis covers only the current state of big tech lending and offers no direct implications for how big tech lenders may compete with banks based on their respective

data advantages in the future. The future landscape of the banking industry may intricately depend on not only capital and risk regulations imposed on these institutions but also regulations of data sharing among banks, fintech lenders, and big tech lenders, as explored by theoretical models of He, Huang and Zhou (2021) and Parlour, Rajan and Zhu (2021).

I. Institutional Background

In this section, we provide the institutional background of MyBank, the pioneer of big tech lending in China, and its syndicated lending program with other traditional banks.

A. Lending of MyBank

MyBank is a subsidiary of Ant Group. Founded in 2015, MyBank has quickly developed into a leading online bank in China. The number of its new borrowers increased from 2.77 million in 2016 to 14.2 million in 2020. By the end of 2020, it had lent to a cumulative of 35.07 million SMEs. The quick expansion of MyBank is crucially related to Ant's ownership of Alipay, the world's largest digital payment platform, which serves over one billion users. In particular, Alipay served 80 million merchants in June 2020, and its total payment volume reached RMB 118 trillion during the 12 months up to June 2020, which was more than 55% of online payment transactions in China. Ant is itself an affiliate company of Alibaba Group ("Alibaba" hereafter), one of the world's largest e-commerce companies. Embedded in Alibaba's ecosystem, most borrowers of MyBank are either merchants who use Alipay to receive customer payments or online vendors on Alibaba's e-commerce platforms, most of whom are SMEs or self-employed.

As an archetype of big tech lending, MyBank displays several important characteristics of big tech lending. First, Alibaba's ecosystem provides MyBank with unique and extensive information to assess the credit risks of its borrowers. Such information includes an Alibaba vendor's historical and current cash flows and ratings from its customers, as well as the profiles and digital footprints of its customers, and an Alipay user's payment flows. The information helps to assess a borrower's ability and willingness to repay and is particularly helpful to the risk assessment of merchants and online vendors, who tend to lack verifiable financial statements or credit records to qualify for loans from traditional banks. Huang et al. (2020) use detailed borrower information from MyBank to show that the unconventional borrower information can complement or substitute for traditional credit records—with further help of machine learning techniques—to substantially improve the assessment of the credit risk of MyBank's borrowers. Ouyang (2021) provides causal evidence to

show that the use of the Alipay payment system facilitates MyBank credit to consumers underserved by traditional banks.

Second, Alibaba's ecosystem also helps MyBank to monitor loan repayment. It is possible for MyBank to monitor the usage of the loans in the ecosystem. The information from the ecosystem helps to detect and punish abnormal usage of the loans unrelated to the stated purposes at loan origination. The possibility for MyBank to exclude a delinquent borrower from the Alipay payment system or the Alibaba's e-commerce platforms also makes the default cost to the borrower particularly high.

Third, MyBank also offers a high level of convenience to its borrowers. Aided with cloud computing and artificial intelligence, MyBank created the so-called 310 lending model: three minutes to apply, one second to approve, and zero human intervention. Borrowers can easily apply for loans either online or via smartphones. By comparison, to apply for a loan from a traditional bank, a borrower needs to visit a bank branch in person, and the application process may take one or two weeks. The unique information from Ant's ecosystem further enables MyBank to accommodate time-varying loan demands from borrowers. For example, to accommodate borrowers' liquidity demands, the credit limits granted to vendors on the Alibaba platform are usually increased shortly before November 11, the largest online sale day on the Alibaba platform. Furthermore, interest on MyBank loans is computed at daily frequency,[7] and borrowers can repay their loans at any time online without any prepayment penalty. The ease of borrowing and repayment is especially attractive to borrowers with emergent and frequent liquidity needs.

Fourth, the marginal cost of MyBank's lending is relatively low. The convenient digital access to merchants in the Alipay payment system and e-commerce vendors on the Alibaba platform allows MyBank to easily reach a large number of potential borrowers at a low marginal cost. Moreover, with the help of technologies such as cloud computing and artificial intelligence, MyBank can quickly assess the borrowers' credit risks and process their applications on a large scale, as discussed by Huang et al. (2020). By comparison, it may take a loan officer of a traditional bank several days of work to assess the credit risk of a borrower, and this lending process may not scale up with the number of borrowers.

[7] In the loan application process, the daily interest rate is highlighted to the borrower so there is no confusion about the interest rate. As we will later discuss, the fast repayment of the big tech loans in our sample also confirms that borrowers are not confused by the quoted daily interest rates, which may confuse borrowers in a fast application process, as highlighted by Burlando, Kuhn and Prina (2021) for fintech lending in Mexico.

Finally, MyBank is more constrained in funding and faces higher funding costs than traditional banks. Unlike traditional banks, MyBank does not have physical branches to collect deposits, which are the most important funding sources for traditional banks. To minimize the use of its own capital in lending, MyBank has developed extensive syndicated lending programs with traditional banks.

B. Syndicated Big Tech Loans

Given the large number of potential borrowers from Alibaba's ecosystem and MyBank's funding constraints, MyBank began to collaborate with other financial institutions to provide syndicated loans to borrowers in June 2018. By the end of 2020, it has collaborated with more than 700 financial institutions.

Our data on big tech loans come from a syndication program between MyBank and one of its leading syndication partners. This syndication partner is a stock commercial bank in China. For security reasons, we cannot reveal the identity of this bank. Instead, we shall call it Bank X throughout the paper. MyBank and Bank X share the funding of the syndication program. While our data do not cover their specific shares, MyBank generally contributes to only 1%–5% of the funding in its syndicate lending programs with banks.

MyBank is responsible for acquiring borrowers, processing loan applications, and determining interest rates and credit limits. Bank X can reject a loan application but cannot determine its interest rate or credit limit. After receiving an application, MyBank sends its proprietary risk assessment, along with the proposed interest rate and credit limit, to Bank X. Then, Bank X combines its own information, such as information from credit reports, with information from MyBank to determine whether to accept or reject the loan application.[8] After the application is approved, the borrower can borrow within the credit limit as long as there is a remaining balance. The credit limit and interest rate are dynamically updated a couple times each month based on updated information.

MyBank is also responsible for managing the loans after origination. It will automatically deduct the amount due from a borrower's Alipay account or bank account. In addition, MyBank has algorithms to verify whether a loan is used for the stated business purpose. As a punishment for deviation, MyBank may choose to terminate the current credit line and reject that borrower's future loan applications. Lastly, MyBank is also responsible for restructuring loans or dealing with

[8] The entire process is automated and takes less than one second to complete.

delinquent borrowers. Besides reporting delinquency on a borrower's credit report, MyBank may threaten to exclude the borrower from the Alipay system or Alibaba's e-commerce platforms.

C. Conventional Bank Loans

While Bank X is not one of the top four state banks in China, it is nevertheless large and offers banking services in almost all the cities and counties in China and serves more than 40% of the Chinese population. It is one of the leading banks in offering business loans to SMEs. Our data cover two types of business loans managed by Bank X. One type is regular loans. A borrower needs to file a loan application in a local branch, and a loan officer will assess the applicant's business risk in person. This process may take about one week.

Bank X has also made great efforts to simplify the lending process by developing its own online lending program. A borrower can apply for a loan online, but the process may still take half a day. The bank assesses the borrower's risk based on machine learning models that combine the bank's proprietary information, such as saving and borrowing records inside the bank, with information from other sources, such as the borrower's credit reports, tax records, and business registration records. As we will summarize later, relative to the regular lending program, this online lending program requires less collateral but relies more on the borrowers' prior credit history. Our data also cover Bank X's online loans.

For both regular and online loans, once Bank X approves a borrower's application, it assigns the borrower an interest rate and a credit limit. The borrower can borrow within the limit as long as there is a remaining balance. The borrower needs to sign a specific loan contract each time he or she takes out a loan and can repay the loan without any prepayment penalty. Upon the expiration of the credit limit, the borrower can typically renew it provided that he or she repays the previous loans on time. Both the regular and online loans are part of Bank X's conventional lending and serve as the benchmark in our analysis for the big tech loans from the syndicated lending program between MyBank and Bank X.

II. Different Views of Big Tech Lending

In this section, we will summarize several views about the nature and consequences of big tech lending. Even though some of them are not specifically proposed for big tech lending in China, they nevertheless provide a broad range of perspectives to guide our empirical analysis.

Regulatory Arbitrage

A popular view of the rapid developments of fintech and big tech lending is regulatory arbitrage. As fintech and big tech lenders often face less stringent risk and capital regulations than traditional banks, their rapid growth may reflect not just technology advancements but also regulatory advantages. Interestingly, Buchak et al. (2018) show that regulation accounted for roughly 60% of the growth of fintech lending in the U.S. mortgage market in 2006–2015, while technology accounted for roughly 30%. Under this regulatory arbitrage view, fintech and big tech loans are similar in nature to traditional bank loans, and they compete with traditional banks to serve similar borrowers and have similar risks. In addition, the convenience fintech lenders offer to borrowers allows them to charge higher interest rates.

The big tech loans in our sample are syndicated by MyBank and a traditional bank. As discussed earlier, Bank X contributes most of the funding to syndicated loans. Thus, even if MyBank faced less stringent regulations than traditional banks, Bank X still needs to comply with the risk and capital regulations for its holdings of the big tech loans in our sample. Therefore, our setting allows us to compare big tech loans and conventional bank loans with minimal confounding effects from their differential exposure to regulations.

Borrower Exploitation

Technology may also bring downsides. A pessimistic view is that in competing with traditional firms and with each other, big tech firms may take advantage of their superior access to massive user data to exploit the weakness and vulnerabilities of borrowers. This view is part of the more general concerns about potential abuses of users by big tech firms. A recent report by the Stigler Committee (2019) argues that by sharing extensive consumer data with other firms, digital platforms may allow firms to use different advertising and pricing strategies for different types of consumers and, in particular, to target vulnerable consumers with certain behavioral weaknesses, such as lack of self-control. Motivated by such concerns, Liu, Sockin and Xiong (2021) develop a theoretical model to analyze data privacy as a mechanism to protect vulnerable consumers.

To compete with banks, fintech and big tech lenders may cater to borrowers' desires to borrow beyond their means. By comparing fintech loans with traditional bank loans in the United States, Di Maggio and Yao (2021) show that fintech lenders do not target borrowers credit-rationed by traditional banks, and, instead, fintech borrowers tend to earn more, live in higher-income neighborhoods, and are more likely to be professionals. Furthermore, they find that fintech

borrowers are more likely to be present-biased, as they tend to carry a significant credit card balance, which tends to skyrocket during holidays, and are more likely to consume the funds from the fintech loans rather than using them to consolidate high-cost credit card debt. Relatedly, Wang and Overby (2021) find that the entry of the fintech lender, Lending Club, led to an increase in bankruptcy filings. Besides targeting present-biased borrowers, the convenience of the quick borrowing process alone may reduce borrowers' deliberations and cause them to overborrow. Burlando, Kuhn and Prina (2021) find that doubling the application time significantly decreases the default risk for loans made by a Mexican fintech lender. Another way to exploit borrowers is through withholding relevant information. Brailovskaya, Dupas, and Robinson (2021) find that in Malawi, fintech lenders offer loans without disclosing late fees, and a majority of the borrowers fail to repay on time and thus pay high late fees.

Under this borrower exploitation view, fintech and big tech lenders may compete with traditional banks in providing credit to borrowers with access to regular financial services, and by exacerbating borrowers' personal biases and vulnerabilities, their lending may increase the default risk of the borrowers and may even trap them in debt.

Monopolizing Banking

As we discussed before, there is an agreement among the existing studies that big tech lenders, by building on their data and technology advantages, promote financial inclusion by extending credit to borrowers underserved or unserved by traditional banks. There are, however, two different views about how much of an advantage big tech lenders have over traditional banks. A concerning view advocated by De la Mano and Padilla (2018) and Vives (2019) argues that by fully exploiting their massive network effects, big tech companies may succeed in monopolizing the origination and distribution of loans to consumers and SMEs, forcing traditional banks to become "low-cost manufacturers" that merely fund the loans intermediated by the big techs. According to this view, the entry of big tech players, such as Google, Facebook, and Amazon, into online banking may have a much more significant impact than fintech firms on competition in retail banking because these platforms have large installed customer bases, established reputations, powerful brands, considerable earnings, and unfettered access to capital markets. In addition, and more importantly, they can leverage superior data about consumer preferences, habits, and conduct, and they control the shopping experiences of many consumers and recently, the distribution and commercialization of many suppliers as well.

Interestingly, a traditional bank provides the majority of the funding for the big tech loans covered by our data, while the big tech lender is responsible for all the other aspects of lending, including the initial identification of borrowers, the determination of interest rates and credit limits, and loan management after origination. This model of collaboration is indeed consistent with the discussion of De la Mano and Padilla (2018). For big techs to eventually take over the banking industry, they would need to cover a wide range of borrowers for a broad set of loan services so that they can compete for lending businesses covered by traditional banks. Our data also allow us to examine this aspect of big tech lending.

Restrained Advantages

A more nuanced view of big tech lending is that while big techs may have found their unique advantages to cover a certain segment of the population previously underserved or unserved by traditional banks, their comparative advantages are limited to financing specific activities by a specific set of consumers and users on the particular platforms and ecosystems. As a result, it would be difficult for big techs to extend their lending beyond this restrained set of credit services. According to this view, big tech lending resembles leasing and financing that large manufacturing firms provide to downstream firms for purchasing their own products (e.g., Murfin and Pratt (2019)) and the lending by homebuilders' finance arms to home buyers to purchase their homes (e.g., Stroebel (2016)). Even though the scale of the credit services covered by big tech lenders can be substantially wider than the set of buyers covered by manufacturing firms and homebuilders, the essence of the restrained advantages in financing might be similar.

This restrained advantage view emphasizes that big tech lending expands the credit coverage of traditional banks. In this respect, it is different from the regulatory arbitrage view and the borrower exploitation view, but is similar to the monopolizing banking view. It differs from the monopolizing banking view in that it highlights that its coverage does not necessarily finance all needs of the borrowers but is specific to certain business activities within the big tech lender's ecosystem. In this regard, the restrained advantage view implies that big tech lending may not be able to fully compete with traditional banks in all lending businesses.

III. The Main Sample

Our data come from Bank X and cover loans from three business lending programs: big tech loans made through the syndicated lending program of MyBank and Bank X, and Bank X's regular

and online loans. According to MyBank, the sample of loans it sends to Bank X for syndication is representative of its overall loan portfolio. Bank X's regular and online loans are independently originated.[9] We obtain a 10% random sample of borrowers in each of the three lending programs and all loans made to these borrowers from August 2019 to December 2020. Note that August 2019 is the first month of the syndicated lending program between MyBank and Bank X. Our loan performance data cover up to May 2021. This sample of borrowers and loans serves as the main sample for our comparison of the big tech loans made through the syndication program with Bank X's regular and online loans. We analyze this main sample of borrowers in this section.

A small number of big tech borrowers had also taken business loans from either Bank X's regular or online lending program during the sample period. We also analyze in the next section a sample of overlapped borrowers who are marginal borrowers that the big tech lender needs to compete for with traditional banks.

A. Preliminary Analysis

We first provide some summary statistics of the borrowers and the loan terms, which serve as a preliminary analysis of the aforementioned views of big tech lending.

Borrower Characteristics

We first report in Table 1 some basic borrower characteristics to show that the big tech loan borrowers in our sample are substantially different from the borrowers of Bank X's regular and online loans. The information about borrower characteristics is from the credit reports voluntarily provided by the borrowers in their credit applications. For a borrower with multiple loan applications in our sample, only data from the first credit report are used in computing the summary statistics reported in this table. Specifically, we have credit reports on 31,406 of the 140,019 big tech loan borrowers in our sample, 49,794 of the 49,795 online loan borrowers, and 22,042 of the 22,115 regular loan borrowers.

We compare borrower demographics in Panel A. The average age of big tech loan borrowers is 32.8, much younger than that of the online and regular loan borrowers, which is 44.2 and 43.0 respectively. The younger age reflects that MyBank has extended credit to borrowers with short credit histories and that its borrower base consists of many young entrepreneurs, in particular

[9] Bank X's regular loan program also makes policy loans, which benefit from government subsidies. We exclude policy loans from our sample because their interest rates and loan performance are affected by government subsidies.

vendors in the Alibaba e-commerce platforms and small merchants who use Alipay for payment transactions. Furthermore, only 66% of the big tech loan borrowers are male, fewer than the fraction of male borrowers of the online and regular loans, which are 79% and 83%, respectively.[10] In terms of education, the big tech loan borrowers are more educated, with 68% having completed at least high school, while the fraction for the online and regular loan borrowers is only 52% and 38%, respectively. In terms of geography, 31% of the big tech loan borrowers are from rural areas, which is substantially larger than the fraction of 15% and 20% among the online and regular loan borrowers, respectively.

Panel B reports the fraction of borrowers in each group that had obtained their first loans in each category from the same lender. Among the big tech loan borrowers, 27% took their first loans, 81% took their first business loans, and 91% took their first uncollateralized business loans from MyBank (which include loans made by MyBank alone and all its syndicated programs with other financial institutions). In contrast, only 4% of the online loan borrowers took their first loans from Bank X's online program, only 5% took their first business loans, and 6% took their first uncollateralized business loans from the same program. These numbers suggest that Bank X's online lending program targets borrowers with extensive credit histories and credit access to its other lending programs and other institutions. Among Bank X's regular loan borrowers, 29% got their first loans from Bank X's regular loan program, 43% got their first business loans, and 58% got their first uncollateralized business loans from the same program. Taken together, MyBank is much more likely to make a borrower's first business loan, and especially the first uncollateralized business loan, than Bank X's online and regular lending programs, suggesting that the big tech lending program improves the credit access of its borrowers.

Panel C reports the total amount of loans taken by the three groups of borrowers from institutions other than MyBank and Bank X. The total loan amount per big tech loan borrower is 334,152 RMB, which is only 25.2% of the total loan amount taken by an average online loan borrower and 40.6% of that taken by an average regular loan borrower. This total amount is further

[10] This finding suggests that the big tech loans in our sample might not aggravate gender inequality, which is a potential concern for big tech lending in general. Chen, Doerr, Frost, Gambacorta and Shin (2021) analyze a survey of respondents from 28 countries and find a fintech gender gap in almost all the countries in that a smaller fraction of women (21%) use fintech products than men (29%). Relatedly, Bartlett, Morse, Stanton and Wallace (2021) find that risk-equivalent Latinx/Black mortgage borrowers in the United States pay significantly higher interest rates than White borrowers, though fintech lenders' rate disparities are smaller than traditional lenders. Fuster, Goldsmith-Pinkham, Ramadorai and Walther (2021) show that Latinx/Black mortgage borrowers in the United States are disproportionately less likely to gain from the introduction of machine learning, and machine learning increases disparity in rates between and within ethnic groups.

decomposed into different categories of loans: collateralized business loans, uncollateralized business loans, collateralized consumptions, uncollateralized consumption loans, mortgage loans, and others. The big tech loan borrowers have a substantially lower amount in each of these categories. This panel again confirms that the big tech loan borrowers have substantially less access to loans from other sources, while the online loan borrowers of Bank X have the best access to loans from other sources.

Overall, Table 1 shows that the big tech lending program serves borrowers who are younger, better educated, more likely from rural areas, and who have more limited access to credit from other sources than the borrowers of Bank X's regular and online loans. These differences in borrower characteristics suggest that big tech lending complements traditional banking services by covering borrowers underserved by traditional banks. Thus, by directly comparing borrowers and big tech loans and conventional bank loans, our analysis confirms the argument made by the existing studies referenced in the introduction that big tech lending promotes financial inclusion.[11]

Loan Characteristics

In Table 2, we summarize the basic terms of the loans in our main sample, which cover loans made to 10% of borrowers of the three lending programs from August 2019 through December 2020. While Panel A presents overall statistics of both collateralized and uncollateralized loans, Panels B, C, D, and E report the distributions of interest rate, credit limit, loan size, and loan maturity solely for uncollateralized loans, which is the focus of our analysis.

Table 2 shows several interesting observations. First, Panel A shows that there are 12,099 collateralized big tech loans and 843,678 uncollateralized big tech loans in our sample, indicating that 98.6% of the big tech loans are uncollateralized. This dominant fraction reflects the fact that the big tech lending program covers mainly borrowers without collateral to qualify for conventional bank loans, as highlighted by Gambacorta et al. (2020). Consistent with the notion that banks heavily rely on collateral to grant loans, 81.4% of Bank X's regular business loans are collateralized. Interestingly, 74.9% of Bank X's online loans are also uncollateralized. This large fraction reflects the bank's effort to use big data to mitigate the heavy reliance of its regular lending program on collaterals. This effort may have also led the online lending program to lend only to

[11] These results also contrast the studies of fintech lending, which often find fintech lending substitutes, rather than complements, bank lending (e.g. Tang (2019), De Roure et al. (2021), Di Maggio and Yao (2021), Bao and Huang (2021), and Gopal and Schnabl (2021)). In particular, Bao and Huang (2021) compare fintech lending with bank lending in consumer credit market in China and find that fintech borrowers have more car loans, mortgages, and credit access than bank borrowers.

borrowers with strong credit records, as consistent with our earlier discussion that the online loan borrowers have the most extensive access to credit from other sources. Given the predominance of uncollateralized loans in the big tech lending program, we choose to focus our analysis on uncollateralized loans hereafter.

Second, in Panel A, uncollateralized big tech loans have an average, *annualized* interest rate of 14.6%, which is substantially higher than uncollateralized online and regular loans, which have an average interest rate of 8.6% and 8.5%, respectively. Panel B further shows the distribution of interest rates across loans in each of the three categories. The 5th percentile of big tech interest rate is already 9%, higher than the median interest rate of 8% for both the online and regular loans. The higher interest rates of big tech loans may reflect the higher risk of the big tech loan borrowers, which as we discussed earlier, are different from the borrowers of the regular and online loans. We shall examine whether this is the case in our later analysis.

Third, Panel A shows that the big tech program offers an average uncollateralized credit limit of RMB 71,963, which is less than half of the average credit limit of Bank X's online and regular lending programs. As credit limit is an important mechanism used by the lender to limit its risk exposure to the borrower, the lower credit limit offered by the big tech lending program may also reflect big tech loan borrowers' greater risks, which we will later analyze.

Fourth, Panel A further shows that the average size of the uncollateralized big tech loans is only RMB 8,367, which is only 11.6% of the average credit limit.[12] This fraction is much lower than the 56.8% and 65.4% of online and regular loans relative to their corresponding credit lines provided by Bank X.[13] This contrast reveals that despite the limited credit access of big tech borrowers, they are reluctant to use big tech loans. It is perhaps reasonable to explain this low take-up ratio by the high interest rates of the big tech loans.

Fifth, Panel A shows that the big tech loans in our sample have an average maturity of 10.0 months, which is similar to the average maturity of the online loans of 9.9 months and somewhat shorter than the average maturity of 13.0 months of the regular loans. Panel E further shows the

[12] The small loan size also reflects the convenience of big tech lending. As the marginal cost of taking a big tech loan is small for both the lender and the borrower, the big tech lending program thus has more small loans.

[13] By separate calculation, the big tech borrowers on average use 27.2% of their credit lines, which is substantially lower than the rate of 85.8% used by Bank X's line loan borrowers and the 74.9% used by bank X's regular loan borrowers.

distribution of loan maturity in each category. The commonly short maturity across these lending programs reflects the reluctance of Chinese financial institutions to provide long-term credit.

Finally, Panel A shows that only 15% of the big tech loans allow one repayment at maturity, which is much lower than the 89% and 71% of Bank X's online and regular loans. This repayment structure is likely used by the lender to limit the borrower's repayment risk.

Overall, the big tech loans in our sample are sharply different from Bank X's regular loans and online loans in all aspects except maturity. Specifically, the big tech loans tend to be uncollateralized, have substantially higher interest rates, and are much smaller in size. Interestingly, as we will show in the next section, these patterns are not simply due to the different borrowers covered by the big tech lending program, because the big tech loans made to borrowers with access to Bank X's conventional loans also display the same patterns.

In the following subsections, we examine the aforementioned views of big tech lending from four dimensions: the borrowers' repayment risk, the adverse selection faced by the big tech lender, the borrowers' repayment speed, and the elasticities of interest rate and credit limit set by the big tech lender.

B. Repayment Risk

We now examine the risk involved in big tech lending. As we discussed through Table 2, big tech loans have substantially higher interest rates than the regular and online loans. This raises a natural question regarding whether the big tech loans are riskier. As we discussed in the introduction, there is also evidence from the literature suggesting that fintech lending tends to be bottom fishing (e.g., Tang (2019) and De Roure et al. (2021)) and fintech lending might exacerbate borrower risk (e.g., Di Maggio and Yao (2021), and Wang and Overby (2021)). The aforementioned views of big tech lending also offer different implications on how the big tech loans might be priced and whether they might be riskier than conventional bank loans. The regulation arbitrage view suggests that big tech loans are similar in nature (and thus have similar risk) to conventional loans but charge a premium for the convenience offered to borrowers. The borrower exploitation view implies that by enabling overborrowing, big tech loans are riskier than conventional bank loans. Finally, the restrained advantage view argues that big tech lenders may be able to effectively screen the risks of borrowers in their ecosystems but may charge high interest rates as a result of their convenience or market power in this particular domain. Motivated by the implications of these views, we test the following hypothesis:

Hypothesis 1: Big tech loans are riskier than conventional bank loans.

We test this hypothesis by examining the repayment risk across the three types of loans in our sample. We measure the repayment risk of a loan by its payment being overdue for at least 30 days.[14] In Table 3, we analyze the performance of the three types of loans in terms of the likelihood of being ever overdue for at least 30 days.[15] To be included in this analysis, we require a loan to mature at least 30 days before May 31, 2021, the ending date of our loan performance data. As reported in Panel A of Table 5, this sample includes 454,407 big tech loans, 68,817 online loans, and 19,335 regular loans.

We report the summary statistics of payment overdue in Panel A. The overall rate of payment overdue is 2.6% for the big tech loans, 1.1% for the online loans, and 1.6% for the regular loans. The highest overdue rate—for big tech loans—is consistent with that big tech borrowers' have the most uncertain businesses. The lowest overdue rate—for Bank X's online loans—may reflect the likely strict credit requirements imposed by this lending program.

Note that the big tech lending program makes loans to many borrowers without a previous credit history. These initial loans are particularly risky. Indeed, Panel A shows that 47.3% of the big tech loans in our sample (215,135 loans) are made to borrowers without any repayment record to MyBank.[16] These loans have an overdue rate of 4.2%, substantially higher than the overdue rates of 1.1% and 1.5% for Bank X's online and regular loans, respectively, made to borrowers without any repayment record to the same lender. As Bank X's online and regular lending programs both require borrowers to have an extensive credit history, these borrowers are likely to have past repayment records to other lenders. Thus, whether a borrower has previously repaid a loan to Bank X is not particularly revealing of the borrower's risk. In contrast, as the big tech borrowers have limited access to loans from other sources, whether they have previously repaid their initial loans to the big tech lender is highly informative of their credit risk.

After repaying their first loans, are the big tech loan borrowers still riskier than other borrowers? Interestingly, Panel A shows that the overdue rate of the big tech loans for borrowers

[14] We acknowledge that even after a borrower is late in repaying a loan for 30 days, the borrower may still repay the loan either partially or fully at a later point. Nevertheless, a greater propensity to be late in repayment is monotonically related to a greater risk of eventually defaulting on the loan.

[15] We have also used an alternative measure of a loan's payment being overdue for more than 60 days. As the results are very similar, we do not report the alternative measure in the paper.

[16] It is possible that a borrower takes multiple loans before paying off any of the loans. Thus, these loans without payback records are not strictly first loans. Nevertheless, they are very similar in nature to first loans.

with a record of previously repaying at least one big tech loan is only 1.2%, very similar to the overdue rates of 1.1% and 1.7% for Bank X's online and regular loans for borrowers with a repayment record. Thus, the greater overdue risk of the big tech loans is concentrated in the initial loans, and there is no evident difference in repayment risk among loans with repayment records across the three groups. This lack of difference in the repayment risk is surprising and motivates a more systematic analysis.

In Panel B, we formally compare the repayment risk by gradually adding control variables, including basic loan contract variables, borrower characteristics, and industry × loan origination month fixed effects and city × loan origination month fixed effects. Relative to the regular loans, the big tech loans (the online loans) have higher (lower) overdue rates in the first two columns when only loan origination month fixed effects and basic loan contract terms are included in the regressions. However, once we adjust for basic borrower demographics and the borrower's prior repayment record in column 3, the big tech loans have lower overdue rates. The big tech loans have an even better performance after controlling for city × origination month fixed effects and industry × origination month fixed effects. Overall, while the big tech loans have higher unconditional overdue rates than the regular loans, after controlling for some basic measures of borrower characteristics, the big tech loans show lower, rather than higher, repayment risk.

Taken together, Table 3 contradicts Hypothesis 1 by showing that the big tech loans do not have higher repayment risk than the conventional bank loans after controlling for basic borrower characteristics. This finding contrasts the aforementioned evidence of the greater risk of fintech lending and helps to rule out the borrower exploitation view of big tech lending, which implies that big tech lending enables overborrowing and thus entails greater risk. The lack of greater repayment risk of the big tech loans is surprising as their borrowers tend to have more uncertain businesses and lack verifiable financial statements for the credit coverage of traditional banks. To fully understand this lack of greater repayment risk, we further examine the borrowers' adverse selection and early repayment in the next two subsections.

C. Adverse Selection

The presence of adverse selection is a key factor that determines the risk faced by a lending program. It remains unclear how much unconventional data can help lenders to screen borrowers. In a recent study of marketplace lending, Chava et al. (2021) show that fintech lenders face more

severe adverse selection than traditional banks.[17] The big tech lender covered by our sample has substantial data advantages relative to typical fintech lenders. Nevertheless, this motivates us to test the following hypothesis:

Hypothesis 2: Big tech loans face more severe adverse selection than conventional bank loans.

For the three lending programs covered by our data, the lender commonly approves a credit line with a given interest rate to a borrower. The borrower may have better information than the lender about its own financial conditions. If so, the borrower's choices of the timing and the quantity in using the credit line may reflect its private information and thus the extent of adverse selection faced by the lender. Chiappori and Salanié (2000) have designed a simple correlation test for information asymmetry in the insurance market to examine whether those who initially choose a more comprehensive insurance coverage are more likely to have an accident ex post. We can adopt this correlation test to examine Hypothesis 2.

Specifically, we test whether there is a positive conditional correlation between a dummy variable on whether a borrower has used up its credit limit at the time of borrowing and another dummy variable on whether the loan becomes overdue for at least 30 days ex post. The borrower's choice to use up the credit limit may reflect information only privately known to the borrower at the time of taking a loan. If after controlling for all publicly observable loan and borrower characteristics, there is still a positive and significant correlation between the dummy for the credit limit being used up and the dummy for ex-post payment overdue, this conditional correlation indicates the presence of private information by the borrowers at the time of taking the loans and thus the existence of adverse selection.

We separately apply this conditional correlation test to the loans in each of the three lending programs. For each lending program, we first run a pair of Probit regressions and then test whether there is a positive correlation between the residuals of these regressions. Specifically, the dependent variable in the first Probit regression is the dummy variable for whether the payment of a loan is overdue for more than 30 days, and the dependent variable in the second regression is the dummy variable for whether the borrower uses up its credit limit at the time of borrowing. These Probit regressions share the same set of independent variables, including loan contract variables,

[17] In a related study, Vallee and Zeng (2019) show offsetting effects of public information production on the adverse selection faced by fintech lenders in marketplace lending platforms.

borrower characteristics variables, and dummy variables on borrower industry, borrower province, and loan origination month.

The first pair of columns in Table 4 report the results for the big tech loans. The key coefficients are the correlation of residuals and the test statistic at the end of the columns. Interestingly, there is a small but negative conditional correlation of –0.004 between whether the borrower uses up its credit limit and whether the loan becomes at least 30 days overdue ex post, indicating a lack of adverse selection. The following pair of columns report the results for Bank X's online loans. While there is a positive conditional correlation of 0.002, the correlation coefficient is not statistically significant, indicating no adverse selection. The last two columns report the results for the regular loans. Interestingly, there is a positive and significant correlation coefficient of 0.04, indicating the presence of adverse selection among Bank X's regular loans.

Taken together, Table 4 rejects Hypothesis 2, as there is no evidence of adverse selection in the big tech loans, even though adverse selection may be a potential concern for Bank X's regular loans. This finding contrasts the evidence of more severe adverse selection faced by fintech lenders relative to traditional banks, as reported by Chava et al. (2021), and instead confirms that superior data collection and monitoring capacities allow big tech lenders to effectively avoid adverse selection by their borrowers. This result thus supports the monopolizing banking view and the restrained advantage view, both of which recognize the advantages of big tech lending.

D. Early Repayment

We now analyze the speed of the borrowers in repaying their loans. This is a new dimension not previously explored by the literature that examines both fintech and big tech lending. As we summarized in Table 2, the three types of loans in our sample have similar maturities, with 6 and 12 months as the two typical loan maturities. In a loan agreement, the lender initially sets the loan maturity to limit the duration of its risk exposure to the borrower. The borrower has the option to repay the loan early without any penalty. Whether and how quickly the borrower chooses to repay the loan reflects what the borrower uses the loan for. If the big tech lender makes a loan to fund the borrower's long-term business expansion (a typical purpose for taking a business loan), it is unlikely that the borrower will repay the loan before the short maturity of 6 or 12 months. The regulatory arbitrage view implies that big tech lending is similar in nature to traditional bank lending. The monopolizing banking view emphasizes that big tech lenders compete with traditional banks for lending businesses. According to these views, we expect the repayment speed of the big

tech loans to be similar to that of conventional bank loans, especially given our earlier findings that big tech loans are not riskier and do not face more severe adverse selection. As for the borrower exploitation view, if big tech lending enables borrowers to borrow beyond their means, it is difficult for them to repay the loan before maturity as they are also likely to face difficulties in finding alternative sources of credit. In contrast, if the borrowers use big tech loans to meet short-term liquidity needs, the borrowers are likely to repay their loans ahead of schedule, and, more importantly, faster than borrowers of Bank X's regular and online loans. The contrast in these views thus motivates us to test the following hypothesis:

Hypothesis 3: There is no difference in the repayment speed of big tech loans and conventional bank loans.

We analyze early repayment by the three groups of borrowers in Table 5. To facilitate the comparison, we impose a filter to include only loan contracts that matured before May 2021, the month when our loan performance data end. Panel A reports the distribution of the ratio of repayment time to loan maturity across the big tech loans and Bank X's online and regular loans. The big tech loans are repaid much earlier than the other loans. On average, the big tech loans are repaid only at 46% of the scheduled maturity, while Bank X's online and regular loans are repaid at 74% and 77% of their respective maturities. The distribution of the repayment time reveals an even more informative picture. Of the big tech loans, 25% of them are repaid at only 4% of the loan maturity, which corresponds to about one week for loans with a 6-month maturity and two weeks for loans with a 12-month maturity. In contrast, 25% of the online loans are repaid at 48% of the loan maturity and 25% of the regular loans are repaid at 61% of the loan maturity. At the median, 50% of the big tech loans are repaid at 28% of the loan maturity, which corresponds to about seven weeks for loans with a 6-month maturity and 14 weeks for loans with a 12-month maturity. In contrast, the median ratio for the online loans is 96% and for the regular loans is 93%, which are both close to maturity.[18] Taken together, Panel A shows that the big tech loans are repaid substantially earlier than the scheduled maturity and much quicker than the conventional loans granted by Bank X.

To systematically compare the repayment time across the three types of loans, we also report regression analysis in Panel B. Specifically, we regress the ratio of repayment time to loan maturity on a list of variables, including two loan type dummies, big tech and online. This specification treats the ratio of Bank X's regular loans as the baseline. We also include other loan characteristics,

[18] Also note that the maximum value for all three types of loans is above 1, which indicates payment overdue.

such as interest rate, credit limit, loan maturity, and borrower characteristics, such as age, county, rural, previous credit history, and whether the borrower has a large deposit in Bank X. We also include industry × loan origination month fixed effects and borrower city × loan origination month fixed effects. We report two different regression specifications in the panel. Across both specifications, the big tech dummy is significantly negative with a large value of –0.40 and –0.46, respectively, confirming that the big tech loans are repaid substantially earlier than Bank X's regular loans.

Taken together, Table 5 clearly rejects Hypothesis 3 and shows that the big tech loans are repaid much earlier than the scheduled maturity and the conventional bank loans. This finding offers a useful dimension to sort out the aforementioned views of big tech lending. To the extent that big tech borrowers do not keep their loans to maturity, it is unlikely that they use the big tech loans either to finance long-term business expansions or to borrow beyond their means, which is inconsistent with the regulatory arbitrage view, the borrower exploitation view, and the monopolizing banking view. Instead, it is more likely that borrowers use big tech loans to meet their short-term liquidity needs, which is most consistent with the restrained advantage view, which suggests that big tech loans serve only certain specific financing needs of the borrowers in the lender's ecosystem.

E. Interest Rate and Credit Limit

Interest rate and credit limit are two key instruments used by the lender to protect itself against the risks in lending to a borrower. As we discussed before, whether a borrower had previously repaid at least one big tech loan has strong predictive power of the borrower's repayment risk. In this subsection, we examine how the big tech lender varies the interest rate and credit limit with respect to the borrower's repayment risk that is measured by its repayment history. Specifically, we test the following hypothesis:

Hypothesis 4: Both the interest rate and credit limit of big tech loans vary elastically with borrower risk.

In contrast to this hypothesis, both the monopolizing banking view and the restrained advantage view imply that big tech lenders may hold certain market power over the borrowers in their ecosystems. Such market power may allow big tech lenders to set inelastic interest rates.

In Table 6, we pool all the big tech loans in our sample and regress the dummy of overdue for more than 30 days of each loan, the logarithm of credit limit, and the interest rate on a set of borrower characteristics. These characteristics include two dummies related to the borrower's repayment history—whether the borrower had previously repaid at least one loan from MyBank and whether the borrower had ever been late in repaying any loan from MyBank. The independent variables also include two dummies related to the borrower's access to conventional loans from Bank X—whether the borrower had repaid a loan from Bank X and whether the borrower had been late in repaying any loan from Bank X. As we mentioned before, a small set of borrowers in our sample have access to conventional loans from traditional banks. These variables capture potential competition with other lenders. We also include MyBank's proprietary risk score variables, industry × loan origination month fixed effects, and city × loan origination month fixed effects as controls.

The first major column of Table 6 confirms that if the borrower has repaid at least one big tech loan before, the repayment risk is significantly lower by 2.82% or 2.61%, depending on whether the regression includes MyBank's risk score variables. This estimated drop in the repayment risk is substantial in magnitude relative to the big tech loans' unconditional repayment risk of 2.6% from Table 3. On the other hand, if the borrower has any previous big tech loan overdue, the repayment risk is higher by 6.99% without controlling for MyBank's risk score variables, even though the higher risk is insignificant due to the small number of borrowers with previous overdue big tech loans.

The second major column shows that if the borrower has repaid at least one big tech loan before, the logarithm of credit limit is significantly higher by 18%, without controlling for MyBank's risk score variables.[19] Interestingly, if the borrow has any overdue big tech loans, the logarithm of the credit limit drops even more dramatically by 77%. Together, these two estimates show that the credit limit provided by the big tech lender is elastic to borrower risk on both the positive and negative sides.

The third major column shows that if the borrower has repaid at least one big tech loan before, there is a statistically significant drop in the interest rate by 31 basis points without controlling for MyBank's risk score variables. This drop in interest rate is rather modest relative to the big tech

[19] After controlling for MyBank's risk score variables, whether the borrower had previously repaid a big tech loan becomes insignificant in explaining the credit limit, possibly due to its information content being captured by the risk score variables of MyBank.

loans' average interest rate of 14.6% from Table 2. In contrast, if the borrower has any overdue big tech loans, the interest rate increases by 282 basis points, which is substantially bigger.

Taken together, Table 6 shows that while the credit limit provided by the big tech lender varies elastically with respect to both increases and decreases of the borrower risk, the elasticity of the interest rate shows a pronounced asymmetry in that the interest rate drops only very modestly in response to a decrease in borrower risk. This inelastic interest rate response is inconsistent with Hypothesis 4 and instead points to the potential market power of the big tech lender over the borrowers in its ecosystem, consistent with both the monopolizing banking view and the restrained advantage view of big tech lending.[20]

F. Convenience

To understand the willingness of the borrowers to accept the high interest rates of the big tech loans, it is useful to highlight another important feature—the convenience provided by the big tech lender for borrowers to quickly borrow and repay. Through a mobile phone, it takes only a few minutes to apply for a loan, and then it takes only a few seconds to repay the loan. This convenience enables a borrower to quickly take a loan to meet short-term liquidity needs and then to quickly repay when the borrower no longer needs the funds. Such a quick cycle reduces the borrower's fixed cost of taking a conventional bank loan (such as making an appointment and paying a visit to a bank branch). The aforementioned views of big tech lending all recognize the convenience facilitated by the technologies that drive fintech and big tech lending. In our data sample, convenience is particularly useful for understanding that the frequent borrow-and-repay cycle may make a borrower less sensitive to the annualized interest rate.

As a borrower may quickly repay a big tech loan, the net interest expense is proportional to the duration of holding the loan and thus may not be as high as the annualized interest rate quoted for the loan. We report the ratio of interest expense to loan size in Table 7, Panel A. The average interest expense to loan size ratio is 5.0% for big tech loans, which is similar in magnitude to the 4.5% for online loans, and the 5.9% for regular loans. This is because the borrowers tend to repay the big tech loans early. Consistent with the pattern of fast repayment presented in Table 5, Panel A, the median interest expense to loan size ratio of big tech loans is only 2.7%, much lower than

[20] Table 6 also shows that the credit limit of big tech loans is elastic with respect to the borrower's access to alternative sources of credit, but the interest rate is also inelastic, suggesting that the big tech lender is either unwilling or unable to compete for marginal borrowers. We will further explore this issue in the next section through a sample of marginal borrowers.

the 4.0% (6.1%) of the online loans (the regular loans). The 5th percentile of the interest expense of the big tech loans is zero because those loans are repaid on the same day of borrowing.

Furthermore, due to their small size, the big tech loans have a substantially lower interest expense per loan relative to Bank X's online and regular loans. From Panel B of Table 7, we see the average interest expense is only 372 RMB for big tech loans, but 4460 RMB for Bank X's online loans and 6563 RMB for Bank X's regular loans. To the extent that big tech loans lower the fixed cost for the borrowers, the small interest expense may make the borrowers not so sensitive to the high annualized interest rates quoted for the big tech loans.

We also report in Panel C of Table 7 the number of loans taken by each borrower during our sample period of 17 months from August 2019 to December 2020. The big tech borrowers on average took 6.0 loans during this period, substantially larger than the average of 2.3 loans by Bank X's online borrowers and 1.6 loans by Bank X's regular borrowers. Furthermore, 5% of the big tech borrowers took more than 20 loans in this 17-month period. This high frequency of borrowing reflects not only the borrowers' short-term liquidity needs but also the convenience provided by the big tech loans.

The frequent borrowing by the big tech borrowers also confirms that they are not confused by the terms of the big tech loans, which is a potential concern. As shown by Brailovskaya et al. (2021), fintech lenders in Malawi exploit borrowers by charging high but undisclosed late fees, leading borrowers to pay high late fees without being fully informed. A particular concern for the big tech loans in our sample is that the borrowers may not understand or pay close attention to the high daily interest rates quoted for these loans. While such borrowers may also exist, the fast repayment and the frequent reborrowing by the overall borrower sample suggest that most of the borrowers understand the borrowing costs and take the loans only to meet their liquidity needs.

IV. Marginal Borrowers

An important issue that may determine the future landscape of the banking industry is how big tech lending might compete with traditional bank lending. So far, there are many conjectures made by commentators but very few facts. We shall anchor on two archetypical views to shed some light on this important issue from our data.

The banking monopolizing view posits that big techs may take advantage of their superior data and technologies to eventually monopolize the lending to consumers and SMEs. For this view

to be realistic, we expect big tech lenders to directly compete with traditional banks for marginal borrowers. In contrast, the restrained advantage view posits that the advantages of big tech lenders might be limited to the financing of certain business or consumption activities by borrowers within the lenders' ecosystems. As a result, big tech lenders may not be able to compete with traditional banks for borrowers outside their ecosystems or even for the borrowers' needs to finance business activities outside their ecosystems. For example, an online vendor that uses Alipay for payments related to its business transactions fits nicely in the ecosystem of MyBank and thus qualifies for MyBank's credit services to cover the financing needs of its online business. However, MyBank may not be able to provide credit to cover the vendor's expansion to open an offline store, which goes beyond the data coverage of MyBank's ecosystem.

A small set of the big tech borrowers also had access to Bank X's regular or online loans. These overlapped borrowers represent the marginal borrowers the big tech lender may need to compete for with traditional banks. Thus, a comparison of the loan terms obtained by these overlapped borrowers across the big tech lending program and Bank X's regular and online lending programs offers a unique window to examine how the big tech lending program competes for marginal borrowers with traditional banks. Motivated by the different implications of the banking monopolizing view and the restrained advantage view, we examine the following hypothesis:

Hypothesis 5: The big tech lender provides more competitive interest rates and credit limits than traditional banks to compete for marginal borrowers, who use big tech loans for similar purposes as they use conventional bank loans.

In Table 8, we compare the terms and performance of the big tech loans with Bank X's regular and online loans made to the full set of overlapped borrowers in Bank X's database. Panel A presents summary statistics of the overlapped borrowers. The sample contains 6,684 unique borrowers, who had taken a total of 42,548 big tech loans.[21] Among these borrowers, 4,929 had taken a total of 12,768 online loans from Bank X, and 1,829 had taken a total of 3,165 regular loans from Bank X.[22]

One would expect these overlapped borrowers to get better terms for their big tech loans than the terms offered to the average big tech borrowers, not only because they have better credit quality

[21] The presence of these overlapped borrowers already indicates that the big tech lender is not concerned about competing with Bank X for marginal borrowers. If there is such a concern, the big tech lender should not provide any credit to these borrowers and especially not invite Bank X to fund such credit lines.

[22] The set of marginal borrowers is likely larger than the overlapped borrowers between MyBank and Bank X, as some big tech borrowers may also have access to loans from other traditional banks, which are not covered by our data.

but also because they represent the marginal borrowers for the big tech lending program to compete for. To our surprise, Panel A shows very similar patterns as Table 2 in the loan terms. First, the big tech loans have an average annualized interest rate of 14.5%, which is almost identical to the average interest rate of 14.6% in our main sample of big tech loans, and which is substantially higher than the average interest rate of 8.7% for the online loans and 9.0% for the regular loans extended to the same borrowers. Second, these borrowers have an average credit limit of 97,762 RMB from the big tech lending program, which is about half of their average credit limit from the online and regular lending programs of Bank X. Third, the size of the big tech loans taken by the overlapped borrowers is again only 15.4% of their available credit limits and is substantially smaller than their online and regular loans from Bank X.

In terms of repayment speed, we again uncover a pattern similar to the main sample (as reported in Tables 5 and 7). From Panel A of Table 8, we see the big tech loans are repaid much faster than the conventional loans from Bank X. Specifically, the average repayment time of the big tech loans is only 41.4% of the scheduled loan maturity, substantially earlier than the repayment time of the same borrowers' online loans (on average at 77.5% of the loan maturity) and regular loans (on average at 83.0% of the loan maturity). In addition, each overlapped borrower had on average taken 6.4 big tech loans in our sample period of 17 months, which is substantially more than the 2.6 online loans and 1.7 regular loans taken by them during the same period. Thus, even for the overlapped borrowers, the big tech loans serve as a differentiated financing tool from the conventional bank loans to fulfill short-term liquidity needs, rather than serving the same purposes as the conventional loans.

One may argue that even if a borrower had access to conventional loans from Bank X, the borrower may not have any remaining credit line when a financing need arises. To address this concern, in Panel B we further classify each of the big tech loans based on whether the borrower's remaining credit from Bank X's regular or online lending program at the time of taking the big tech loan was sufficient to cover the big tech loan and whether the available conventional credit line had a lower interest rate than that of the big tech loan. Even more surprisingly, 57% of the big tech loans in this sample were taken when the borrowers had cheaper and sufficient credit lines available from Bank X. The average interest rate of these big tech loans was 14.7%, while the average interest rate from the borrowers' available credit lines from Bank X was only 8.3%. By revealed preferences, for the borrowers to take on these big tech loans at the higher interest rates, the convenience of the big tech loans must overweigh the higher interest cost.

Interestingly, Panel B of Table 8 also shows that those big tech loans taken when the borrowers had cheaper and sufficient credit lines from Bank X are repaid quicker (on average at 39.8% of their maturity) than those big tech loans taken when such cheaper options were not available to the borrowers (on average at 44.3% of their maturity). This difference again confirms that the borrowers took the big tech loans despite their higher interest rates because they might have expected that they would quickly repay those loans and the higher annualized interest rates were less of a concern given the convenience offered by the big tech loans.

To control for the loan characteristics, we use regressions to formally compare the interest rates, credit limits, loan sizes, and repayment speed of different loans taken by the overlapped borrowers in Panel C. The benchmark group in all these regressions is the big tech loans that were taken without a cheaper and sufficient credit line available from Bank X at the time of borrowing. All the specifications include borrower fixed effects so that the results reflect within-borrower comparisons. The regression results confirm the findings in Panels A and B. Both the regular and online loans from Bank X have a significantly lower interest rates, higher credit limits, larger loan sizes, and slower repayment speed relative to the big tech loans, and the big tech loans taken when a cheaper credit line was available are repaid earlier.

We also compare the repayment risk of the different loans taken by the overlapped borrowers. Interestingly, Panel A shows that the rate of payments overdue for more than 30 days is just 0.4% for the big tech loans, which is substantially lower than the overdue rate of 0.9% for the online loans and 1.5% for the regular loans taken by the same borrowers. As expected, the repayment risk of the big tech loans in this sample is lower than that reported in Table 3 for our main sample because the overlapped borrowers tend to have better credit quality.

We formally compare the repayment risk in Panel D of Table 8. The first two columns include only borrowers with both big tech loans and regular loans from Bank X during the sample period, and the last two columns include only borrowers with both big tech loans and online loans from Bank X. The dependent variable is the indicator variable on whether a loan is at least 30 days past due in all the columns. The benchmark group is the big tech loans that were taken without a cheaper credit line available from Bank X at the time of borrowing. Borrower fixed effects are added to columns 2 and 4 but not to columns 1 and 3. From columns 1 and 3, the overdue rate of the regular loans is higher by 0.66% and that of the online loans is higher by 0.73%, both relative to that of the big tech loans without controlling for borrower fixed effects. Yet, columns 2 and 4 show that there is no significant difference in the overdue rates after the inclusion of borrower fixed effects.

These results indicate that the borrowers do not show any preferences among these different loans when they run into financial distress in repaying their loans. Lastly, the regressions also commonly show that the big tech loans taken when cheaper credit lines were available from Bank X tend to have lower overdue rates, again consistent with our earlier argument that borrowers might have taken big tech loans to meet short-term liquidity needs.

Overall, Table 8 shows highly similar patterns in interest rates, credit limits, loan sizes, and repayment speed of the overlapped sample as the main sample. These patterns suggest that the big tech lender uses the same lending policies for borrowers with or without access to alternative credit sources and that borrowers with access to alternative credit also use the big tech loans to meet their short-term liquidity needs just as the big tech borrowers in the main sample. These surprising findings contradict Hypothesis 5 and offer several important implications. First, they suggest that the higher interest rates of the big tech loans are *not* simply a result of the big tech lender exerting its market power to price discriminate borrowers with no outside options. Second, the observation that the overlapped borrowers with access to cheaper credit are still willing to take on the big tech loans with higher interest rates strongly confirms the convenience provided by the big tech loans to serve the borrowers' short-term liquidity needs. Third, the fact that the big tech lender does not offer more-competitive interest rates to compete for other credit needs of these marginal borrowers confirms the restrained advantage view that big tech lending is possibly constrained to only funding specific activities of the borrowers inside the lender's ecosystem.

One may argue that as the number of the overlapped borrowers is small, the big tech lender may not be so concerned about losing their business. To the extent that the borrowers' characteristics are continuous, the lack of any difference in the big tech lender's strategies to compete for the overlapped borrowers with easily observed access to conventional credit services from Bank X also indicates that the big tech lender does not compete for borrowers with credit access offered by other financial institutions. This set is likely bigger. Furthermore, perhaps more importantly, the big tech lender may lose even more lending businesses from not covering the borrowers' other financing needs beyond short-term liquidity.

V. The COVID-19 Crisis

Another important issue is whether big tech lending is robust to severe economic shocks that disrupt the economy. Interestingly, our sample covers the onset of the COVID-19 pandemic, which

started in February 2020 and presented an unprecedented shock to every economy in the world. Recent studies by Ben-David et al. (2021) and Bao and Huang (2021) have shown that fintech lending in both the United States and China during the COVID-19 crisis was not as robust as bank lending. We examine the performance of the big tech lending program after the COVID-19 shock in this section.

The COVID-19 crisis is particularly interesting for several reasons. First, to the extent that big tech lending is largely based on behavioral patterns uncovered from historical data, a natural concern is that the COVID-19 shock may have generated a structural break in the economy and thus invalidated model predictions that are based on pre-COVID-19 data. Second, as many small businesses suffered liquidity shocks during the COVID-19 pandemic, it is particularly relevant to examine whether the big tech lending program was able to meet these liquidity needs despite the possible structural changes in the economy. Third, as big tech loans tend to be repaid much quicker than conventional bank loans, a big tech lender might have been able to quickly detect any change in the repayment speed and delinquency rate of its borrowers and to consequently adjust its lending strategies in response to the shock.

To examine the performance of the big tech loans after the COVID-19 shock, Figure 1, Panel A depicts the monthly loan issuance in millions of RMB of the three types of loans over the sample period. The amount of big tech loan issuance increased steadily over the sample period, while there was a sharp decrease in both online and regular loans for Bank X in February 2020, the start of the COVID-19 pandemic in China. As February 2020 was also the month of the Chinese New Year, Bank X's loan issuance might have shrunk for seasonal reasons related to the holiday. Nevertheless, big tech lending was stable both before and after the start of the COVID-19 pandemic.

Panel B depicts the average interest rates of each type of loan issued in each month over the sample period. The interest rates of all three types of loans were stable during the sample period. During the months after February 2020, there were steady decreases in the interest rates for all three types of loans, possibly due to the monetary policies implemented by the Chinese government to reduce interest rates and to incentivize financial institutions to provide funding to small businesses after the COVID-19 shock.

In Table 9, Panel A, we further compare the loan provisions between Hubei province and other provinces during the three months surrounding February 2020.[23] Hubei province was the epicenter of COVID-19 in China and its economy was the most severely affected by the COVID shock. The comparison between Hubei and other provinces thus provides a useful cross-sectional test of how the three lending programs in our sample reacted to the COVID-19 shock. The variables in the regressions are all at the loan type-geography-month level, where the geography is either Hubei province or all the other provinces combined. The dependent variables include the logarithm of the total loan amount, the logarithm of the number of loans, the fraction of loans issued to new borrowers, and the average interest rate. Bank X's regular loans is the benchmark group in all the regressions. The "post-COVID-19 shock" indicator is equal to one for the three months after February 2020, and zero otherwise. The key variable of interest is the triple interaction term between the big tech loan indicator, the Hubei province indicator, and the post-COVID-19 shock indicator.

There is no significant difference in total loan amounts issued by the three lending programs after February in Hubei compared to the other provinces. Yet, consistent with big tech loans' being better at satisfying borrowers' liquidity needs, column 2 shows a larger number of big tech loans originated in Hubei province after the COVID-19 shock. Interestingly, from the last column, we see the interest rates of big tech loans are also lower in Hubei province after the shock. Since the analysis in this table makes no further adjustment to borrower characteristics, we should be cautious in interpreting the findings.

Panel B of Table 9 compares the overdue rate of loans issued from January to March 2020, that is, one month before and two months after the COVID-19 shock. We restrict the event window to one month before the COVID-19 shock because big tech loans are repaid quickly and a longer window would lead to many loans having been repaid even before the start of the pandemic. We make the post-event window two months after the shock because February is the Chinese New Year and the number of regular and online loans issued by Bank X is normally low due to the holiday season.[24]

[23] We combine the loan issuances of all the other provinces because the number of loans for some of the provinces is low and thus may create outliers to our analysis after taking the logarithm.

[24] Note that all the loan contracts in our sample mature after the COVID-19 shock. Therefore, our analysis does not compare the big tech loans relative to bank loans that *mature* before versus after the COVID-19 shock. Instead, we compare the loans that are *originated* before versus after the COVID-19 shock.

In all the columns in Panel B, the dependent variable is whether a loan is at least 30 days overdue, and the benchmark group is Bank X's regular loans. The post-COVID-19 shock indicator is equal to one for February and March 2020, and zero for January 2020. The key coefficient of interest is the interaction term between the big tech loan indicator and the post-COVID-19 shock indicator. We do not compare the loan performance between Hubei and other provinces because the number of Bank X's regular and online loans in Hubei is too small to appropriately assess the loan performance. We gradually add controls on loan contract variables, borrower characteristics, and fixed effects into the regression across the specifications.

Across all the specifications, we find a significantly negative coefficient on the key interaction term, suggesting a smaller increase in the overdue rate for big tech loans originated after the COVID-19 shock relative to Bank X's regular loans. Moreover, the magnitude of the estimated coefficient becomes larger from column 2 to column 3 when we control for city × month fixed effects and industry × month fixed effects, suggesting that the smaller increase in the overdue rate of big tech loans originated after the COVID-19 shock is not due to big tech's ability in the selection and timing of local markets, but rather due to its ability in screening borrowers in the same local market in the same time period after the COVID-19 shock.

Overall, Table 9 shows that the big tech lending program remained robust to the COVID-19 shock in terms of both the number of loans originated and loan performance. Thus, despite the unprecedented economic stresses brought by the COVID-19 pandemic, the big tech lending program managed to provide financing to meet borrowers' short-term liquidity needs without incurring greater delinquency risks.

VI. Conclusion

By comparing a sample of big tech business loans with a sample of conventional bank loans in China, we uncover several important features of big tech lending. First, we confirm the argument that big tech lending facilitates financial inclusion by providing uncollateralized credit to borrowers unserved or underserved by traditional banks. Second, despite big tech borrowers likely being riskier than the borrowers of conventional bank loans, the big tech loans do not show more severe adverse selection than the conventional bank loans, suggesting that the big tech lender has the ability to screen for the risk of its borrowers. Third, after controlling for previously paying off at least one loan, there is no significant difference in the delinquency rate of big tech loans and

conventional bank loans. Fourth, the loan issuance and delinquency risk of the big tech loans remained stable even after the onset of the COVID-19 crisis, suggesting that big tech lending can be robust to severe economic shocks.

Fifth, we also uncover sharp characteristics of the big tech loans—they tend to be smaller in size and have substantially higher interest rates, and their borrowers tend to repay them long before the debt matures and borrow more frequently. These characteristics suggest that the big tech loans serve the borrowers' short-term liquidity needs rather than financing long-term business expansions or over-borrowing. Finally, the big tech loans made to the borrowers with and without access to cheaper alternative credit display the same characteristics—small size, high interest rates, fast repayment, and frequent borrowing. The lack of differences in these characteristics highlights the big tech lender's restrained advantages in serving the short-term liquidity needs of borrowers in its ecosystem, rather than in competing with traditional banks to finance the borrowers' activities outside its ecosystem.

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Table 1: Borrower Characteristics

This table presents summary statistics of individual borrowers based on the credit reports voluntarily provided by the borrowers in their credit applications. When a borrower has multiple loans, only the credit report associated with the first loan is included. The sample contains 31,046 big tech borrowers, 49,794 Bank X online borrowers, and 22,042 Bank X regular borrowers over the period from August 2019 through December 2020. Policy loans are excluded from the sample. Panel A presents the demographics of borrowers in each lending program. Panel B reports the fraction of borrowers who borrow their first loan (first business loan, first uncollateralized business loan) from the corresponding lending program. Panel C reports the total amount of loans in RMB that an average borrower in a lending program borrowed from other institutions. A borrower without any loan of a certain type from another institution is treated as zero in computing the averages.

Panel A: Borrower Demographics

	Age	Male	Undergrad	High School	Rural	County	City
Big Tech Borrowers	32.8	66%	38%	30%	31%	29%	40%
Online Borrowers	44.3	79%	18%	34%	15%	62%	23%
Regular Borrowers	43.0	83%	12%	26%	20%	58%	22%

Panel B: First Loans

	First Loan	First Business Loan	First Uncollateralized Business Loan
Big Tech Borrowers	27%	81%	91%
Online Borrowers	4%	5%	6%
Regular Borrowers	30%	43%	58%

Panel C: Other Loans by Each Borrower in RMB

	Collateralized Business Loans	Uncollateralized Business Loans	Collateralized Consumption Loans	Uncollateralized Consumption Loans	Mortgage Loans	Others	All
Big Tech Borrowers	117,172	36,099	40,467	97,946	13,661	28,807	334,152
Online Borrowers	741,676	180,595	160,123	49,872	96,760	96,760	1,325,786
Regular Borrowers	429,065	159,087	73,096	30,252	65,385	65,385	822,270

Table 2: Summary Statistics of Loan Terms

This table presents summary statistics of loan terms in our sample. The data include three types of individual business loans: big tech loans, Bank X online loans, and Bank X regular loans. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. Policy loans are excluded from the sample. Except for Panel A, the panels cover only uncollateralized loans. Panel A presents the mean of each basic contract term for each of the three types of loans. Panels B, C, D, and E present the distribution of interest rates, credit limits, loan size, and maturities.

Panel A: Overall Statistics

	Number of Loans	Interest Rate	Credit Limit (RMB)	Loan Size (RMB)	Maturity (Months)	Repay Once
Collateralized						
Big Tech	12,099	9.0%	840,509	135,741	11.2	63%
Online	37,917	5.1%	1,186,890	296,619	13.4	93%
Regular	152,991	5.5%	1,277,106	352,571	14.9	90%
Uncollateralized						
Big Tech	843,678	14.6%	71,963	8,367	10.0	15%
Online	113,233	8.6%	180,858	99,487	9.9	90%
Regular	34,933	8.5%	183,644	120,284	13.0	71%

Panel B: Distribution of Interest Rate (Uncollateralized)

	Mean	Std.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Big Tech	14.6%	3.5%	4.4%	9.0%	10.8%	12.0%	14.4%	16.2%	19.8%	21.6%	21.6%
Online	8.6%	1.4%	4.2%	8.0%	7.0%	8.0%	8.0%	10.0%	10.0%	10.0%	18.0%
Regular	8.5%	2.2%	4.2%	5.1%	5.9%	7.0%	8.0%	10.0%	12.0%	12.6%	16.2%

Panel C: Distribution of Credit Limit (Uncollateralized)

	Mean	Std.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Big Tech	71,963	66,773	1,000	8,000	12,000	29,000	55,000	92,000	145,000	198,000	500,000
Online	180,858	99,293	10,000	50,000	50,000	100,000	170,000	300,000	300,000	300,000	1,000,000
Regular	183,644	264,013	1,000	50,000	50,000	60,000	100,000	200,000	400,000	500,000	5,000,000

Panel D: Distribution of Loan Size (Uncollateralized)

	Mean	Std.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Big Tech	8,367	16,852	1	180	360	900	3,150	9,000	19,525	35,100	2,000,000
Online	99,487	88,457	22	8,000	10,000	30,000	80,000	150,000	270,000	300,000	1,000,000
Regular	120,284	162,212	100	10,000	10,000	40,000	80,000	120,000	300,000	450,000	5,000,000

Panel E: Distribution of Loan Maturity (Uncollateralized)

	Mean	Std.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Big Tech	10.0	2.8	1	6	6	6	12	12	12	12	12
Online	9.9	4.6	1	2	3	6	12	12	12	12	24
Regular	13.0	7.5	1	6	6	12	12	12	12	24	240

Table 3: Payment Overdue

This table presents analysis on the repayment risk of three types of individual business credit loans: big tech loans, Bank X online loans, and Bank X regular loans. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. Policy loans are excluded from the sample. The maturity of the loans are shorter or equal to 12 months, and all of them matured at least 30 days before May 31, 2021, the ending date of the loan performance data. Panel A presents summary statistics of overdue payments by whether the borrower had at least one payback record from the corresponding lending program. For example, 239,272 big tech loans went to borrowers who had paid off at least one big tech loan. The dependent variable in Panel B is 100 times the indicator on whether a loan is ever overdue by at least 30 days. Big Tech (Online) is an indicator variable that is equal to one if the loan is a big tech (Bank X online) loan, and zero otherwise. The benchmark group in all the specifications is Bank X regular loans. Ever Clear is an indicator that is equal to one if the borrower paid off at least one loan from the corresponding lending program. Exist Loan is an indicator that is equal to one if the borrower has at least one outstanding loan from the corresponding lending program. Ever Overdue is an indicator that is equal to one if the borrower was ever overdue by at least 30 days on at least one loan from the corresponding lending program. Loan origination month fixed effects, city × loan origination month fixed effects, and industry × loan origination month fixed effects are included in the corresponding specifications. Standard errors in parentheses are clustered at the loan origination month. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A: Summary Statistics of Payment Overdue

	Number of Loans			Ever Overdue >= 30days		
	w/o payback record	w payback record	Total	w/o payback record	w payback record	Total
Big Tech	215,135	239,272	454,407	4.2%	1.2%	2.6%
Online	4,048	64,769	68,817	1.1%	1.1%	1.1%
Regular	6,706	12,629	19,335	1.5%	1.7%	1.6%

Panel B: Regression Analysis

	Ever Overdue >=30 days × 100			
Big Tech	1.33***	0.56**	-0.60**	-0.84***
	(0.22)	(0.24)	(0.26)	(0.25)
Online	-0.27*	-0.01	0.65***	0.46*
	(0.16)	(0.23)	(0.25)	(0.25)
Loan Term: 6 months		-1.75***	-1.72***	-1.78***
		(0.48)	(0.47)	(0.47)
Loan Term: 12 months		0.22	0.26	0.17
		(0.53)	(0.53)	(0.54)
Repay Once		-2.00***	-1.63***	-1.62***
		(0.22)	(0.16)	(0.15)
Ever Clear			-2.77***	-2.77***
			(0.33)	(0.33)
Exist Loan			1.20***	1.19***
			(0.18)	(0.18)
Ever Overdue			8.34	9.39
			(6.93)	(6.92)
Has Large Deposit			-0.95***	-0.93***
			(0.07)	(0.08)
Log(age)			-0.30**	-0.39***
			(0.13)	(0.14)
Male			0.01	0.01
			(0.08)	(0.08)
County			-0.55***	-0.43***
			(0.06)	(0.07)
Rural			-0.54***	-0.43***
			(0.09)	(0.09)
Origination Month FEs	Yes	Yes	Yes	No
Industry × Origination Month FEs	No	No	No	Yes
City × Origination Month FEs	No	No	No	Yes
Cluster Variable	Origination Month	Origination Month	Origination Month	Origination Month
Adjusted *R*-squared	0.00	0.01	0.02	0.03
Observations	542,559	542,559	542,559	542,559

Table 4: Adverse Selection

This table presents the correlation test of adverse selection on each type of loans. The sample includes three types of individual business credit loans: big tech loans, Bank X online loans, and Bank X regular loans. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. All the loans matured at least 30 days before May 31, 2021, the ending date of the loan performance data. Policy loans are excluded from the sample. All the columns are estimated using a Probit model. The dependent variable in odd columns is an indicator variable on whether the loan originated is overdue by at least 30 days. The dependent variable in even columns is an indicator variable on whether the borrower uses up his or her remaining credit limit at the time of borrowing. For each pair of Probit regressions, the correlation between their residuals and the associated test statistics on the significance of the correlation are presented. Loan origination month fixed effects, province fixed effects, and industry fixed effects are included and indicated in the corresponding columns. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	Big Tech loan		Bank X Online loan		Bank X Regular loan	
	Ever overdue >=30 days	Use up credit limit	Ever overdue >=30 days	Use up credit limit	Ever overdue >=30 days	Use up credit limit
Interest Rate	0.94***	-6.48***	4.41***	1.82***	1.11	-4.51***
	(0.13)	(0.17)	(1.31)	(0.44)	(1.14)	(0.50)
Log(Remaining Limit)	-0.06***	-0.64	-0.10***	-0.32***	-0.11***	-0.25***
	(0.00)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)
Loan Term: 6 months	-1.50***	0.90***	0.46***	0.18***	0.09	0.32***
	(0.048)	(0.26)	(0.08)	(0.02)	(0.16)	(0.05)
Loan Term: 12 months	-1.13***	0.83***	0.78***	0.70***	0.39**	0.58***
	(-0.43)	(0.26)	(0.07)	(0.02)	(0.15)	(0.05)
Repay Once	-0.43***	0.37***	0.18**	0.31***	-0.01	-0.28***
	(0.02)	(0.02)	(0.07)	(0.02)	(0.06)	(0.03)
Ever Clear	-0.56***	0.17***	-0.06	0.04***	0.14**	-0.05**
	(0.01)	(0.01)	(0.06)	(0.02)	(0.06)	(0.02)
Exist Loan	0.26***	0.80***	-0.02	-0.12***	0.05	-0.49***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.07)	(0.03)
Ever Overdue	0.75	-4.39	-3.12	0.18	8.85	-6.99
	(0.52)	(17.19)	(32.2)	(0.64)	(39.1)	(39.1)
Has Large Deposit	-0.25***	0.27***	-0.27***	0.14***	-0.23***	0.14***
	(0.03)	(0.029)	(0.04)	(0.01)	(0.07)	(0.03)
Log(Age)	-0.01	0.72***	0.41***	0.09***	-0.00	0.15***
	(0.02)	(0.03)	(0.09)	(0.03)	(0.12)	(0.05)
Male	-0.00	0.08***	0.14***	0.02	-0.01	-0.23***
	(0.01)	(0.01)	(0.04)	(0.01)	(0.07)	(0.03)
County	-0.11***	-0.08***	-0.17***	-0.05***	-0.05	-0.02
	(0.01)	(0.01)	(0.04)	(0.01)	(0.06)	(0.03)
Rural	-0.09***	-0.16***	-0.20***	-0.08***	0.05	-0.04
	(0.01)	(0.02)	(0.05)	(0.02)	(0.08)	(0.03)

Origination Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Province FEs	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo *R*-squared	0.10	0.33	-7.93	0.10	0.04	0.07
Observations	447,955	447,955	61,229	61,229	17,968	17,968
Correlation between the residuals of the two equations	-0.004		0.002		0.04	
χ^2 test of zero correlation between the residuals	10.382		0.206		27.375	
p-value of the χ^2 test	0.001		0.650		0.000	

Table 5: Early Repayment

This table analyzes early repayment of loans in our main sample. The data include three types of individual business loans: big tech loans, Bank X online loans, and Bank X regular loans. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. All the loans matured at least by May 31, 2021, the last day of the loan performance period. Policy loans are excluded from the sample. Panel A reports the distribution of the ratio of payback time to loan maturity. Panel B reports the results from regressing the ratio of payback time to loan maturity on a set of variables. Big Tech (Online) is an indicator variable that is equal to one if the loan is a big tech (Bank X online) loan, and zero otherwise. In all the specifications, the benchmark group is Bank X regular loans. Loan origination month fixed effects, city × origination month fixed effects, and industry × origination month fixed effects are included in the corresponding specifications. Standard errors in parentheses are clustered at loan origination month. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A: Distribution of the Ratio of Repayment Time to Loan Maturity

	N	Mean	Std.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Big Tech	515,711	0.46	0.44	0.00	0.00	0.01	0.04	0.28	1.00	1.00	1.00	11.13
Online	74,921	0.74	0.37	0.00	0.03	0.10	0.48	0.96	1.00	1.00	1.00	18.48
Regular	21,253	0.77	0.32	0.00	0.06	0.18	0.60	0.93	1.00	1.00	1.00	2.54

Panel B: Regression Analysis of Early Repayment

	Repayment Time to Maturity	
Big Tech	-0.40***	-0.46***
	(0.01)	(0.01)
Online	-0.01	0.06***
	(0.01)	(0.01)
Interest Rate	-0.01	-0.03
	(0.06)	(0.04)
Log(Credit Limit)	-0.00	-0.00
	(0.00)	(0.00)
Loan Term: 6 months	0.04***	0.03***
	(0.01)	(0.01)
Loan Term: 12 months	0.00	-0.02*
	(0.01)	(0.01)
Loan Term: greater than 12 months	-0.12***	-0.06
	(0.04)	(0.04)
Repay Once	-0.13***	-0.09***
	(0.01)	(0.00)
Log(Age)		0.06***
		(0.01)
Male		-0.01***
		(0.00)
County		-0.01***
		(0.00)
Rural		-0.03***
		(0.00)
Ever_Clear_BigTech		-0.35***
		(0.01)
Exist_Clear_BigTech		0.11***
		(0.01)
Ever_OVD_BigTech		0.25***
		(0.04)
Has Large Deposit		-0.05***
		(0.00)
Industry × Origination Month	No	Yes
City × Origination Month	No	Yes
Cluster Variable	Origination Month	Origination Month
Adjusted *R*-squared	0.07	0.23
Observations	611,885	611,885

Table 6: Interest Rate and Credit Limit of Big Tech Loans

This table presents the analysis on how the big tech lender set interest rates and credit limits on the sample of big tech loans originated over the period of August 2019 to December 2020 with maturities of 6 months and 12 months. All the loans matured at least 30 days before May 31, 2021. The dependent variables are 100 times interest rates, the logarithm of credit amount, and 100 times the indicator on whether a loan is ever overdue at least 30 days. The following borrower variables are included in all the specifications but their coefficients are not displayed: whether a borrower has at least RMB10,000 in his or her deposit account at Bank X, the logarithm of borrower age, the gender of the borrower, whether the borrower is from county area, and whether the borrower is from a rural area. The linear terms of risk-related variables supplied from the big tech firm are included in even columns, but their coefficients are not displayed. City × loan origination month fixed effects and industry × loan origination month fixed effects are included in all specifications. Standard errors in parentheses are clustered at loan origination month. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	Big Tech Loans					
	Ever Overdue>=30 × 100		Log(Credit Limit)		Interest Rate × 100	
Ever Clear Big Tech Loan	-2.82***	-2.61***	0.18***	-0.03***	-0.31***	0.03
	(0.38)	(0.34)	(0.01)	(0.01)	(0.03)	(0.04)
Big Tech Loan Ever Overdue	6.99	3.01	-0.77***	0.00	2.82***	0.80***
	(8.34)	(8.74)	(0.1)	(0.05)	(0.35)	(0.23)
Ever Clear Bank X Loan	-0.22***	-0.37***	0.20***	0.10***	-0.06	-0.05
	(0.10)	(0.11)	(0.01)	(0.01)	(0.05)	(0.05)
Bank X Loan Ever Overdue	28.04	28.29	-1.15**	-0.45***	4.61***	2.62
	(24.8)	(25.08)	(0.51)	(0.09)	(0.89)	(1.62)
Interest Rate	6.11***	2.74***				
	(0.76)	(0.79)				
Log(Credit Limit)	-0.17***	0.13**				
	(0.04)	(0.05)				
Loan Term: 12 months	2.09***	2.08***				
	(0.16)	(0.15)				
Repay Once	-1.56***	-1.01***				
	(0.18)	(0.11)				
Risk Score Variables	No	Yes	No	Yes	No	Yes
Borrower Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Loan origination Month	Yes	Yes	Yes	Yes	Yes	Yes
City × Loan Origination Month	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted *R*-squared	0.03	0.04	0.14	0.56	0.04	0.24
Observations	453357	453357	453357	453357	453357	453357

Table 7: Convenience and Interest Expense

This table reports the summary statistics of the number of loans taken by each borrower, interest expense per loan, and interest expense per borrower during our sample period. The data include three types of uncollateralized business loans: Big tech loans, Bank X online loans, and Bank X regular loans. Policy loans are excluded from the sample. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. Loans in Panels B and C matured before May 31, 2021, the last day of our performance data. Panel A reports the ratio of interest expense to loan size, Panel B reports interest expense per loan, and Panel C reports the number of loans taken by each borrower.

Panel A: Interest Expense/Loan Size

	Count	Mean	Std.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Big Tech	515711	5.0%	5.5%	0.0%	0.0%	0.1%	0.4%	2.7%	8.1%	13.8%	16.2%	33.9%
Online	74921	4.5%	3.4%	0.0%	0.1%	0.4%	1.4%	4.0%	7.9%	9.3%	10.0%	18.1%
Regular	21253	5.9%	3.4%	0.0%	0.4%	1.0%	3.4%	6.1%	8.1%	10.0%	11.8%	20.1%

Panel B: Interest Expense Per Loan

	Count	Mean	Std.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Big Tech	515711	372	1001	0	0	1	7	61	320	969	1669	68772
Online	74921	4460	6075	0	6	96	454	2178	6618	13200	18740	60566
Regular	21253	6563	10319	0	16	321	1203	3699	7737	15000	23869	339549

Panel C: Number of Loans Per Borrower

	No. Borrowers	Mean	Std.	Min	5%	10%	25%	50%	75%	90%	95%	Max
Big Tech	140019	6	9.5	1	1	1	1	3	7	13	20	518
Online	49795	2.3	3.2	1	1	1	1	1	2	4	7	100
Regular	22115	1.6	1.8	1	1	1	1	1	1	3	4	61

Table 8: Overlapped Borrowers

This table presents the analysis on the overlapped sample of borrowers who borrow both big tech loans and at least one type of Bank X loan over the period of August 2019 to December 2020. The sample contains 58,481 individual business credit loans from 6,684 unique borrowers. Panel A presents the summary statistics of variables in this overlapped sample. The ratio of payback time over contract maturity is computed based on loans that matured before May 31, 2021, the last day of our loan performance data. The indicator variable on whether a loan is ever at least 30 days overdue is computed based on loans that matured at least 30 days before May 31, 2021. All the other variables in the panel are based on the full sample of 58,481 loans. Panel B presents summary statistics on the subsample of big tech loans classified by whether the borrower has a Bank X credit limit available at the time of taking a big tech loan. For the classification, we require the remaining Bank X credit limit to be larger than the corresponding big tech loan amount and the interest rates of the Bank X credit limit to be lower than the corresponding big tech loan. Panel C compares interest rates, credit limits, loan sizes, and payback speed. The indicator variable Regular (Online) indicates Bank X regular (online) loan. The benchmark group is big tech loans without credit available from Bank X defined above at the time of borrowing. The last column on the ratio of payback time over contract maturity is based on loans that are mature before May 31, 2021. Panel D compares the overdue payments. All the loans mature at least 30 days before May 31, 2021, with maturities no greater than 12 months. The dependent variable is 100 times the indicator on whether a loan is ever overdue at least 30 days. The subtitle indicates the subsample of loans used in the comparison analysis. For example, Columns 1 and 2 are based on borrowers with both big tech loans and Bank X regular loans. Borrower fixed effects are included and indicated in the corresponding column. Loan origination month fixed effects are included in all the specifications. In both Panels C and D, standard errors in parentheses are clustered at the loan origination month. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A: Summary Statistics

	No. of Borrowers	No. of Loans	Interest Rate	Credit Limit	Loan Size	Repay Once	Maturity	Payback to Maturity	No. of Loans Per Borrower	Ever Overdue >=30 days
Big Tech	6,684	42,548	14.5%	97,762	15,097	22.9%	10.0	41.4%	6.4	0.4%
Online	4,929	12,768	8.7%	169,447	82,916	75.3%	9.8	77.5%	2.6	0.9%
Regular	1,829	3,165	9.0%	179,186	125,293	66.1%	12.8	83.0%	1.7	1.5%

	Number of Loans	Number of Borrowers	Big Tech Loan Interest Rates	Interest rates on Bank X Credit Limit	Loan Size	Remaining Bank X Credit Limit	Loan Term	Payback to Maturity
With Credit Limit from Bank X	24302	4669	14.7%	8.3%	14493	171632	9.9	39.8%
Without Credit Limit from Bank X	18246	4356	14.3%	9.1%	15900	9840	10.1	44.3%

Panel C: Regression Analysis

	Interest Rates	Log(Credit Limit)	Log(Loan Size)	Payback to Maturity
Regular	-0.05***	0.95***	1.90***	0.23***
	(0.00)	(0.03)	(0.05)	(0.02)
Online	-0.05***	0.56***	1.46***	0.22***
	(0.00)	(0.02)	(0.02)	(0.01)
Big Tech × Bank X Credit Available	0.00***	-0.03***	-0.12***	-0.02***
	(0.00)	(0.01)	(0.01)	(0.00)
Loan Term: 6 months	0.00	0.13***	0.39***	-0.03**
	(0.00)	(0.02)	(0.02)	(0.01)
Loan Term: 12 months	-0.00***	0.22***	0.62***	-0.09***
	(0.00)	(0.01)	(0.02)	(0.01)
Loan Term: >=12 months	-0.02***	0.42***	0.99***	0.07**
	(0.00)	(0.04)	(0.04)	(0.03)
Repay Once	-0.01***	0.16***	0.08***	0.01
	(0.00)	(0.01)	(0.01)	(0.01)
Interest Rate			-0.23	-0.91***
			(0.37)	(0.14)
Log(Credit Limit)			0.66***	0.02***
			(0.02)	(0.00)
Borrower FEs	Yes	Yes	Yes	Yes
Origination Month FEs	Yes	Yes	Yes	Yes
Cluster Variable	Origination month	Origination month	Origination month	Origination month
Adjusted *R*-squared	0.81	0.77	0.63	0.65
Observations	58481	58481	58481	41824

Panel D: Comparing Payment Overdue

	Ever overdue >=30 days × 100			
	Big Tech vs. Regular		Big Tech vs. Online	
Regular	0.66*	-0.53		
	(0.38)	(0.45)		
Online			0.73**	0.13
			(0.34)	(0.33)
Big Tech × Bank X Credit Available	-1.04***	-0.57**	-0.42***	-0.15
	(0.23)	(0.26)	(0.16)	(0.19)
Loan Term: 6 months	0.89***	-0.66**	0.14	0.29*
	(0.35)	(0.30)	(0.29)	(0.17)
Loan Term: 12 months	1.79***	0.36	0.75**	0.71***
	(0.36)	(0.22)	(0.30)	(0.18)
Repay Once	-0.82***	0.08	-0.41**	0.39**
	(0.20)	(0.19)	(0.16)	(0.17)
Borrower FE	No	Yes	No	Yes
Origination Month FE	Yes	Yes	Yes	Yes
Cluster Variable	Origination month	Origination month	Origination month	Origination month
Adjusted *R*-squared	0.01	0.53	0.00	0.50
Observations	5724	5724	19365	19365

Table 9: The COVID-19 Shock

This table presents analysis on the performance of the lending programs under the COVID-19 shock. Panel A presents aggregate analysis on the supply of loans from November 2019 through April 2020. The analysis is at the loan type-geography-month level. The sample is based on a 10% random sample of three types of individual business credit loans: big tech loans, Bank X online loans, and Bank X regular loans. Geography includes two areas: Hubei province and all the other provinces combined. Ant (Online) is an indicator variable that is equal to one if the loan is a big tech (Bank X online) loan, and zero otherwise. In all specifications, the benchmark group is Bank X regular loans. Post-COVID-19 Shock is an indicator variable on whether the loan is originated on or after February 2020. Panel B presents the analysis on overdue rates for loans that are originated from January 2020 through March 2020. All the loans matured at least 30 days before May 31, 2021, the ending date of the loan performance data. Policy loans are excluded from the sample. The dependent variable in Panel B is 100 times the indicator on whether a loan is ever overdue at least 30 days. Borrower variables, loan origination month fixed effects, city × loan origination month fixed effects and industry × loan origination month fixed effects are included and indicated in the corresponding columns. Borrower variables include an indicator on whether a borrower has at least RMB10,000 in his or her deposit account at Bank X, the logarithm of borrower age, the gender of the borrower, whether the borrower is from a county area, whether the borrower is from a rural area, whether the borrower ever previously paid off a loan from the corresponding lending program, whether the borrower has an outstanding loan from the corresponding lending program, and whether the borrower was ever overdue at least 30 days on a loan from the corresponding lending program. Standard errors in parentheses are clustered at the loan origination month. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A: Provincial Credit Provision

	Log(Total Loan Amount)	Log(No. of Loans)	Fraction of New Borrowers	Average Interest Rate
Big Tech	-2.41***	1.19***	0.27***	0.08***
	(-0.22)	(-0.16)	(-0.06)	(0.00)
Big Tech × Post COVID-19 Shock	0.57	0.40	-0.11	0.00
	(-0.66)	(-0.48)	(-0.09)	(0.00)
Big Tech × Hubei	0.67**	0.57***	0.05**	0.00
	(-0.27)	(-0.11)	(-0.02)	(0.00)
Big Tech × Hubei × Post COVID-19Shock	0.08	0.13**	0.01	-0.01***
	(-0.09)	(-0.06)	(-0.02)	(0.00)
Online	-1.42***	-0.53***	-0.14***	0.02***
	(-0.14)	(-0.09)	(-0.01)	(0.00)
Online × Post COVID-19 Shock	0.53**	0.29*	0.06***	0.00
	(-0.23)	(-0.16)	(-0.01)	(0.00)
Online × Hubei	0.47*	0.40***	0.05***	0.00*
	(-0.26)	(-0.11)	(-0.01)	(0.00
Online × Hubei × Post COVID-19 Shock	-0.25	-0.15	-0.07***	-0.01*
	(-0.22)	(-0.12)	(-0.01)	0.00
Hubei FEs	Yes	Yes	Yes	Yes
Year-month FEs	Yes	Yes	Yes	Yes
Cluster Variable	Origination Month	Origination Month	Origination Month	Origination Month
Adjusted *R*-squared	0.95	0.98	0.88	0.99
Observations	36	36	36	36

Panel B: Loan Performance

	Ever Overdue >= 30 days*100			
Big Tech	2.01***	-0.85***	-0.88***	-2.21***
	(0.01)	(0.17)	(0.18)	(0.30)
Big Tech × Post COVID-19 Shock	-0.53***	-0.79**	-1.20***	-1.10***
	(0.18)	(0.35)	(0.26)	(0.17)
Online	-0.52***	0.92***	1.00***	0.91***
	(0.00)	(0.20)	(0.21)	(0.20)
Online × Post COVID-19 Shock	0.03	-0.13	-0.61*	-0.51*
	(0.24)	(0.42)	(0.35)	(0.30)
Loan Term: 6 months		-1.53***	-1.54***	-1.38***
		(0.44)	(0.48)	(0.52)
Loan Term: 12 months		0.45	0.41	0.62
		(0.59)	(0.61)	(0.66)
Repay Once		-2.20***	-2.16***	-1.80***
		(0.13)	(0.13)	(0.10)
Interest Rate				6.79***
				(1.27)
Log(Loan Size)				-0.40***
				(0.08)
Borrower Variables	No	Yes	Yes	Yes
Origination Month	Yes	Yes	No	No
Industry × Origination Month	No	No	Yes	Yes
City × Origination Month	No	No	Yes	Yes
Cluster Variable	Origination Month	Origination Month	Origination Month	Origination Month
Adjusted *R*-squared	0.00	0.02	0.03	0.03
Observations	191,616	191,616	191,616	191,616

Figure 1: Total loan amounts and average interest rates over time

This figure presents the total loan amounts (in millions of RMB) and average annualized interest rates over time. Panel A presents the total loan amounts over time, and Panel B presents the average interest rates of loans over time. The sample includes three types of individual business loans: big tech loans, Bank X online loans, and Bank X regular loans, respectively. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. Policy loans are excluded from the sample.

Panel A. Total loan amounts over time



Panel B. Average interest rates over time

