The Big Tech Lending Model*

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Abstract

By comparing uncollateralized business loans made by a big tech lending program with conventional bank loans, we find that big tech loans tend to be smaller and have higher interest rates and that borrowers of big tech loans tend to repay far before maturity and borrow more frequently. This lending program channels credit to small businesses underserved by banks without incurring excessive risks (even during the COVID-19 crisis). We highlight several mechanisms—screening, monitoring, convenience, and high interest rates—which work together to serve borrowers' short-term liquidity rather than long-term financing needs, thereby limiting the lender's risk exposure.

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Big tech companies across the world have started to offer lending services in recent years, either directly or in partnership with financial institutions. For example, Amazon, Apple, eBay, Google, and Paypal in the United States and Alibaba, Baidu, JD and Tencent in China all offer credit services. See Table 1 for a list of big tech firms that offer payment and credit services across the world. Aided by advantages in information, distribution, technology, and monitoring embedded in these big tech companies' ecosystems, the global 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)). While prior studies highlight the capacity of big tech lenders to provide credit and assist the business development of borrowers underserved or unserved by traditional banks (Luohan Academy Report (2019), Frost, Gambacorta, Huang, Shin, and Zbinden (2019), Cornelli et al. (2020), Huang, Zhang, Li, Qiu, Sun, Wang, and Berger (2020), Ghosh, Vallee, and Zeng (2021), Ouyang (2021), Gambacorta, Huang, Li, Qiu, and Chen (2022), Chen, Huang, Lin, and Sheng (2021)), several key questions remain. First, is big tech lending riskier than traditional bank lending? Is big tech lending robust to severe economic shocks that may create structural breaks to the risk assessment models used by big tech lenders? These questions represent the key concern of financial regulators about big tech lending. The recent evidence of fintech lending exacerbating borrower risk and drying up during the COVID-19 crisis makes this concern even more relevant.[1] Second, what are the likely mechanisms contributing to the performance of big tech loans?

We aim to address these issues by comparing big tech business loans made by the syndication of MyBank, a pioneer big tech lender to small and medium enterprises (SMEs) in China, with a large retail bank, which we refer to hereafter as Bank X for security reasons. China has the world's most active big tech lending—with a loan volume of $516 billion in 2019—which is about 90% of the global volume. MyBank is a subsidiary of Ant Group, whose major shareholder is Alibaba Group ("Alibaba" hereafter). Embedded in Alibaba's ecosystem, MyBank's borrowers are mostly SMEs and self-employed. Founded only in 2015, it had cumulatively lent to 35.07 million SMEs by 2020. The amount of MyBank's SME loans outstanding at the end of June 2020 is 421.7 billion

[1] Ben-David, Johnson and Stulz (2021) find that during the COVID-19 pandemic in March 2020, fintech lending to small businesses in the United States collapsed due to the drying up of loan supply as fintech lenders became financially constrained and lost 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.

RMB (or $61 billion), more than five times the amount of SME loans outstanding of 80.1 billion RMB at the end of 2020 by WeBank, its major big tech competitor in China. As the largest big tech lender in SME lending in the world, the loans made by MyBank may offer valuable insights about big tech lending, even though different big tech lenders may have different lending models determined by their access to different ecosystems and thus different pools of borrowers.

MyBank's lending is primarily funded by syndication with traditional banks. Bank X is one of MyBank's top syndication partners, and its syndicated loans with MyBank are representative of MyBank's syndicated loan portfolio across the country. In this syndication program, both banks contribute funding to each loan.[2] MyBank is responsible for acquiring borrowers, processing loan applications, and managing the loans after origination; it also recommends interest rates and credit limits to Bank X. The latter decides whether to accept a loan. Bank X evaluates the recommended interest rates and credit limits by MyBank and normally follows the recommendations.

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, including over 855,000 big tech loans. By comparing loans made by these three lending programs in the same month, city and industry, we can control for macroeconomic, regional, and industry conditions, in addition to borrower and loan characteristics in our analysis of big tech loans.

The big tech lending program in our sample serves borrowers with substantially more limited access to credit from other sources relative to Bank X's regular and online lending programs. The big tech loans are also 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%, with a range from 4.4% to 21.6%. In contrast, Bank X's uncollateralized regular loans have an average interest rate of 8.5%, with a range from 4.2% to 16.2%, and Bank X's online loans have an average interest rate of 8.6%, with a range from 4.2% to 18.0%. The uncollateralized credit

[2] According to the Chinese banking regulations, each institution in an online syndication loan must contribute at least 30% of the funding.

limit offered by the big tech lending program is less than half of that offered by Bank X's regular and online 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 by at least 30 days. The overall delinquency rate is 2.6% for the big tech loans, which is higher than the rate of 1.6% for the regular loans and 1.1% for the online 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 loans made to borrowers that have previously 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 regular and online loans. Our regression analysis confirms that the big tech lending program has a similar delinquency rate as the two conventional lending programs, despite its coverage of a pool of borrowers underserved or even unserved by traditional banks.

Our sample also covers the onset of the COVID-19 crisis in China in February 2020. We systematically compare the delinquency rate of loans originated before and after the start of the COVID-19 crisis. Interestingly, our analysis shows that the risk of the big tech loans remained stable, even slightly reduced, relative to Bank X's conventional loans after the onset of the COVID-19 crisis. This finding shows the robustness of the big tech lender's risk assessment model to a severe economic shock and is in sharp contrast to the aforementioned evidence in Footnote 1 that fintech loans exacerbated borrower default risk and became more fragile after the COVID-19 crisis started.

How does the big tech lending program manage to provide credit—without incurring greater risks—to a pool of borrowers that traditional banks are unwilling to cover? It is impossible to attribute this success to any single mechanism. Instead, we highlight that four mechanisms likely work together to facilitate this lending program. First, the two standard mechanisms—screening and monitoring—are both relevant to the big tech lending program. By using a wide range of data users leave in the digital platforms associated with the big tech lender's ecosystem such as borrowers' transactions and cash flows, the big tech lending program is able to assess the credit risk of a large pool of small businesses, which are underserved or unserved by traditional banks due to their lack of collaterals and well-documented incomes and cashflows in the standard financial system. As for monitoring, observing a borrower's financial transactions and other activities in the ecosystem also enables the big tech lender to monitor whether the borrower has used the borrower for the stated purpose. In addition, the threat of excluding a borrower from the lender's ecosystem also adds to the cost of default.

In addition to these two standard mechanisms, we also highlight two other mechanisms that are specific to the lending of fintech and big tech companies—convenience and high interest rates, which further strengthen the lender's screening of the borrowers. By seamlessly integrating the credit services with other activities in the big tech lender's ecosystem, the big tech lending program offers great convenience to the borrowers. Such convenience reduces the borrower's nonmonetary fixed cost and thus the overall cost of using the big tech loans, helping the lender to select borrowers with short-term liquidity needs who especially value convenience. In addition, the high interest rates of the big tech loans may also serve as a self-screening mechanism for borrowers with short-term liquidity needs. As interest costs grow with the financing period, using the big tech loans as long-term financing is particularly costly. As a result, borrowers may choose to use the big tech loans to meet short-term liquidity rather than long-term financing needs. These self-screening mechanisms are complemented by the monitoring and deterrence capabilities of the big tech lender to prevent borrowers from abusing the credit for excessive risk taking. In terms of risk, these self-screening mechanisms also help to reduce the duration of the lender's risk exposure.

Even though our data access does not allow us to isolate these mechanisms, we are able to provide evidence to highlight the presence of advantageous selection in the big tech loans, which likely reflects the joint effects of these mechanisms. Specifically, we adopt the correlation test proposed by Chiappori and Salanié (2000) to examine the presence of adverse selection in each of these lending programs. Each program allows an authorized borrower to take a loan within a credit limit at a specified interest rate. This setting permits us to test whether borrowers who choose to use up their credit limits are more likely to become delinquent later after controlling for all public observables. A positive correlation indicates that the borrower may either have private information about its future financial distress or use the credit to engage in excessive risk taking. Interestingly, even though this test shows evidence of adverse selection among Bank X's regular loans, we find advantageous selection in the big tech loans: borrowers who choose to use up their credit limits in the big tech lending program are less likely to become delinquent later. Such advantageous selection validates the effectiveness of the mechanisms used by the big tech lender to screen and monitor borrowers, and contrasts the finding of Chava et al. (2021) that fintech lenders in the United States face more-severe adverse selection than banks.

We also provide supportive evidence of the self-screening mechanisms by analyzing the repayment speed of the big tech loans. 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 in our main sample tend to be repaid far before the maturity date 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 the 61% for the regular loans and 48% for the online loans. This sharp difference is robust in regression analysis after controlling for loan and borrower characteristics, showing that borrowers are likely to use the big tech loans to meet short-term liquidity rather than long-term financing needs.

By analyzing a small set of big tech borrowers with access to Bank X's regular or online loans, we find that these overlapped borrowers may choose to use the big tech loans even when they have available credit lines from Bank X at substantially lower interest rates. By revealed preferences, this finding highlights the importance of convenience in overcoming the higher interest rates of the big tech loans. This sample of overlapped borrowers provides even sharper evidence of the self-screening mechanisms. When a borrower chooses to use a big tech loan when cheaper credit from Bank X is available, the big tech loan tends to be smaller in size, the borrower tends to repay the loan earlier, and the big tech loan tends to have lower repayment risk than when the cheaper credit is unavailable. These findings jointly confirm that such borrowers choose the big tech loans to meet their short-term liquidity rather than long-term financing needs, and the fast repayment, in turn, reduces the big tech lender's risk exposure.

The Related Literature

There have been extensive studies of fintech lending, as recently reviewed by Berg, Fuster, and Puri (2021) and Allen, Gu, and Jagtiani (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.[3] Yet, fintech lenders may not have an information advantage compared to

[3] 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

traditional banks that use soft information in lending.[4] Second, fintech lending mainly substitutes for bank lending, especially when banks are constrained, rather than targeting borrowers without access to regular bank credit.[5] Third, although technology may not necessarily allow fintech 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.[6] Fourth, fintech lending may worsen, rather than improve, the borrowers' financial health.[7] Fifth, fintech lending may not be robust to severe economic shocks such as the COVID-19 pandemic, as mentioned in Footnote 1.

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,

alternative data can be particularly useful in screening "invisible primes"—borrowers with low credit scores and short credit histories.

[4] 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.

[5] 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, that is, 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, although they have less income and education and are less likely to be 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 for 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.

[6] Fuster, Plosser, Schnabl and Vickery (2019) show that fintech lenders in the United States 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.

[7] 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 operation of 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.

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 tech lending. Ghosh, Vallee, and Zeng (2021) and Ouyang (2021) highlight the roles of mobile payments in facilitating credit inclusion using data from India and China. By using loan data from MyBank, 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. Gambacorta, Huang, Li, Qiu, and Chen (2022) 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 advertising expenses and sell new products. Our study adds to this literature by systematically examining the risks of big tech lending, its robustness to a large economic shock—the COVID-19, and the mechanisms that contribute to its performance. In addition to the standard screening and monitoring mechanisms, we highlight that convenience and high interest rates of the big tech loans help to further screen the short-term liquidity needs of small businesses underserved by traditional banks without incurring excessive risks.

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 was founded in 2015 as one of the earliest private banks in China. Its core business is lending to SMEs or self-employed vendors, many of whom do not even have basic business registration records with the government. Since its founding, 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 cumulatively lent to 35.07 million SMEs. The quick expansion of MyBank is crucially related to its major shareholder, Ant Group, and Ant Group's major shareholder, Alibaba. Ant Group owns Alipay, the world's largest digital payment platform, which serves over one billion users. Alipay served 80 million merchants in June 2020, and its total payment volume reached 118 trillion RMB during the 12 months preceding June 2020, which was more than 55% of online payment transactions in China. As for Alibaba, it operates one of the world's largest e-commerce platforms. In its founding year of 2015, MyBank mainly lent to online vendors on Alibaba's e-commerce platform. With the prevalence of digital payment, in 2017, MyBank expanded its business by lending to offline borrowers who use Alipay for payment services. In recent years, MyBank further lent to rural borrowers by cooperating with local governments and lent to borrowers along supply chains. Currently, lending to vendors on the Alibaba platform accounts for less than 15% of MyBank's loans, and the Alipay payment platform plays an important role in MyBank's lending in most of the remaining 85% of loans.

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 risk of its borrowers.[8] Such information includes a vendor's historical and current cash flows, ratings from its customers if it is on the Alibaba platform, industry information, as well as the profiles and digital footprints of its customers. 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

[8] Like fintech lenders, MyBank also uses alternative data from other sources in its risk assessments, such as wage bills, tax and social insurance information, and vendors' fee payment records.

from MyBank to show that the unconventional borrower information can complement or substitute for traditional credit records, which MyBank also uses in loan issuance, to substantially improve the assessment of credit risks of its borrowers, especially with the further help of machine learning techniques. 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 loans after origination. Since it is possible for MyBank to monitor the usage of the loans in the ecosystem, MyBank may detect and punish abnormal usage of loans unrelated to the stated purposes at loan origination, for example, if a borrower uses a loan from MyBank to pay back loans from other lenders rather than the originally stated purpose of meeting a business payment.

Third, MyBank offers a high level of convenience to its borrowers. Aided by 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 online (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 MyBank's ecosystem further enables it 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 a daily frequency,[9] and borrowers can repay their loans at any time online without any prepayment penalty. As the lending services of MyBank are seamlessly integrated with the Alipay platform and the Alibaba's e-commerce platform, a loan from MyBank can be directly channeled to transactions on these platforms. Such conveniences are especially attractive to borrowers with emergent and frequent liquidity needs.[10]

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.

[9] 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 repeated borrowing by big tech borrowers 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.

[10] Interestingly, as we will discuss in our later analysis, these conveniences may induce some borrowers to take a loan from MyBank even when they have credit available from other sources at substantially lower interest rates.

Moreover, with the help of technologies such as cloud computing and artificial intelligence, MyBank can quickly assess 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 to assess a borrower's credit risk, and this lending process may not scale up with the number of borrowers.

Finally, MyBank is more constrained in funding than traditional banks. As an online bank, MyBank faces more restrictions in collecting deposits, which are the most important funding sources for traditional banks. MyBank is not allowed to issue asset-backed securities, tier-2 capital bonds, or perpetual bonds in the interbank market.[11] As a result, MyBank has developed extensive syndicated lending programs with traditional banks.

B. Syndicated Big Tech Loans

MyBank started to provide syndicated loans in June 2018. By the end of 2021, it had collaborated with more than 40 banks. Our data cover a syndication program between MyBank and one of its leading syndication partners, Bank X, which is a leading bank in lending to SMEs in China. Bank X offers banking services in almost all cities and counties in China.

In the syndication lending program, both MyBank and Bank X contribute funding to the loans, and the losses in the case of default are proportional to the funding. MyBank is responsible for acquiring borrowers, processing loan applications, and managing the loans after origination. After receiving an application, MyBank produces proprietary risk assessments and recommends loan terms, such as interest rate and credit limit, to Bank X.[12] After receiving the recommendation from MyBank, Bank X combines its own information with the information from MyBank to determine whether to accept or reject the loan application. Bank X mainly rejects loan applications that they determine to be highly risky; whether the applicant is its own client in other lending programs is not a major factor in this decision.[13] Bank X also evaluates the recommended interest rates and credit limits and normally follows the recommendations from MyBank. After the application is

[11] According to banking regulations in China, private banks, like MyBank, are allowed to have a maximum of one physical branch in the headquarters city, and they are prohibited from setting up any branch elsewhere. While private banks can collect deposits by setting up online accounts for clients, such online accounts are severely restricted in the maximum amount of deposit and transfer. For example, deposit to or transfer from an online account is capped at a maximum of 10,000 RMB per day, and a maximum of 200,000 RMB per year.

[12] While a credit report is part of the borrower information that MyBank uses to produce its proprietary risk assessments and recommended loan terms, a credit report does not reveal the lenders of an applicant's other loans. Thus, MyBank may not know whether an applicant has previously borrowed from Bank X.

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

approved, the borrower can borrow within the credit limit. The credit limit and interest rate are updated a couple of times each month based on new 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 at loan origination. As punishment for deviation, MyBank may choose to terminate the current credit line and reject the borrower's future loan applications. Last, MyBank is also responsible for restructuring loans or dealing with delinquent borrowers.

Even though our data sample covers only loans made by one big tech lending program, this program shares several features that are common to other big tech lending programs across the world. Table 1 lists over 20 big tech lending programs in China, the U.S., Latin Amaerica, Korea, Japan, Southeast Asia, India, and Africa. All of these lending programs are related to online payment or other services provided by big tech firms. All of these programs, except Square Capital in the U.S., offer consumer loans or credit cards. Most of these programs also offer SME loans, which are the focus of our analysis. It is common for these programs to target platform users by offering certain lending products exclusively to platform users. It is also common for these programs to collaborate with banks for funding, just like the lending program covered by our sample. These programs also allow only small credit limits and short loan maturities. The typical maturity is 12 months, and only four programs allow maturities longer than 12 months.

C. Conventional Bank Loans

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 about half a day. The bank assesses the borrower's risk based on machine learning models that combine the bank's proprietary information, such as savings 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 needs to sign a specific loan contract each time it takes out a loan and can repay the loan without any prepayment penalty. The borrower can borrow any amount within the limit. In particular, there is no restriction on the minimum size of a loan. There is no extra service fee either. Upon the expiration of the credit limit, the borrower can typically renew it provided that she repays the previous loans on time. Both the regular and online loans are part of Bank X's conventional lending. By comparing loans made by the three lending programs in the same month, city, and industry, we can control for macroeconomic, regional, and industry conditions in our analysis of the big tech loans.

II. Summary Statistics

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 recommends to Bank X for syndication is representative of its overall loan portfolio. Bank X's regular and online loans are independently originated. 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 through December 2020.[14] August 2019 was 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 analysis, which we analyze in this section. Even though this sample period is relatively short, the sample covers a large number of loans and is sufficiently large to compare the differences between the three lending programs. Furthermore, this sample also nicely covers the start of the COVID-19 crisis in February 2020 and thus allows us to analyze the impacts of this large economic shock on the big tech lending program. A small set of big tech borrowers also took business loans from either Bank X's regular or online lending program. We also analyze a sample of such overlapped borrowers in a later section. In this section, we report summary statistics of borrowers and loans in our main sample.

[14] 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.

A. Borrower Characteristics

Table 2 reports basic borrower characteristics to show that borrowers of big tech loans in our sample are substantially different from borrowers of Bank X's regular and online loans. The information about borrower characteristics is from the credit reports voluntarily provided by 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.[15] The substantially smaller fraction of big tech borrowers with credit reports reflects a selection bias that borrowers with a more-limited or poor credit history are less likely to voluntarily provide credit reports in their credit applications, hence the population of big tech borrowers is likely to have worse credit records and more-limited credit access.

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 are 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 vendors in the Alibaba e-commerce platform 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 the online and regular loan borrowers, which are 79% and 83%, respectively.[16] 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% for the online and regular loan borrowers.

[15] While credit reports were used in the risk assessment of all of the big tech borrowers, only those who had voluntarily provided credit reports in their credit applications were available to us.

[16] 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, although 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.

Panel B reports the fraction of borrowers in each group that 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 includes 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. Despite the selection bias for big tech borrowers with no alternative credit to not provide their credit reports, the total loan amount per big tech loan borrower (for those who had provided their credit reports) is 334,152 RMB, which is only 24.0% of the total loan amount taken by an average online loan borrower and 40.7% of that taken by an average regular loan borrower. This total amount is further 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 2 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 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 confirming the argument made by the existing studies referenced in the introduction that big tech lending promotes financial inclusion.[17] Furthermore, given that the big tech borrowers have worse credit records and more-limited credit access, they are likely riskier. This leads to the aforementioned concerns by policymakers and the public about the risk of the big tech loans, which we systematically examine later.

B. Loan Characteristics

In Table 3, we summarize the basic terms of the loans in our main sample, which cover loans made to 10% of borrowers from 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 rates, credit limits, loan sizes, and loan maturities solely for uncollateralized loans, which is the focus of our analysis.

Table 3 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 mainly covers borrowers without collateral to qualify for conventional bank loans, as highlighted by Gambacorta et al. (2022). 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 borrowers with strong credit records, 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

[17] These results also contrast the studies of fintech lending, which tend to find that 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 markets in China and find that fintech borrowers have more car loans, mortgages, and credit access than bank borrowers.

rates is already 9%, higher than the median interest rate of 8% for both the regular and online loans. The higher interest rates of big tech loans may reflect that the big tech borrowers are riskier and are different from the borrowers of the regular and online loans. We shall examine whether this is the case in our later analysis.

Third, Panels A and C show that the big tech program offers an average uncollateralized credit limit of 71,963 RMB, 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.

Fourth, Panels A and D further show that the average size of uncollateralized big tech loans is 8,367 RMB, which is only 11.6% of the average credit limit.[18] This fraction is much lower than the ratio of 56.8% and 65.4% for Bank X's online and regular loans.[19] This contrast reveals that despite the limited credit access of big tech borrowers, their take-up ratio of the big tech credit line is low, possibly due to the high interest rates.

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

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 characteristics of 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.

[18] 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 has more small loans.

[19] 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.

III. Risk

A key question that concerns both policymakers and the public is whether big tech lending is riskier than traditional bank lending. 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)). These findings about fintech lending thus motivate the following hypothesis about the risk of big tech lending:

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. As the borrowers covered by the big tech lending program are largely different from the borrowers of Banks X's conventional lending programs, our analysis cannot address whether the big tech lender has advantages or disadvantages relative to Bank X. Instead, the aim of our analysis is to use the performance of Bank X's regular and online loans as controls to examine whether the big tech lender is able to cover its targeted borrowers without taking greater risks. As these lending programs cover a large number of uncollateralized loans across the whole country over the same period, we can compare loans made in the same month, city, and industry, thus controlling for macroeconomic, regional, and industry conditions.

We measure the repayment risk of a loan by its payment being overdue for at least 30 days.[20] In Table 4, we analyze the performance of the three types of loans in terms of the likelihood of being ever overdue for at least 30 days.[21] 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 4, this sample includes 454,407 big tech loans, 68,817 online loans, and 19,335 regular loans.

We report the summary statistics of payments overdue in Panel A. The overall rate of payments overdue is 2.6% for the big tech loans, 1.1% for the online loans, and 1.6% for the

[20] 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.

[21] 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.

regular loans.[22] The highest overdue rate—for big tech loans—is consistent with big tech borrowers having the worst credit quality. The lowest overdue rate—for Bank X's online loans—reflects the 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.[23] 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? Panel A shows that the overdue rate of the big tech loans for borrowers 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 for loans with repayment records across the three groups.

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. These fixed effects control for the macroeconomic, regional, and industry conditions. 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

[22] From Ant's IPO disclosure, the 30 days overdue rate of MyBank's SME loans in the first seven months of 2020 ranged from 2.06 in Janurary 2020 to 2.72% in June 2020. The numbers thus confirm the representativeness of our sample over MyBank's overall portfolio.

[23] 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.

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 4 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 and loan characteristics and macroeconomic, regional, and industry conditions. This finding contrasts with the aforementioned evidence of a greater risk for fintech lending. This result is surprising as borrowers of the big tech loans tend to have more uncertain businesses and lack verifiable financial statements to qualify for cheaper loans from traditional banks.

IV. The COVID-19 Crisis

Is big tech lending 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, and thus allows us to examine the performance of the big tech lending program after the COVID-19 shock. It is not clear whether big tech lending would be robust to the COVID-19 shock ex ante. As big tech lending is largely based on behavioral patterns uncovered from historical data, an important concern is that large economic shocks, like the COVID-19 shock, may generate a structural break in the economy and thus invalidate model predictions that are based on historical data. Corroborating to this concern, recent studies by Ben-David et al. (2021) and Bao and Huang (2021) show that fintech lending in both the United States and China during the COVID-19 crisis was not as robust as bank lending.

Table 5 compares the overdue rate of loans issued from January through 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 the Chinese New Year is celebrated in February, and the number of regular and online loans issued by Bank X is normally low due to the holiday season.[24]

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

In all the columns of Table 5, the dependent variable is whether a loan is at least 30 days overdue, and the benchmark group is Bank X's regular loans.[25] 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 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 just 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.

One natural concern is whether the result above is a result of the big tech lender reducing its loan origination than the benchmark lending program after the COVID-19 shock. Figure 1 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 also happened to be the month of the Chinese New Year, Bank X's loan issuance might have shrunk for seasonal reasons related to the national holiday. In addition, the amount of big tech loans originated in March 2020 after the COVID-19 shock increased relative to January 2020 before the COVID-19 shock, while the amount of Bank X's regular loans, the benchmark group in Table 5, decreased slightly in March 2020 relative to January 2020. Overall, the amount of loan origination does not explain the difference in the risk performance after the COVID-19 shock.

Overall, results in this section show that the big tech lending program remained robust to the COVID-19 shock in terms of both the amount of loans originated and loan performance. Thus,

[25] Note that our measure of loans overdue for more than 30 days is immune from the government policy that changed the definition of non-performing loans to encourage banks to extend loan repayment from business owners after the COVID-19 shock.

despite the unprecedented economic stresses brought by the COVID-19 pandemic, the big tech lending program managed to provide financing without incurring greater delinquency risks.

V. Mechanisms

How does the big tech lender manage to make loans, without incurring excessive risks, to a pool of borrowers that traditional banks are unwilling to cover? To accomplish this challenging task, it likely entails more than any single mechanism. In this section, we discuss a set of mechanisms that are potentially relevant to the big tech lending program covered by our sample. There are at least four mechanisms.

The first is the screening of borrowers permitted by the unique data access of the big tech lender to a set of potential borrowers in its ecosystem. By using a wide range of data users leave in the ecosystem such as borrowers' cash flows, the big tech lender is able to assess their risks and screen those credit-worthy ones. This is a standard mechanism well recognized as important for lending. While traditional banks may assess a borrower's risk by using both hard information (such as a borrower's income and credit history) and soft information (from a loan officer's interactions with the borrower), data limitations prevent banks from covering certain clienteles such as small firms that lack verifiable income and credit records, and the fixed costs of personal interactions also prevent banks from collecting soft information about the small firms. This gap in the information access of traditional banks provides an opportunity for the big tech lender to fill. By using the high-dimensional data users accumulate in digital platforms, big tech lenders may be able to cover a pool of potential borrowers outside the coverage of traditional banks.

The second mechanism is another classic one—monitoring. By observing a borrower's financial transactions and other activities on the platforms, the big tech lender may be able to determine whether the borrower has used the borrowed fund for the stated purpose and, in the event of default, whether the borrower fails to repay the debt because of the lack of willingness or financial capability. The threat of potentially excluding a borrower from the lender's digital platforms also adds to the cost of default, in addition to the usual costs in reputation and future access to credit markets. This monitoring mechanism may complement the screening mechanism and provides at least some discipline to a credit-worthy borrower from abusing its credit access to engage in excessive risk taking. While in traditional bank lending, loan offices may use personal visits to exert direct monitoring of a borrower, such monitoring activities are costly. The rise of digital platforms makes it possible for big tech lenders to monitor—at a low marginal cost—a large number of borrowers outside the traditional bank system.

In addition to these two standard mechanisms, there are two other mechanisms that are particularly associated with the lending of fintech and big tech companies. Both of them help to screen borrowers with short-term liquidity needs, thereby limiting the duration of the lender's exposure to borrower risks. One such mechanism is convenience. By seamlessly integrating the credit services with other business activities in the big tech lender's ecosystem, the big tech lending program offers great convenience to its borrowers. A borrower may not only receive the borrowed fund very quickly in a few seconds but also use the fund directly in the system without taking any additional transfers. Such convenience reduces the borrower's nonmonetary fixed cost and thus the overall cost of using the big tech loans, helping the lender to select borrowers with short-term liquidity needs and thus particularly valuing convenience.

The high interest rates of the big tech loans may also serve as a self-selection mechanism for borrowers with short-term liquidity needs. As interest costs grow with the financing period, the interest cost of using the big tech loans as long-term financing would be particularly high. As a result, those borrowers who expect to repay quickly are more willing to accept the high annualized interest rates of big tech loans. That is, borrowers may self-select to use the big tech loans to meet short-term liquidity rather than long-term financing needs. Such a self-screening mechanism may rely on the big tech lender's monitoring and deterrence capabilities to prevent borrowers from abusing the credit for excessive risk taking and thus to ensure the borrowers' intention to repay when taking the credit. The convenience of big tech loans may also facilitate this self-selection mechanism by reducing the fixed cost of using the big tech loans and thus making the variable interest cost the most relevant factor at the margin.

Even though our data do not allow us to fully identify these mechanisms, we will provide some evidence to support these mechanisms. Some of the evidence is more forceful, while some is more suggestive.

A. A Test of Adverse Selection

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 future financial distress, and may abuse its credit access to engage in excessive risk taking. If so, the borrower's choices of the timing and the amount of the credit line used may reflect their private information and excessive risk taking. 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 adopt this correlation test to examine the presence of potential adverse selection in each of the three lending programs covered by our data sample.

Specifically, we test whether there is a positive conditional correlation between a dummy variable on whether a borrower had their 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 the borrower's private information at the time of taking a loan or the borrower's private action after taking the 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 payments overdue, this conditional correlation indicates either the presence of private information by the average borrowers at the time of taking the loans or excessive risk taking by the borrowers after taking the loans, and we broadly interpret such a positive correlation as a reflection 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 their credit limit at the time of borrowing. These Probit regressions share the same set of independent variables, including loan contract variables, borrower characteristics variables, and dummy variables on borrower industry, borrower province, and loan origination month.

The first pair of columns in Table 6 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. Surprisingly, there is a small but negative conditional correlation of –0.004 between whether the borrower uses up their credit limit and whether the loan becomes at least 30 days overdue ex post. This negative correlation indicates advantageous selection rather than adverse selection. The following pair of columns report the results for Bank X's online loans. The correlation coefficient is positive but insignificant, indicating no adverse selection. The last two columns report the results for Bank X's 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.

Overall, Table 6 shows a sharp contrast between the big tech lending program and Bank X's regular loan program—there is clear evidence of adverse selection in Bank X's regular loans but the opposite in the big tech loans. The significantly negative correlation in the residual test of the big tech loans indicates the presence of advantageous selection in the big tech loans.[26] That is, when a big tech borrower chooses to use up its credit limit from the big tech lending program, it is less likely to face financial distress or take on excessive risk. The lack of evidence for adverse selection in the big tech loans contrasts with the recent study of Chava et al. (2021), which shows that in marketplace lending in the United States, fintech lenders face more-severe adverse selection than traditional banks.[27]

B. Early Repayment

The borrowers' repayment speed provides a useful dimension to examine how borrowers use the loans, which is, in turn, relevant for the risks of the 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 3, the three types of loans in our sample have similar maturities, with 6 and 12 months as the two typical loan maturities. A borrower has the option to repay the loan early without any penalty. If the borrower takes a loan to fund their 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. Similarly, if the borrower borrows beyond their means, as documented for some fintech lending (e.g. Di Maggio and Yao (2021)), they cannot repay early either. In contrast, if the borrower takes the loan to meet their short-term liquidity needs, the borrower is likely to repay the loan ahead of schedule.

We analyze early repayment by the three groups of borrowers in Table 7. To facilitate the comparison, we impose a filter to include only loan contracts that matured before May 2021, the

[26] Pelosi (2021) has proposed a mechanism of advantageous selection, through which a negative correlation between loan size and loan default arises because safer borrowers with a larger loan demand conduct more-intensive searches for cheaper loans. This mechanism is more applicable to the cheaper loans from Bank X rather than the more expensive big tech loans. It cannot explain our finding of the negative correlation between the use up of the credit limit and loan default for the big tech loans. As we will show in the next subsection, the tendency of borrowers with short-term liquidity needs to take up the big tech loans may provide a mechanism for advantageous selection.

[27] 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.

month when our loan performance data ended. 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 within 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.[28] In contrast, 25% of the online loans are repaid within 48% of the loan maturity, and 25% of the regular loans are repaid within 61% of the loan maturity. At the median, 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.[29] Taken together, Panel A shows that the big tech loans are repaid substantially earlier than the scheduled maturity and much quicker than 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. We regress the ratio of repayment time to loan maturity on a list of variables, including two loan type dummies for big tech loans and Bank X' online loans. This specification thus treats the ratio of Bank X's regular loans as the baseline. We also include other loan characteristics, 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 further 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.

[28] On the left side of the distribution, 5% of the big tech loans are repaid on the same day, and 10% are repaid within 1% of the loan maturity. As there are over half a million loans in this sample, such extremely fast repayments are unlikely due to data entry errors or borrowers experimenting with the new borrowing app. As we will show later, the big tech borrowers on average take six loans in our short sample period of 17 months, and 5% of the big tech borrowers even take more than 20 loans. We also find a positive correlation between fast repayment and the frequency of borrowing, which is consistent with the borrowers taking the loans to meet their short-term liquidity needs.

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

Taken together, Table 7 shows that the big tech loans are repaid much earlier than the scheduled maturity and bank loans. 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. Instead, it is more likely that borrowers use big tech loans to meet their short-term liquidity needs.

As fast repayment reduces the big tech lender's risk exposure, from the perspective of risk management, it is beneficial for the lender to serve the borrowers' short-term liquidity needs. The lender's unique data access makes it possible to identify the borrowers' short-term liquidity needs. For example, the lender may be able to determine the needs of online vendors on the Alibaba e-commerce platform right before major holidays. By analyzing patterns in the vendors' cashflows, the lender may be able to predict when they need funds to pay for supplies and whether and when they are likely to repay their loans through future cash flows from customers. Even when the lender can identify the borrowers' short-term liquidity needs to some extent, there is still an important issue about whether a borrower may abuse the credit extended by the lender to take excessive risk unrelated to its usual business. As we discussed earlier, the big tech lender covered by our sample has certain capacities to monitor the borrowers' business transactions and loan usage in its ecosystem. The threat of excluding a borrower, upon default, from the lender's ecosystem also adds to the costs of default, thus serving as a deterrence to such potential abuses. Relatedly, as we discussed earlier, the high interest rates may also serve as a self-screening mechanism for borrowers with short-term liquidity needs.

Another screening mechanism is the convenience of the big tech lending. As short-term liquidity needs tend to have quick borrow-and-repay cycles, the convenient process provided by the big tech lending program is particularly appealing to borrowers with such liquidity needs. 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. As the loans from MyBank are seamlessly integrated with the Alipay platform and Alibaba's e-commerce platform, this convenience enables a borrower to instantly take a loan to meet their funding needs without any delay. In contrast, it may take a borrower quite some time and effort to make an appointment and pay a visit to a bank branch to borrow a traditional bank loan. As we will show in the next subsection, convenience may even motivate some borrowers to use the big tech loans even when they have access to credit from Bank X at substantially lower interest rates.

Panel A of Table 8 reports the interest expense of the loans made by the three lending programs. Because of the big tech loans' small size and fast repayment, the average interest expense per loan is only 372 RMB. The median interest expense is only 61 RMB, and the 75th percentile of interest expense is only 320 RMB. Such low interest expenses make the convenience of the big tech loans particularly appealing to the borrowers. By comparison, consistent with Bank X's conventional loans being more likely used to fulfill longer-term financing needs, the repayment speed is much slower as shown by Table 7. The average interest expense per loan is 4460 RMB for Bank X's online loans and 6563 RMB for Bank X's regular loans, much higher than the interest expense of the big tech loans.

By enabling borrowers to borrow funds whenever needed and to repay immediately whenever new cash flows become available, the big tech lending program saves the borrowers the need to keep liquid funds to stand by liquidity needs. This feature in turn helps attract borrowers with short-term liquidity needs. Panel B of Table 8 reports the number of loans taken by each borrower during our sample period of 17 months from August 2019 through 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 again reflects the borrowers' self-selection to use the big-tech loans to meet their short-term liquidity rather than long-term financing needs.[30]

C. Overlapped Borrowers

Our data also covers a small set of overlapped borrowers who had access to both the big tech loans and Bank X's conventional loans. This sample of overlapped borrowers allows us to compare the terms and performance of different loans made to the same borrowers and thus sharpens our analysis on several fronts. First, we provide direct evidence of convenience in driving some borrowers to use the big tech loans even when they have access to credit from Bank X at substantially lower interest rates. Second, we show the borrowers' self-screening in using the big

[30] 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 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 to meet their short-term liquidity needs.

tech loans to meet short-term liquidity needs, resulting in lower risk. Third, we also provide some evidence of the big tech lender's information advantage over Bank X in covering these borrowers.

In Table 9, we compare the terms and performance of the big tech loans with Bank X's regular and online loans, all made to the full set of overlapped borrowers in Bank X's database that have taken not only the big tech loans but also at least one online loan or regular loan from Bank X in our sample period. Panel A presents summary statistics of the overlapped borrowers. The sample contains 6,684 unique borrowers, who took a total of 42,548 big tech loans. Among these borrowers, 4,929 took a total of 12,768 online loans from Bank X, and 1,829 took a total of 3,165 regular loans from Bank X.[31]

Interestingly, Panel A of Table 9 shows very similar patterns in the loan terms as Table 3. 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. 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 see that the big tech loans are repaid much faster than the conventional loans from Bank X. Specifically, the average repayment time for 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 taken, on average, 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 they took during the same period. Overall, the smaller loan size, faster repayment, and repeated borrowing suggest that, 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 bank loans.

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%

[31] 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.

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 4 for our main sample because the overlapped borrowers tend to have better credit quality.

As shown in the summary statistics above, the big tech loans have much higher interest rates relative to Bank X's loans extended to the same borrowers. Why do these borrowers still use the big tech loans? A simple argument is that they may not have any remaining credit line from Bank X when a financing need arises. To address this argument, Panel B classifies 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. 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%. Although we expect the borrowers to strictly prefer loans with lower interest rates, this panel shows that this is not the case. Instead, by revealed preferences, this finding directly supports the presence of other nonmonetary factors—convenience—in motivating these borrowers to use the big tech loans despite their substantially higher interest rates than the readily available alternative credit.[32]

Next, we further examine what the overlapped borrowers might have used the big tech loans for. In Panel C of Table 9, we pool together all of the loans taken by the overlapped borrowers and regress four basic loan characteristics, including interest rates, log of credit limit, log of loan size and the ratio of payback time to loan maturity, on the interaction term between an indicator for big tech loan and another indicator for whether the borrower has cheaper credit available from Bank X at the time of taking the big tech loan. We also include borrower fixed effects to control for borrower heterogeneity and origination month fixed effects to control for macroeconomic conditions. The regression results confirm the summary statistics reported in Panels A and B. The regular and online loans from Bank X have significantly lower interest rates, higher credit limits, larger loan sizes, and slower repayment speeds relative to the big tech loans. In particular, the

[32] If the borrower takes a loan from a traditional bank, it may take a few hours or even longer for the funds to be transferred to the borrower's bank account. The delay may force the borrower to suspend a business transaction in the middle of the process. When the funds arrive, the borrower may have to restart the process from the beginning. Thus, the instantaneously available funds from the big tech lender and the seamless integration of the borrowing process with the transactions on the Alipay platform and Alibaba's e-commerce platform can be particularly valuable.

coefficient on the interaction term of the two indicators is significantly negative in the last two columns for the log of loan size and the ratio of payback time to loan maturity, indicating that if a borrower chooses to use a big tech loan when cheaper credit from Bank X is available, the big tech loan tends to be smaller by 12% and the borrower tends to repay the loan earlier by 2% of the loan maturity than when the cheaper credit is not available. These results thus confirm that the overlapped borrowers' self-selection to use the big tech loans to meet their short-term liquidity needs. As they expect themselves to repay the loans quickly, the higher annualized interest rates are less of a concern.

We formally analyze the repayment risk of the big tech loans taken by the overlapped borrowers in Panel D of Table 9. The dependent variable is the indicator variable on whether a loan is at least 30 days past due in all the columns. The first two columns include only borrowers with both big tech loans and regular loans from Bank X and the benchmark group is the regular loans from Bank X. Similarly, the last two columns include only borrowers with both big tech loans and online loans from Bank X and the benchmark group is the online loans from Bank X. The coefficient on the big tech loan indicator in each column compares big tech loans without a cheaper credit line available from Bank X with the corresponding benchmark group. 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 big tech loans without a cheaper credit line available from Bank X is lower by 0.66% than Bank X's regular loans, and lower by 0.73% relative to Bank X's online loans. Yet, Columns 2 and 4 show that after including borrower fixed effects, there is no significant difference in the overdue rates, implying that the borrowers do not show any preferences among these different loans when they run into financial distress in repaying their loans. Thus, in this sample of overlapped borrowers, there is not any significant difference in monitoring after loan origination between the big tech lending program and the two conventional lending programs of Bank X. That is, we expect traditional banks to have strong monitoring capacities through their long-term relationship with and other services they provide to borrowers, and the big tech lender has a similarly strong monitoring capacity over the overlapped borrowers.

More importantly, in Column 1, the overdue rate of the big tech loans taken by the overlapped borrowers between the big tech lending program and Bank X's regular lending program, when cheaper credit from Bank X credit is available is 1.04% lower relative to the big tech loans taken when the cheaper credit is unavailable. This difference is highly significant. It remains significant, albeit smaller, after including borrower fixed effects in Column 2. This difference for the sample of overlapped borrowers between the big tech lending program and Bank X's online lending program is 0.42% and significant in Column 3 but becomes insignificant after including borrower fixed effects in Column 3. Overall, the lower risk of the big tech loans taken when cheaper credit is available again confirms the self-selection mechanism. When a borrower chooses to use a big tech loan despite its substantially higher interest rate than the alternative, the borrower is likely to use the loan for short-term liquidity and thus will repay quickly. The fast repayment in turn reduces the lender's risk exposure.

Finally, we use the different loans made to the same overlapped borrowers to examine the information advantage of the big tech lending. We analyze whether the loan terms provided by the big tech lending program are more correlated with whether a borrower later ran into financial distress (i.e., being delinquent on at least one of its loans). Specifically, we compare the differences in credit limit, interest rate, loan size, and the number of loans between borrowers who become delinquent for at least 30 days ex post on at least one loan and the other borrowers who never become overdue on loan payments in Panel E of Table 9. We label a borrower as overdue regardless of whether the borrower becomes overdue on a big tech loan or a loan from Bank X. This setting allows us to control for the differences in monitoring after loan origination between the lending programs, and thus focus on differences in the screening of borrowers. We only keep loans originated before the first payment overdue of each borrower because the overdue information may affect subsequent loan originations and loan terms. We average and aggregate credit limit, interest rate, loan size, and the number of loans for each borrower-lending program, so the level of analysis is at the borrower-lending program level. We include borrower fixed effects to control for the differences in borrowers to focus on differences in lending programs. The key coefficient is the interaction term between the big tech indicator and the borrower overdue indicator.

The first four columns in Panel E of Table 9 include only borrowers with both big tech loans and regular loans from Bank X during the sample period, and the last four columns include only borrowers with both big tech loans and online loans from Bank X. In Columns 1 and 2, there is no significant differences between the big tech lending program and Bank X's regular lending program in terms of the association of credit limit and interest rate with ex-post borrower overdue. In Columns 5 and 6, relative to Bank X's online lending program, the credit limit from the big tech lending program is smaller, and the interest rate is higher for borrowers that run into distress ex post, suggesting that the big tech lending program has information advantage relative to Bank X's online lending program, but similar to Bank X's regular program which may use more soft information in lending. Interestingly, in Columns 3 and 7, relative to Bank X's regular and online lending programs, the size of big tech loans is smaller for borrowers who run into distress ex post, while there is no difference in the number of loans in Columns 4 and 8.

Overall, our analysis of the overlapped borrowers shows that some borrowers prefer to use the big tech loans even when they have access to cheaper credit from Bank X, revealing the advantage of big tech lending in convenience. Such convenience, in combination with high interest rates, helps the big tech lender to screen borrowers with short-term liquidity needs. We also provide evidence that the big tech lending program may have some information advantages over the overlapped borrowers relative to bank X's online lending program.

VI. Conclusion

By comparing a sample of big tech business loans made by a pioneer big tech lending program in China with a sample of conventional bank loans, we characterize several key features of the big tech lending: big tech loans tend to be smaller with higher interest rates, and borrowers tend to repay far before maturity and borrow more frequently. These sharp patterns suggest that big tech loans mainly serve the short-term liquidity needs rather than the long-term financing needs of the borrowers in its ecosystem. Interestingly, the high interest rates and the convenience of the big tech lending may help select borrowers with short-term liquidity needs, which in turn limits the exposure to borrowers' risks. These mechanisms, in addition to the lender's screening and monitoring capacities facilitated by its technology and ecosystem, help the big tech lender to provide credit to borrowers in its ecosystem that are underserved by traditional banks, without experiencing more-severe adverse selection or incurring greater risks than banks even during the COVID-19 crisis.

Interestingly, the key features of the big tech lending, smaller loan sizes, higher interest rates, and faster repayment and repeated borrowing of borrowers, remain the same for big tech loans made to borrowers with access to bank credit. Our findings motivate a nuanced view of the restrained advantages of big tech lending: the big tech lender may have unique advantages in providing credit services to a set of borrowers underserved or unserved by traditional banks, but such credit services target the borrowers' short-term liquidity needs rather than long-term financing needs, inside the big tech lender's ecosystem. Such big tech lending thus resembles leasing and financing that large manufacturing firms provide to downstream firms for purchasing their own products (e.g., Murfin and Pratt (2019)) and lending by homebuilders' finance arms to finance buyers' home purchases (e.g., Stroebel (2016)), even though the scale of credit services covered by big tech lenders can be substantially wider than that by manufacturing firms and homebuilders. This big tech lending model—by design—does not directly compete with traditional banks for the full spectrum of credit services, in contrast to a compelling view made by De la Mano and Padilla (2018) and Vives (2019) of big tech lenders using their advantages in data and technology to eventually monopolize the origination and distribution of loans to consumers and small and medium enterprises.

Finally, it should be clear that our analysis covers only the current state of one big tech lending program in China and offers no direct implications for how big tech lenders in other countries and in the future may compete with banks. The future landscape of the banking industry depends on not only capital and risk regulations imposed on these institutions but also on regulations of data sharing among banks, fintech lenders, and big tech lenders, as explored by the theoretical models of He, Huang, and Zhou (2021) and Parlour, Rajan, and Zhu (2021).

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Table 1: Summary of Selected Big Tech Lending

Country	Big Tech Firm	Big Tech Category	Digital Payment	SME Loans	Consumer Loans/ Credit Card	Targeting Platform User	Collaborate with Banks	(Example) SME Lending Program	Max SME Loan Maturity	Max SME Loan Limit
China	Alibaba	Online Retailer	♦	♦	♦	♦	♦	Wangshangdai	24 months	$285 k
China	Tencent	Social Media	♦	♦	♦	♦	♦	Weihudai	24 months	$29 k
China	JD	Online Retailer	♦	♦	♦	♦	♦	Jingxiaodai	12 months	$285 k
China	Baidu	Search Engine	♦	♦	♦		♦	Duxiaoman	12 months	$29 k
China	Suning	Retailer	♦	♦	♦	♦	♦	Weishangdai	12 months	$285 k
US	Amazon	Online Retailer	♦	♦	♦	♦	♦	Amazon Lending	12 months	$750 k
US	PayPal	Payment System	♦	♦	♦	♦	♦	PayPal Working Capital	12 months	$125 k
US	eBay	Online Retailer	♦	♦	♦	♦		Working Capital Loan	12 months	$150 k
US	Square Capital	Software/Hardware	♦	♦		♦	♦	Small Business Loan	18 months	$250 k
US	Apple	Software/Hardware	♦		♦	♦	♦			
US	Google	Search Engine	♦		♦		♦			
Latin America	Mercado Libre	Online Retailer	♦	♦	♦	♦		Fix Installment Loan	24 months	$196 k
Korea	Samsung	Software/Hardware	♦		♦	♦	♦			
Korea	Kakao	Social Media	♦		♦					
Korea	KT	Telecommunication	♦		♦					
Japan	Rakuten	Online Retailer	♦	♦	♦	♦		Super Business Loan Express	36 months	$105 k
Japan	Line	Social Media	♦		♦	♦	♦			
Southeast Asia	Grab	Delivery/Ride Hailing	♦	♦	♦	♦		Grab Business Loan	9 months	$100 k
Southeast Asia	PT Gojek	Delivery/Ride Hailing	♦		♦	♦				
India	Ola Cabs	Ride Sharing	♦		♦					
East Africa/Egypt/India	Vodafone M-Pesa	Telecommunication	♦	♦	♦	♦	♦	M-Shwari/KCB M-PESA	6 months	$8 k
France/Africa	Orange SA	Telecommunication	♦		♦					

Table 2: 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 other institutions 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	163,020	1,392,046
Regular Borrowers	429,065	159,087	73,096	30,252	65,385	62,828	819,713

Table 3: 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%	6.0%	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 4: Payments 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 maturities of the loans are shorter than 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 payments overdue 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 Payments 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 5: The COVID-19 Shock

This table presents the analysis of overdue rates for loans that were 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 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 RMB 10,000 in their 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.

	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

Table 6: Adverse Selection

This table presents the correlation test of adverse selection on each type of loan. 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 their 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 7 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*Loan Issuance Month	No	Yes
City*Loan Issuance Month	No	Yes
Cluster Variable	Origination month	Origination month
Adjusted R-squared	0.07	0.23
Observations	611885	611885

Table 8: Convenience and Interest Expense

This table reports the summary statistics of interest expense per loan and the number of loans taken by each 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 A and B matured before May 31, 2021, the last day of our performance data. Panel A reports interest expense per loan and Panel B reports the number of loans taken by each borrower.

Panel A: 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 B: 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 9: 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 through 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 had 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 speeds. 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 payments overdue. 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 analysis. For example, columns 1 and 2 are based on borrowers with both big tech loans and Bank X regular loans. Panel E compare the association of loan terms and loan origination of different lending programs to whether a borrower became overdue at least 30 days. A borrower is defined as overdue if he or she is overdue on *any* loan, regardless whether it is a big tech loan or a Bank X's regular loan or online loan. The dependent variables, logarithm of average credit limit, average interest rates, average loan size, and number of loans are aggregated at borrower-lending program level. For an overdue borrower, only loans before his/her first overdue date are included in calculation. The subtitle indicates the subsample of loans used in the analysis. In Panels C to E, fixed effects, if included, are indicated in the corresponding column, 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	Ever Overdue >=30 days	Payback to Maturity	No. of Loans Per Borrower
Big Tech	6,684	42,548	14.5%	97,762	15,097	22.9%	10.0	0.4%	41.4%	6.4
Online	4,929	12,768	8.7%	169,447	82,916	75.3%	9.8	0.9%	77.5%	2.6
Regular	1,829	3,165	9.0%	179,186	125,293	66.1%	12.8	1.5%	83.0%	1.7

Panel B: Summary Statistics by Whether the Borrower Had a Bank X Credit Limit Available at the Time of Taking a Big Tech Loan

	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 on Loan Characteristics

	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	Originatio n month
Adjusted R-squared	0.81	0.77	0.63	0.65
Observations	58481	58481	58481	41824

Panel D: Compare payment overdue

	Ever overdue >=30 days × 100			
	Big Tech vs. Regular		Big Tech vs. Online	
Big Tech	-0.66*	0.53	-0.73**	-0.13
	(0.38)	(0.45)	(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

Panel E: The correlation between loan characteristics and borrower overdue ex post

	Big Tech vs. Regular				Big Tech vs. Online			
	Log(Avg. credit limit)	Log(Avg. interest rates)	Log(Avg. loan size)	Log(No. loans)	Log(Avg. credit limit)	Log(Avg. interest rates)	Log(Avg. loan size)	Log(No. loans)
Big Tech	-1.06***	0.06***	-2.61***	0.80***	-0.68***	0.06***	-1.87***	0.62***
	(0.03)	(0.00)	(0.05)	(0.04)	(0.02)	(0.00)	(0.03)	(0.02)
Big Tech × Borrower Overdue	-0.26	-0.01	-0.56***	-0.23	-0.24***	0.01***	-0.65***	-0.10
	(0.22)	(0.01)	(0.23)	(0.16)	(0.11)	(0.00)	(0.19)	(0.16)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origination Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Variable	Month	Month	Month	Month	Month	Month	Month	Month
Adjusted R-squared	0.54	0.51	0.7	0.27	0.41	0.57	0.59	0.24
Observations	1724	1724	1724	1724	4894	4894	4894	4894

Figure 1: Credit Supply Over Time

This figure presents the total loan amounts (in millions of RMB) 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.