The Big Tech Lending Model[*]

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Abstract

This paper examines the efficacy of a big tech lending program in providing uncollateralized loans to small businesses, which are typically underserved by traditional banks. Our comparative analysis with traditional bank loans shows that big tech loans are successful in credit provisioning without heightened risk, even during the COVID-19 pandemic, unlike peer-to-peer (P2P) lending. We show that the big tech lending program's convenience and high interest rates enable it to target borrowers with immediate, short-term financial needs, thereby screening loans with smaller sizes and faster repayments, and ultimately reducing the program'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. 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 lending volume by the other types of fintech lenders that mainly consists of P2P lenders or standalone fintech lenders that directly lend to borrowers online but are unaffiliated with big tech companies (Cornelli et al. (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 et al. (2019), Cornelli et al. (2020), Huang, et al. (2020), Ghosh et al. (2021), Ouyang (2021), Chen et al. (2022), Hau et al. (2023), Gambacorta et al. (2023)), 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 P2P lending exacerbating borrower risk and drying up during the COVID-19 crisis makes this concern even more relevant.[1] Second, how does big tech lending differ from traditional bank lending?

We aim to address these issues by analyzing big tech business loans made by the syndication of MyBank, a leading big tech lender to small and medium enterprises (SMEs) in China. MyBank, a subsidiary of Ant Group and linked to Alibaba Group, specializes in lending to SMEs within Alibaba's ecosystem. Since its establishment in 2015, MyBank has quickly become the largest big tech lender in China. As of June 2020, MyBank's SME loan portfolio totaled 421.7 billion RMB (approximately $61 billion). This figure is particularly notable given that China accounted for 90% of the global big tech lending volume in 2019 (Cornelli et al. (2020)).

Our study centers on a sample of big tech loans issued by MyBank in partnership with a traditional bank, referred to as Bank X for confidentiality. This partnership involves loan

[1] Ben-David et al. (2021) find that during the COVID-19 pandemic in March 2020, P2P lending to small businesses in the United States collapsed due to the drying up of loan supply as lenders became financially constrained and lost their ability to fund more loans. Bao and Huang (2021) show that in China, standalone fintech lenders expanded credit to new and financially constrained borrowers after the start of the pandemic, but the delinquency rate of these loans tripled, even though there was no significant change in the delinquency rate of bank loans.

syndication, a common funding approach for MyBank's lending activities. Bank X, a key syndication partner of MyBank, provides a representative sample of MyBank's nationwide syndicated loan portfolio. 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. It also 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.

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 regular 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 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,

[2] According to the Chinese banking regulations, each relevant institution must contribute at least 30% of the funding to syndications for online lending.

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 right 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 P2P lending 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? To explain this success, we uncover an important observation—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 big tech loans have short maturities of either 6 or 12 months, similar to Banks X's regular and online loans. Despite the short maturity, 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 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. This fast repayment speed indicates that borrowers are likely to use the big tech loans to meet short-term liquidity rather than long-term financing needs, which, in turn, may reduce the big tech lender's risk exposure to the borrowers.

How does the big tech lender screen borrowers with short-term liquidity needs? Recent literature, such as the work by Huang et al. (2020), Ouyang (2021), Gambacorta et al. (2023), and Hau et al. (2023), has underscored the role of big tech lenders' distinct information in lending. While acknowledging the role of information in the big tech lender's screening in general, our study centers on two other critical factors—convenience and high interest rates—in attracting borrowers with immediate, short-term financial needs. Regarding convenience, the seamless integration of lending services into the big tech ecosystem significantly minimizes the nonmonetary costs of borrowing, like time and effort, thereby reducing the total cost of credit access for borrowers. This efficiency entices borrowers who seek swift liquidity solutions over prolonged financing. Such convenience as a key advantage of fintech lending has been corroborated by Buchak et al. (2018) and Fuster et al. (2019) in mortgage markets. Besides convenience, the typically higher interest rates of big tech loans also act as a self-selection tool. Since the cost of borrowing increases with the loan duration, these loans are less suitable for long-term financing. Instead, big tech borrowers are more likely to be those with short-term needs, who expect to repay fast and are thus less concerned about high interest rates.

To examine these mechanisms, we focus on a subset of overlapped borrowers who had access to both big tech loans and Bank X's conventional loans. This sample allows us to control for unobservable differences in risk and liquidity demand across borrowers and thus test whether the convenience and high interest rates of big tech loans serve to screen short-term financial needs even within the same borrower.

Interestingly, despite potentially better credit profiles, these overlapped borrowers are charged an average annualized interest rate of 14.5% for big tech loans. This rate is similar to that for big tech loans in the main sample, and is substantially higher than Bank X's online (8.7%) and regular (9.0%) loan rates for the same borrowers. Yet, these borrowers still opt for big tech loans despite their higher interest rates. Specifically, 57% of the big tech loans in the sample were taken at times when the borrowers had sufficient and cheaper credit lines from Bank X. This choice indicates a strong preference for the convenience offered by big tech loans.

We find that even among the same borrowers, big tech loans are repaid much earlier than those from Bank X. This quicker repayment confirms that borrowers use big tech loans to address short-term liquidity needs. Interestingly, big tech loans, taken when cheaper credit options from Bank X are available at the time of borrowing, are repaid even more rapidly. This indicates that borrowers willing to bear the higher interest rates of big tech loans are focused on quick repayment. The observation that the big tech lender does not reduce interest rates to compete for these borrowers' longer-term financing needs implies a strategic use of high interest rates. These rates serve as a screening mechanism, discouraging their use for long-term financing needs. Instead, they attract borrowers with short-term liquidity needs who prioritize convenience and are less concerned about higher interest costs, given their plans for quick repayment.

In terms of loan performance, we find that the rate of payments being overdue by at least 30 days is just 0.4% for the big tech loans in the sample of overlapped borrowers. This is substantially lower than the overdue rates of 0.9% for the online loans and 1.5% for the regular loans taken out by the same set of borrowers. Importantly, we observe an even lower risk associated with big tech loans taken when cheaper credit options from Bank X are available. This finding supports the idea that the screening of borrowers' specific short-term financial needs helps to reduce the lender's risk exposure. Taken together, our analysis demonstrates that the big tech lender leverages the convenience of its credit offerings and the use of high interest rates, to screen and attract borrowers who require immediate and short-term financial needs.

The Related Literature

There have been extensive studies of fintech lending, as recently reviewed by Allen et al. (2021) and Berg et al. (2022). This literature has accumulated important understandings about the other types of 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, P2P lenders may not have an information advantage compared to traditional banks that use soft information in lending.[4] Second, P2P lending or standalone fintech lenders mainly substitute for bank lending, especially when banks are constrained, rather than targeting borrowers without access to regular bank credit.[5] Third, technology facilitates fast and convenient application

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[3] By using data from an e-commerce company in Germany, Berg et al. (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 et al. (2022) show that alternative data can be particularly useful in screening "invisible primes"—borrowers with low credit scores and short credit histories.

[4] Chava et al. (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 et al. (2022) 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 standalone 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 (2022) document that standalone fintech lenders in the U.S. often partnered with banks for funding, and they increased lending to small businesses after the 2008 financial crisis to substitute for the reduction in lending by banks. Beaumont et al. (2021) use French data to show a nuanced complementarity for lending by fintech platform lending and lending by banks: small and medium-sized enterprises may use uncollateralized fintech loans to acquire tangible assets that they can then pledge to obtain bank loans.

processes, which is a key advantage of fintech lenders.[6] 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. Fourth, some P2P lenders and standalone fintech lenders may worsen, rather than improve, the borrowers' financial health.[7] Fifth, P2P lenders and standalone fintech lenders may not be robust to severe economic shocks such as the COVID-19 pandemic, as mentioned in Footnote 1.

Like other types of fintech lending, big tech lending also relies on the use of unconventional data to assess credit risk. However, big tech lenders have certain advantages due to their access to the big techs' platforms and ecosystems, such as extensive customer bases, powerful brands, potentially better data about borrower preferences and behaviors, and capacities to monitor customer activities inside the ecosystems. These advantages may make the nature and consequences of big tech lending different from other types of fintech lending.

There are only a few studies of big tech lending. The Luohan Academy Report (2019) and Frost et al. (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 et al. (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 et al. (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 et al. (2023) highlight that by relying on massive user data flows in digital platforms rather than physical collaterals, big tech credit does not

[6] Fuster et al. (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 et al. (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 (2022) conduct a difference-in-difference analysis by exploiting variations in the timing that state regulators granted approval for the operation of P2P lender Lending Club and find an increase in bankruptcy filings following the approval. Aggarwal et al. (2023) 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 et al. (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.

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 et al. (2019) and Hau et al. (2023) 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 lending helps mitigate financial frictions of online vendors close to such banks. Chen et al. (2022) show that big tech credit from MyBank helps to reduce firm sale volatility.

Our study adds to this literature by systematically evaluating several key aspects of big tech lending: its associated risks, resilience during the COVID-19 pandemic, and the underlying factors driving its success. A notable aspect we highlight is a novel mechanism where the convenience and higher interest rates of big tech loans reinforce the lender's ability to screen borrowers with short-term liquidity demands, ultimately reducing the lending risk.

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, 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. Furthermore, interest on MyBank loans is computed at a daily frequency,[8] 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. In addition, 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.

Second, Alibaba's ecosystem provides MyBank with unique and extensive information to assess the credit risk of its borrowers. 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.[9] The information helps to assess a borrower's ability and willingness to repay and is particularly helpful to the risk assessment of merchants and online vendors, who tend to lack verifiable financial statements or credit records to qualify for loans from traditional banks. Huang et al. (2020) use detailed borrower information from MyBank to show that the unconventional borrower information can substantially improve the assessment of credit risks of its borrowers on top of traditional credit records that MyBank also uses in loan issuance, especially with the further help of machine learning techniques. Ouyang (2021) provides

[8] 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 these borrowers are not confused by the quoted daily interest rates.

[9] Like the other 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.

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

Third, 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.

Fourth, the marginal cost of MyBank's lending is relatively low. The convenient digital access to merchants in the Alipay payment system and e-commerce vendors on the Alibaba platform allows MyBank to easily reach a large number of potential borrowers at a low marginal cost. Moreover, with the help of technologies such as cloud computing and artificial intelligence, MyBank can quickly assess 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.[10] MyBank is not allowed to issue asset-backed securities, tier-2 capital bonds, or perpetual bonds in the interbank market. 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 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

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[10] 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.

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.[11] 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. Bank X also evaluates the recommended interest rates and credit limits and normally follows the recommendations from MyBank. After the application is approved, the borrower can borrow within the credit limit.[12] 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. Lastly, MyBank is also responsible for restructuring loans or dealing with delinquent borrowers.

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 America, Korea, Japan, Southeast Asia, India, and Africa. These lending programs are all related to online payment or other services provided by big tech firms. Except Square Capital in the U.S., they all 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 five programs allow maturities longer than 12 months.

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

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

C. Conventional Bank Loans

Our data cover two types of business loans independently 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.

Our data also cover Bank X's online loans. 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 credit online, but the process may still take about half a day. In addition, it may take another half a day each time for the borrower to apply for a loan within the credit limit. 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 substantially less collateral but relies more on the borrowers' prior credit history.

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 she 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.

II. Summary Statistics

Our dataset is obtained from Bank X and encompasses loans from three distinct business lending programs: syndicated loans from the syndication lending program of MyBank and Bank X, as well as Bank X's own regular and online loans. MyBank asserts that its recommended loans for Bank X's syndication are reflective of its overall loan portfolio. Bank X independently originates its regular and online loans. We gathered a 10% random sample of borrowers from each lending program and tracked all loans disbursed to these borrowers from August 2019 to December 2020. The syndication between MyBank and Bank X commenced in August 2019. Our loan performance data extend until May 2021.

This particular set of borrowers and their associated loans constitute the main dataset for our study. Despite the relatively brief sampling period, the dataset includes a substantial number of loans, providing a robust basis for comparing the three lending programs. Notably, this period also encompasses the onset of the COVID-19 crisis in February 2020, offering insights into how this significant economic shock influenced the big tech lending program.

A subset of big tech borrowers also received business loans from Bank X's regular or online programs. We further examine a sample of these overlapped borrowers in subsequent sections. This section presents an overview of the borrower and loan characteristics within our main dataset.

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.[13] As borrowers with a more-limited or poor credit history are less likely to voluntarily provide credit reports in their credit applications, the substantially smaller fraction of big tech borrowers with credit reports already reflects that 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.[14] In terms

[13] 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.

[14] 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 et al. (2023) 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 et al. (2022) 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 et al. (2022) show that Latinx/Black mortgage borrowers in the United States are

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.

Panel B reports the fraction of borrowers in each group that obtained their first loans in each category from the same lending program. 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. This 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 only 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. As big tech borrowers with no alternative credit do not provide their credit reports, the selection biases the measured credit access of big tech borrowers upward. Despite the selection bias, 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 except uncollateralized consumption loans, which are typically the most accessible loans for borrowers with low credit quality in China. This

disproportionately less likely to gain from the introduction of machine learning, and machine learning increases disparity in rates between and within ethnic groups.

panel again confirms that the big tech loan borrowers have substantially less access to loans from other sources, while Bank X's online loan borrowers have the best credit access.

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 online and regular 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.[15] 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 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. (2023). 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

[15] These results also contrast the studies of the other types of fintech lending, which tend to find that they substitute, rather than complement, bank lending (e.g. Tang (2019), Di Maggio and Yao (2021), Bao and Huang (2021), De Roure et al. (2022), and Gopal and Schnabl (2022)). In particular, Bao and Huang (2021) compare standalone 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.

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 rates is already 9%, higher than the median interest rate of 8% for both the online and regular loans. The higher interest rates of big tech loans may reflect that the big tech borrowers are riskier and are different from the borrowers of the online and regular 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. This fraction is much lower than the ratio of 56.8% and 65.4% for Bank X's online and regular loans.[16] 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, confirming the commonly short maturity of these loans.

Overall, the big tech loans in our sample are sharply different from Bank X's online loans and regular 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,

[16] Note that a borrower may take multiple loans from a lending program. By separate calculation, 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 online loan borrowers and the rate of 74.9% used by bank X's regular loan borrowers.

as we will show in the later section, these patterns are not simply due to the different characteristics of borrowers covered by the big tech lending program, instead, the big tech loans made to borrowers with access to Bank X's conventional loans also display the same patterns.

III. Repayment Risk

A critical issue for both policymakers and the public is the comparative risk associated with big tech lending versus traditional bank lending. Prior research, including studies by Tang (2019) and De Roure et al. (2022), suggests that P2P lending often targets less favorable market segments, a practice known as "bottom fishing." Further, studies like those by Di Maggio and Yao (2021) and Wang and Overby (2022) indicate that P2P lending may amplify borrower risk. These findings motivate us to examine the following hypothesis about the risk of big tech lending:

Hypothesis 1: Big tech loans carry higher risk than conventional bank loans.

We test this hypothesis by examining the repayment risk across the three types of loans in our sample. Even though the borrowers covered by the big tech lending program differ significantly from those of Banks X's conventional lending programs, we can use the performance of Bank X's online and regular loans as controls to examine whether the big tech lender manages to serve its borrowers without incurring excessive risk. Given that these programs encompass a vast array of unsecured loans distributed nationwide over the same timeframe, we can compare loans made in the same month, city, and industry, thus controlling for macroeconomic, regional, and industry conditions.

We test this hypothesis by using both the full sample and a focused subset of loans made immediately before and after the onset of the Covid-19 crisis. We measure the repayment risk of a loan by its payment being overdue for at least 30 days.[17]

A. The Main Sample

In Table 4, we analyze the performance of the three types of loans based on their likelihood of being overdue by at least 30 days. For a loan to be considered in this analysis, it must have

[17] 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. 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 results with the alternative measure in the paper.

reached maturity at least 30 days prior to May 31, 2021, the cut-off date for our loan performance data. As reported in Panel A of Table 4, this sample includes 454,407 big tech loans, 68,817 Bank X's online loans, and 19,335 Bank X's regular loans.

Panel A presents the summary statistics for overdue payments. The overall rate of payments overdue is 2.6% for big tech loans, 1.1% for online loans, and 1.6% for regular loans.[18] The highest rate of overdue payments observed in big tech loans aligns with our prior that borrowers in this category generally exhibit the poorest credit quality among the three groups. Conversely, the lowest rate of overdue payments in Bank X's online loans can be attributed to the stringent credit standards applied by this particular lending program.

It's important to note that the big tech lending program often extends loans to many borrowers lacking a prior credit history, making these initial loans notably risky. As illustrated in Panel A, a significant portion of the big tech loans in our dataset—47.3% or 215,135 loans—are issued to borrowers who have no repayment history with MyBank.[19] These loans exhibit an overdue rate of 4.2%, which is considerably higher than the overdue rates of 1.1% and 1.5% for Bank X's online and regular loans, issued to borrowers also without any repayment history with the bank.

Given that Bank X's online and regular lending programs typically require a comprehensive credit history, their borrowers are likely to have a record of past repayments with other lenders. Therefore, the absence of a previous loan repayment history to Bank X itself does not necessarily indicate a borrower's risk level. On the other hand, for big tech borrowers who generally have limited access to loans from other sources, the repayment or non-repayment of their initial loans to the big tech lender is a significant indicator of their credit risk.

When focusing on borrowers with previous repayment records, the question arises whether big tech loans are still riskier compared to other types of loans. As detailed in Panel A, the overdue rate for big tech loans issued to borrowers who have successfully repaid at least one big tech loan stands at only 1.2%. This rate is remarkably similar to the overdue rates of 1.1% for Bank X's online loans and 1.7% for its regular loans, all extended to borrowers with a history of repayment. Therefore, the heightened overdue risk associated with big tech loans appears to be predominantly

[18] 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 consistency of these statistics with ours thus confirm the representativeness of our sample over MyBank's overall loan portfolio.

[19] 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.

linked to the initial loans issued to new borrowers. For subsequent loans with a history of repayment, there is no significant difference in repayment risk among the three loan categories.

In Panel B, we conduct a panel regression analysis to assess repayment risk more formally. The dependent variable in this regression is a binary indicator of whether a loan has been overdue for over 30 days. The primary independent variables are two binary indicators, representing if a loan is from the big tech lending program or Bank X's online lending program. The coefficients for these variables measure the relative repayment risk associated with big tech and online loans compared to Bank X’s regular loans, which serve as the baseline category.

The analysis methodically incorporates various control variables and fixed effects. Initially, the first column includes indicators for the two loan programs and progresses in the second column to include basic loan contract variables, such as the loan's maturity period (either 6 months or 12 months) and the requirement for a one-time repayment. Both columns also account for origination month fixed effects. Preliminary findings indicate that big tech loans exhibit higher overdue rates compared to regular loans, whereas online loans show lower overdue rates.

In the third column, we introduce a set of borrower characteristics, including factors like previous full repayment of a loan, any existing loans at the initiation of the current loan, a history of overdue payments, and maintenance of a large deposit. This column also considers demographic factors that might be relevant for borrower risk, such as the borrower's age and gender, and geographical indicators, including whether the borrower resides in a county (a small town in China) or a rural area. The fourth column further enhances the model by adding industry × loan origination month and city × loan origination month fixed effects. These additions help control for variations in economic conditions over time. This expanded model allows for a comparison of big tech loans to Bank X loans within similar borrower segments. Finally, the fifth column introduces two critical loan characteristics: interest rates and loan size. These factors are not only crucial to lender profits but also provide insights into borrower risk. By including these variables, the analysis further refines the comparison to focus on loans that are observably similar in nature.

The introduction of borrower demographics and prior repayment history in column 3 marks a significant shift in the observed patterns: big tech loans demonstrate lower rates of overdue payments. This trend becomes more pronounced with the incorporation of industry × loan origination month and city × loan origination month fixed effects in the fourth column. The performance of big tech loans improves even further with the addition of interest rates and loan size in the fifth column. Initially, big tech loans seemed to exhibit higher overdue rates compared to regular loans. However, a more nuanced analysis that accounts for borrower characteristics, economic conditions, and loan specifics reveals a different picture: big tech loans have lower repayment risks when comparisons are made within similar borrower segments and loan types.

Additionally, the coefficients for the control variables are in line with our expectations. Notably, borrowers with a history of fully repaying their loans or maintaining large deposits are associated with lower overdue risks. In contrast, those with existing loans or a history of overdue payments tend to have higher overdue risks. Moreover, the two essential loan contract terms—interest rates and loan sizes—exhibit a significant and logical correlation with overdue risks. Specifically, higher interest rates are linked to increased overdue risks, while larger loan sizes are associated with lower overdue risks. This trend reflects the overall efficacy of these lending programs in evaluating borrower risk.

Taken together, the findings presented in Table 4 challenge Hypothesis 1, demonstrating that big tech loans do not carry a higher repayment risk than conventional bank loans. This conclusion emerges after adjusting for fundamental borrower and loan characteristics. This stands in stark contrast to the previously discussed evidence that suggests a higher risk profile for P2P lending.

B. The Covid-19 Crisis

The resilience of big tech lending to significant economic disruptions is a pivotal question, especially in the context of the COVID-19 pandemic. This global crisis, which began in February 2020, posed an unparalleled challenge to economies worldwide. Our dataset, encompassing the period of the pandemic's onset, offers a unique opportunity to evaluate the performance of big tech lending in the face of such a shock.

Prior to the pandemic, it was uncertain whether big tech lending could withstand a disruption as severe as COVID-19. Given that big tech lending heavily relies on historical data to discern behavioral patterns, a major concern is the potential for large economic shocks like COVID-19 to cause a structural break in the economy. Such a break could render predictions based on past data ineffective or inaccurate. Supporting this apprehension, recent research by Ben-David et al. (2021) and Bao and Huang (2021) indicates that during the COVID-19 crisis, P2P lending in the United States and standalone fintech lending in China did not demonstrate the same level of robustness as traditional bank lending. This raises the concern that big tech lenders may also face unique vulnerabilities in times of extreme economic upheaval.

Table 5 focuses on analyzing the overdue rate of loans issued in a specific time frame: January through March 2020. This period encompasses the month prior to and the two months following the COVID-19 shock. The rationale for selecting such a narrow event window is twofold: First, we limit the pre-event window to just one month preceding the COVID-19 shock. The decision for this brief duration is driven by the nature of big tech loans, which typically feature rapid repayment schedules. A longer pre-event window would likely include numerous loans that were fully repaid before the onset of the pandemic, thereby skewing the analysis. Second, the post-event window extends for two months following the COVID-19 shock. This timeframe is chosen in consideration of the Chinese New Year, which falls in February. During this holiday season, Bank X's issuance of online and regular loans typically declines. Consequently, limiting the post-event window to one month, like the pre-event window, might not accurately reflect the usual lending activity and could distort the analysis of the impact of the COVID-19 shock on loan performance. We thus extend the window to two months.

By analyzing the overdue rates within this defined window, we aim to capture a more precise picture of how these lending programs, fared in the immediate aftermath of the COVID-19 shock, considering the unique repayment dynamics and seasonal variations in lending activity.[20]

In Table 5, the dependent variable is whether a loan is at least 30 days overdue, using Bank X's regular loans as the reference group. The Post COVID-19 Shock indicator is set to one for loans issued in February and March 2020, and zero for those in January 2020. The focal point of our analysis is the interaction term between the big tech loan indicator and the Post COVID-19 Shock indicator. As we progress through the table, we sequentially add controls for basic loan contract variables in column 2, borrower characteristic variables and economic condition fixed effects in column 3, and interest rate and loan size in column 4 into our regression model.

Across all specifications, a consistently negative coefficient is noted for this crucial interaction term. This indicates that the increase in overdue rates for big tech loans issued after the COVID-19 shock is relatively smaller compared to those for Bank X's regular loans. Notably, the magnitude of this coefficient increases from column 2 to column 3, particularly with the inclusion of city × month and industry × month fixed effects. Furthermore, the introduction of interest rate and loan size in column 4 does not significantly alter the coefficient's magnitude. This suggests

[20] 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.

that the comparatively smaller rise in overdue rates for big tech loans after the COVID-19 shock is not simply due to strategic market selection or timing by the big tech lender. Rather, it appears to be more linked to its effective borrower screening in the same local markets for comparable loans during the same period. This finding highlights the resilience and adaptability of big tech lending amidst substantial economic upheavals.

A pertinent question arises regarding whether the results from our analysis could be attributed to a reduction in loan issuance by the big tech lender compared to Bank X's regular lending program during the same period. Figure 1 addresses this concern by illustrating the monthly loan issuance, measured in millions of RMB, for each of the three loan types throughout the sample period. The data shows that the issuance of big tech loans experienced a steady increase over the sample timeframe. In contrast, both online and regular loans from Bank X witnessed a significant decline in February 2020, coinciding with the onset of the COVID-19 pandemic in China. It's important to note that February 2020 was also the month of the Chinese New Year, a factor that could potentially account for the seasonal dip in Bank X’s loan issuance due to the national holiday.

Furthermore, the data reveals that the volume of big tech loans originated in March 2020 (post-COVID-19 shock) actually increased in comparison to January 2020 (pre-COVID-19 shock). Meanwhile, the issuance of Bank X’s regular loans, which serve as the benchmark in Table 5, showed a slight decrease in March 2020 relative to January 2020. These trends suggest that the differences in risk performance observed after the COVID-19 shock are not simply a consequence of changes in the amount of loan origination.

IV. Meeting Short-term Liquidity as the Lending Model

How does a big tech lender offer credit to a segment of borrowers often neglected by traditional banks, without taking on undue risk? Existing literature, e.g., Huang et al. (2020), Ouyang (2021), Gambacorta et al. (2023), and Hau et al. (2023), has highlighted information advantages of big tech lenders in screening borrowers with low credit risk. Building on this literature, we further propose and examine a novel screening strategy employed by the big tech lender to attract borrowers with short-term liquidity needs. When borrowers seek loans to meet immediate, short-term liquidity needs, they are inclined to repay swiftly, substantially reducing the lender's risk of non-repayment. Targeting such needs can thus provide the big tech lender a strategic advantage, particularly when engaging with borrowers whose income streams may be highly unpredictable.

In this section, we first present a prominent trend in our data: big tech loans are typically repaid much earlier than their scheduled maturity, and also much earlier than traditional bank loans. This reflects the distinct role of big tech lending in catering to borrowers' short-term liquidity needs. We then propose that the ease of obtaining a big tech loan coupled with its high interest rates function as a natural screening mechanism, filtering in borrowers who are willing to accept these terms due to their immediate cash needs. To further support this hypothesis, we analyze the borrowing patterns of a set of "overlapped borrowers" — individuals who have taken loans from both the big tech lender and the traditional lender, Bank X. Our aim in examining the borrowing and repayment pattern within this group of borrowers is to test whether the higher interest rates and convenience aid the big tech lender in screening for short-term liquidity needs, and whether such screening reduces the risk of overdue payments.

A. Fast Repayment

Borrowers' repayment speed is a dimension that is little explored by existing literature on big tech lending or other types of fintech lending. As revealed by summary statistics in Table 3, the three types of loans in our dataset—big tech, online, and regular loans—exhibit similar maturities, predominantly featuring 6-month and 12-month terms. Importantly, borrowers have the flexibility to repay these loans early without incurring any penalties.

In scenarios where a borrower secures a loan for long-term business expansion, a typical rationale for business loans, it's improbable that they would settle the loan prior to the relatively short 6 or 12-month maturity. This assumption is based on the nature of business investments, which often require time to generate returns. Similarly, in cases where borrowers overextend themselves financially—a situation noted in some fintech lending practices by Di Maggio and Yao (2021)—early repayment is also unlikely due to their constrained financial capabilities.

Conversely, when a loan is procured to satisfy short-term liquidity needs, it is plausible that the borrower will repay the loan well before its scheduled maturity. This early repayment is indicative of the borrower's immediate need for funds and their ability to quickly redirect resources to settle the debt as soon as their short-term financial obligations are met or their cash flow situation improves. Thus, repayment speed offers valuable insights into the borrower's financial behavior and the role of the loan in their overall financial strategy.

In Table 6, we delve into the patterns of early repayment among the three borrower groups. To ensure a consistent basis for comparison, we apply a criterion that includes only those loan contracts that matured before May 2021, aligning with the end date of our loan performance data. Panel A of Table 6 presents the distribution of the ratio of actual repayment time to the scheduled loan maturity for big tech loans, as well as Bank X's online and regular loans.

The data reveal a pronounced trend: big tech loans are repaid significantly sooner than the other types of loans. On average, big tech loans are settled at just 46% of their planned maturity duration. In comparison, the online and regular loans from Bank X are repaid at 74% and 77% of their respective maturity periods. This difference becomes even more stark when looking at the distribution of repayment times. Notably, 25% of big tech loans are repaid within merely 4% of the loan's maturity period, equating to approximately one week for a 6-month loan and two weeks for a 12-month loan.[21] In stark contrast, for Bank X's online loans, 25% of them are repaid within 48% of the loan maturity, and for regular loans, this figure is 61%. At the median, big tech loans are repaid at 28% of their maturity time, corresponding to about seven weeks for a 6-month loan and 14 weeks for a 12-month loan. Meanwhile, the median repayment time for online and regular loans is much closer to full maturity, at 96% and 93%, respectively.[22]

In Panel B, we undertake a more formal comparison of repayment time across the three loan types by regressing the ratio of repayment time to loan maturity against a set of explanatory variables. These variables include loan type indicators, with dummies for big tech loans and Bank X's online loans, effectively setting Bank X's regular loans as the reference group. This regression model incorporates various loan terms that might affect payback speed, such as interest rate, credit limit, and loan maturity.[23] It also accounts for borrower characteristics that are relevant for borrower risk or liquidity demand, including age, a dummy for residence in a county, a dummy for residence in a rural area, past credit history, and whether the borrower maintains a large deposit

[21] 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.

[22] Note that the maximum value for all three types of loans is above 1, which reflects payments overdue.

[23] In our previous regression analysis focusing on overdue payments, we ensured that all loans matured at least 30 days before May 31, 2021. This was necessary to consistently measure the probability of a loan being overdue by at least 30 days. However, for the analysis of repayment time, this requirement is not applicable. Consequently, a small portion of the loans in this sample have a maturity of 13 months. To accommodate this variation, we have included an additional indicator variable to identify loans whose maturity exceeds 12 months.

at Bank X. To further control for broader economic and regional factors, the model includes fixed effects for industry × loan origination month and borrower city × loan origination month.

The coefficient for the big tech loan dummy is significantly negative, registering at –0.40 and –0.46 in the respective models. These figures clearly suggest that big tech loans are repaid substantially earlier, 40% to 46% earlier relative to their loan maturities.[24]

The findings presented in Table 6 collectively indicate that big tech loans are typically repaid well before their scheduled maturity dates, much earlier than traditional bank loans. This trend strongly suggests that borrowers are more inclined to use big tech loans to address immediate, short-term liquidity needs rather than for long-term business expansion purposes. Even though the rapid repayment reduces the interest the lender can collect from the borrowers, it significantly reduces the duration of the lender's risk exposure. Thus, from a risk management standpoint, focusing on borrowers seeking to fulfill short-term liquidity needs is highly advantageous.

B. Screening for Short-term Liquidity Needs

How does the big tech lender target borrowers' short-term liquidity needs? The process through which the big tech lender screens for short-term liquidity needs is likely multifaceted, given the complexities involved. The lender's unique access to data may provide insights into when these borrowers might need funds for inventory, for instance, before major holidays, and estimate their capacity to repay the loans from future sales. In addition to this well-known mechanism, we propose two other mechanisms: the high interest rates and convenience of big tech loans.

Firstly, the big tech lender's strategy of charging relatively high interest rates serves as an effective self-screening tool. The higher cost of borrowing over an extended period makes these loans less attractive for long-term financing, thereby naturally filtering out borrowers seeking longer-term loans. Instead, while these rates are higher on an annualized basis, they do not significantly burden borrowers who plan to repay quickly, typically those with immediate liquidity needs. As noted in Panel A of Table 7, due to the smaller loan sizes and faster repayment rates of

[24] In Table 6, we observe that a higher interest rate is linked to faster repayment, though this relationship is statistically insignificant. This coefficient reflects two contrasting effects of interest rates on repayment speed. Firstly, as indicated in Tables 4 and 5, higher interest rates are indicative of greater borrower risk. Riskier borrowers typically have slower repayment rates, and some may even become overdue, suggesting a positive correlation between interest rates and the ratio of payback time to maturity. However, as we hypothesize and later demonstrate, since the interest cost increases with the duration of borrowing, higher interest rates may also act as a filter for borrowers with imminent liquidity needs who anticipate rapid repayment. From this perspective, a negative relationship between interest rates and the ratio of payback time to maturity would be expected.

big tech loans, the actual interest expense incurred by borrowers is relatively low (only 61 RMB on average). This cost structure makes big tech loans particularly appealing for short-term liquidity requirements, leading to a self-selection process where borrowers with immediate needs prefer these loans over more traditional options.

Secondly, the ease and speed of accessing big tech loans make them particularly suited for short-term liquidity borrowing, which often places high value on immediacy and convenience. The process is streamlined and integrated within a broader digital ecosystem, enabling swift application, approval, and disbursement of funds in seconds through just a few clicks on a mobile app. This is in stark contrast to the more time-consuming and cumbersome procedures of traditional banking.[25] The literature, e.g., Buchak et al. (2018) and Fuster et al. (2019), has also recognized such convenience as a key advantage of other types of fintech lending.

The convenience of big tech lending, or the low non-monetary cost associated with each borrowing instance, results in big tech loans being borrowed much more frequently. As reported in Panel B of Table 7, during our sample period, big tech borrowers took an average of 6.0 loans, and 5% of them took more than 20 loans over 17 months. These figures significantly exceed the number of loans taken out through Bank X's online and regular programs.[26] The big tech lending program's ability to allow borrowers to access funds as needed and repay them promptly as soon as new cash flows become available reduces the necessity for borrowers to maintain large liquid reserves for unexpected expenses. This further attracts borrowers with frequent short-term liquidity demands.

The observations from Table 7 motivate us to specifically test whether the big tech lending program's high interest rates, in combination with its convenience, serve to screen borrowers'

[25] 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.

[26] 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 Aggarwal et al. (2023), digital 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.

short-term liquidity needs, leading to lower overdue risk. We outline this in the following hypothesis:

Hypothesis 2: The high interest rates and convenience of the big tech lending act as screening mechanisms to identify and attract borrowers who have immediate, short-term financial needs.

Alternatively, it's possible that the high interest rates are motivated by other factors unrelated to the early repayment of big tech loans. The high interest rates may simply reflect a higher risk premium associated with borrowers of low credit quality. Another possibility is that the borrowers of big tech loans lack access to alternative credits, thus empowering the big tech lender to charge higher interest rates over these borrowers.

To test Hypothesis 2 against these alternatives, we utilize a set of overlapped borrowers who had access to both big tech loans and Bank X's conventional loans. By focusing on these overlapped borrowers, we can control for unobservable differences in risk and liquidity demand across borrowers, and test whether the high interest rates and convenience of big tech loans serve to screen short-term financial needs even within the same borrower. Furthermore, the alternative credit access of these overlapped borrowers also diminishes the big tech lender's market power.

C. A Test of the Overlapped Sample

We compare the terms and characteristics of different loans made to the overlapped borrowers in Table 8. 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 from August 2019 through December 2020. Among these, 4,929 took 12,768 online loans, and 1,829 took 3,165 regular loans from Bank X. [27]

These borrowers, having access to Bank X's online or regular loans, are likely to have better credit profiles than typical big tech borrowers. Hence, the risk premium associated with loans made to these borrowers should be lower than the typical big tech borrowers. Moreover, their alternative credit access diminishes the big tech lender's market power.

Interestingly, the big tech loans in this group exhibit an average annualized interest rate of 14.5%, similar to our main sample, and substantially higher than the rates for Bank X's online (8.7%) and regular (9.0%) loans to the same borrowers. This contradicts the argument that the

[27] 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.

overlapped borrowers' lower credit risk would qualify them for lower interest rates and doesn't support the diminished market power hypothesis either. Instead, it aligns with the hypothesis that the high interest rates of big tech loans serve an additional function to screen borrowers' short-term liquidity demand.

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.

If the big tech lender effectively screens borrowers' short-term liquidity needs, we would expect a quicker repayment of the big tech loans than the conventional loans from Bank X, even within the same group of borrowers. This is precisely what we observe. The average repayment time for big tech loans is just 41.4% of the scheduled loan maturity. This is significantly quicker than the repayment time for the same borrowers' online loans from Bank X, which is, on average, 77.5% of the loan maturity, and regular loans, which average at 83.0% of the loan maturity.

In addition, consistent with the big tech lending's convenience, 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 characteristics of the big tech loans taken by the overlapped borrowers—such as their smaller size, faster repayment, and higher frequency of borrowing—indicate that these loans are utilized differently compared to conventional bank loans from Bank X even within the same borrowers. These observations collectively suggest that big tech loans serve borrowers' short-term liquidity needs, rather than fulfilling the same functions as conventional bank loans.

However, a question that remains is why these borrowers choose big tech loans despite their significantly higher interest rates compared to Bank X's loans extended to the same borrowers. One possible explanation could be the availability of credit lines. It might be the case that when these borrowers face immediate financing needs, they no longer have sufficient credit available from Bank X, leading them to opt for big tech loans despite the higher costs.

To address this argument, Panel B undertakes an analysis of each big tech loan in relation to the borrower's available credit from Bank X's online or regular lending programs. Specifically, the panel categorizes the big tech loans based on two criteria jointly at the time of borrowing:

whether the borrower had enough remaining credit from Bank X to cover the big tech loan, and whether the interest rate on the available conventional credit line was lower than the interest rate of the big tech loan. Surprisingly, the analysis reveals that 57% of the big tech loans in the sample were taken at times when the borrowers had access to sufficient and cheaper credit lines from Bank X. The average interest rate on these big tech loans was 14.7%, substantially higher than the average interest rate of 8.3% on the available credit lines from Bank X.

This finding shows that the overlapped borrowers prefer big tech loans despite having access to cheaper credit from Bank X. This behavior suggests that factors other than interest rates and credit availability are influencing their financing decisions. Among these factors, convenience stands out as a particularly compelling motivator. The ease and speed with which borrowers can access big tech loans, often through streamlined digital processes, appear to be significant advantages that outweigh the higher interest rates associated with these loans.

Continuing with Panel B, such big tech loans are repaid quickly, with the average repayment time being just 39.8% of the loan maturity. This is even faster than other big tech loans taken when cheaper credit from Bank X is unavailable, which have an average repayment time of 44.3% of the loan maturity. This increased speed in repayment suggests that borrowers, when willing to bear the higher interest rates of big tech loans, tend to repay even more swiftly. This pattern implies that higher interest rates may act as a self-screening mechanism, discouraging the use of big tech loans for long-term financing. Instead, these loans are predominantly utilized by borrowers who place a high value on convenience and are less sensitive to the cost of interest, likely driven by their short-term liquidity needs.

The regression analysis in Panel C of Table 8 pools together all loans accessed by the overlapped borrowers to provide a deeper analysis on two key loan attributes: the logarithm of the loan size and the ratio of repayment time to loan maturity. In this regression, we use two indicators to represent online loans and regular loans from Bank X, with big tech loans serving as the baseline for comparison. Additionally, the model incorporates an interaction term between a big tech loan indicator and an indicator for the availability of more affordable credit from Bank X at the time of obtaining the big tech loan. This term is crucial as it quantifies the differences in scenarios where cheaper credit is available versus when it is not. Similar to the regressions in Table 6 Panel B, various loan characteristics are included in the analysis. To account for individual differences and external factors, borrower fixed effects are included to control for borrower heterogeneity, and origination month fixed effects are used to account for macroeconomic conditions.

The regression results reinforce the summary statistics presented in Panels A and B. They show that both online and regular loans from Bank X feature significantly larger loan sizes and exhibit slower repayment speeds compared to big tech loans, even within the same borrowers. Specifically, big tech loans taken by these borrowers are repaid 22% faster compared to Bank X's online loans and 23% faster relative to Bank X's regular loans. A particularly noteworthy finding is the significantly negative coefficient of the interaction term. This indicates that when borrowers who have access to cheaper credit from Bank X still choose a big tech loan, these loans tend to be 12% smaller in size, and their repayment is expedited by an additional 2% of loan maturity, compared to big tech loans taken when cheaper credit from Bank X is not available.

In column 2, there is a significantly negative relationship between interest rate and repayment time, consistent with the notion that high interest rates function as a screening mechanism for loans intended to address short-term liquidity needs. Quantitatively, this relationship accounts for about a 12.0% difference in repayment time between big tech loans and Bank X regular loans in our sample.[28] This finding contrasts with the repayment speed analysis in Table 4 Panel B for the main sample, where the coefficient on the interest rate is insignificant. The difference arises from the inclusion of borrower fixed effects, which largely control for unobservable risks at the borrower level. Consequently, within the same borrower, a higher interest rate primarily serves to identify borrowers' short-term liquidity needs for loans. This approach effectively separates the interest rate's role as an indicator of higher loan risk, which usually suggests a slower repayment speed, due to the control provided by the borrower fixed effects.

Taken together, results reported in Table 8 support Hypothesis 2 that the convenience and high interest rates of the big tech loans serve to screen borrowers' short-term liquidity needs. The fact that these borrowers take smaller loans and repay them more quickly underlines their prioritization of the immediacy and convenience offered by big tech loans. The higher interest rates of big tech loans become less concerning for these borrowers due to their expectations of quick repayment.

While convenience likely plays a pivotal role in the decision of overlapped borrowers to opt for big tech loans, especially for short-term liquidity needs, this preference is bound by the specific purpose of these loans. If the big tech lender were to decrease its interest rates, it could potentially encourage borrowers to use these loans more frequently and for larger amounts. This implies a potential strategy for the lender to expand its program, particularly for overlapped borrowers whose credit profiles would qualify them for lower rates. However, the fact that the big tech lender

[28] This is illustrated by the calculation: (14.5% - 9%) × 0.91 / (83.0% - 41.4%).

continues to charge high interest rates to these borrowers, similar to other borrowers, signifies a deliberate choice. This strategy suggests that the lender is not primarily aiming to broaden its lending program by serving borrowers' diverse financing needs through lower rates.

Instead, the consistent application of high interest rates appears to be a tactical strategy, aligning with the concept of using these rates as a screening mechanism. By maintaining higher rates, the big tech lender effectively targets and caters to a specific segment of the market: borrowers who have immediate, short-term liquidity needs and are willing to pay a premium for the convenience and quick access to funds that big tech loans provide. This approach signifies a focused strategy on the lender's part, prioritizing the fulfillment of specific customer needs over wider market expansion.

D. Loan Performance

We now examine the performance of the loans made to the overlapped borrowers. Interestingly, the rate of payments being overdue for more than 30 days is notably low at just 0.4% for big tech loans. This is substantially lower than the 0.9% for online loans and 1.5% for regular loans taken out by the same borrowers.[29] The reduced risk level observed in big tech loans among these overlapped borrowers, compared to the broader borrower pool in Table 4, aligns with the expectation of superior credit quality in this subgroup. The relatively lower repayment risk of big tech loans compared to both regular and online loans from Bank X within this subset of borrowers is somewhat unexpected.

To delve deeper into these observations, we conduct a regression analysis focusing on loan performance among the overlapped borrowers, further exploring Hypothesis 2. Our particular focus is on the variation in loan performance depending on whether an overlapped borrower has access to alternative credit from Bank X. Our hypothesis posits that when a borrower opts for a big tech loan despite the availability of cheaper alternative credit from Bank X, it is likely due to an urgent liquidity need. This urgency is expected to lead to quicker repayments and, consequently, a lower repayment risk, especially relative to situations where no alternative credit is available.

The regression analysis is detailed in Table 9. The dependent variable in all columns is an indicator of whether a loan is at least 30 days overdue. The first two columns include borrowers who have accessed both big tech loans and regular loans from Bank X, with regular loans serving as the benchmark group. Similarly, the last two columns focus on borrowers with both big tech

[29] Due to its straightforward nature, this statistic is not reported in a separate table.

loans and online loans from Bank X, using the online loans as the benchmark group. A key variable in our analysis is the interaction between the big tech loan indicator and the availability of alternative credit from Bank X. All model specifications incorporate basic loan contract variables and loan origination month fixed effects. Additionally, borrower fixed effects are included in columns 2 and 4 to account for individual borrower differences, but these are omitted in columns 1 and 3.

Columns 1 and 3 show that big tech loans exhibit a lower repayment risk when compared to both regular and online loans from Bank X, a finding that is consistent with the summary statistics. However, this observed difference becomes insignificant in columns 2 and 4 once borrower fixed effects are incorporated into the analysis. These results indicate that while big tech loans generally show a lower overdue risk than Bank X's conventional loans when issued to the same group of borrowers, this reduced risk is not attributable to variations within individual borrowers. Rather, it stems from compositional differences in the borrower pool. Specifically, a greater proportion of big tech loans are made to borrowers who are safer within the overlapped sample.

More interestingly, column 1 shows that the overdue rate for big tech loans taken by overlapped borrowers—when cheaper credit from Bank X is available—is 1.04% lower compared to when such credit is unavailable. This significant difference suggests that borrowers are more likely to repay on time when they choose big tech loans despite the availability of cheaper alternatives. The significance of this difference persists, albeit to a lesser extent, even after including borrower fixed effects in column 2.

For the sample of overlapped borrowers between the big tech lending program and Bank X's online lending program, this difference in overdue rates is 0.42% and is statistically significant in column 3. It loses significance after the inclusion of borrower fixed effects in column 4.

Overall, the consistently lower risk associated with big tech loans taken when cheaper credit options are available supports the notion of a self-screening mechanism. While big tech loans are generally used for short-term liquidity needs, they are even more likely to be utilized for such needs when cheaper credit from Bank X is accessible. According to Table 8, these loans are repaid more swiftly, further reducing the repayment risk.

E. Additional Analysis

The big tech lending program's borrower screening efficacy is rooted in more than just high interest rates and convenience. Previous research, such as Huang et al. (2020), Ouyang (2021), Gambacorta et al. (2023), and Hau et al. (2023), has highlighted MyBank's unique data capabilities in borrower screening. While this isn't the main focus of our study, our data also provide supplementary evidence. We've explored the information advantages of the big tech lender in two segments: the sample of overlapped borrowers and the main sample. Due to space constraints, detailed results are reported in the Internet Appendix, but here we offer a brief summary.

In the sample of overlapped borrowers, we analyze the loan terms set by the big tech lending program and their correlation with subsequent loan performance. Table A1 in the Internet Appendix examines terms like loan size, number of loans, credit limit, and interest rate, focusing on loans originated before the first overdue payment to understand differences in initial borrower screening. Our findings indicate that for borrowers in financial distress later, big tech loans are smaller, suggesting a cautious approach to loan sizing. In addition, the borrowing frequency remains uniform across all programs. Taken together, these results imply that a smaller total amount of big tech loans are originated to borrowers who end in financial distress ex post. As for credit limits and interest rates, while they show no significant difference in predictive power between the big tech and Bank X’s regular program, an information advantage is apparent for the big tech program over Bank X's online program, demonstrated by smaller credit limits and higher interest rates for distressed borrowers. Thus, Table A1 shows that big tech loans to overlapped borrowers correlate more strongly with their loan performance, indicating a nuanced screening approach that leverages informational advantages.

For the main sample, we apply a general test for the screening capability of the three lending programs, following Chiappori and Salanié (2000). We investigate if borrowers whose loans become overdue post-origination are more likely to have maximized their credit limit pre-origination, controlling for observable loan and borrower characteristics. A positive correlation would indicate either the use of private information about future financial risk when maximizing credit limits or riskier post-borrowing behavior. Table A2 in the Internet Appendix reveals a negative conditional correlation for the big tech lending program, suggesting advantageous selection. In contrast, Bank X’s regular program shows a positive correlation, indicative of adverse selection. These results reinforce the big tech lender's superior screening capabilities, aligning with findings from the overlapped borrower sample.

V. 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 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 information advantages 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 incurring greater risks than banks even during the COVID-19 crisis.

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, big tech lenders, and the other fintech lenders, as explored by the theoretical models of Parlour et al. (2022) and He et al. (2023).

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Table 1: Summary of Selected Big Tech Lending

This table lists key big tech lenders around the world. Data on each big tech lender comes from the corresponding company website.

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 a subset of borrowers in the main sample who voluntarily provided credit reports in their credit applications. The main sample covers a 10% random sample of borrowers from the big tech lending program, Bank X online lending program, and Bank X regular lending program from August 2019 through December 2020. The sample of borrowers with credit reports covers 31,046 out of 140,019 big tech borrowers, 49,794 out of 49,795 Bank X online borrowers, and 22,042 out of 22,115 Bank X regular borrowers in the main sample. When a borrower has multiple loans from a lending program, only the credit report associated with the first loan is included in the calculation. 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 each lending program borrowed from institutions other than the three lending programs. A borrower without any loan of a certain type from the other institutions is treated as zero in computing the averages. All variables are defined in Appendix A.

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 the main sample. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. The data include three types of business loans: big tech loans, Bank X online loans, and Bank X regular loans. 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 sizes, and maturities. All variables are defined in Appendix A.

Panel A: Overall Statistics

	Number of Loans	Interest Rate	Credit Limit	Loan Size	Maturity	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: Payment Overdue

This table presents the analysis on the repayment risk in the main sample. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. 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 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 at the time of borrowing. For example, 239,272 big tech loans went to borrowers who had paid off at least one big tech loan. Panel B presents a regression analysis on payment overdue. The dependent variable 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. All variables are defined in Appendix A. Loan origination month fixed effects, industry × loan origination month fixed effects, and city × 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***	-1.76***
	(0.22)	(0.24)	(0.26)	(0.25)	(0.31)
Online	-0.27*	-0.01	0.65***	0.46*	0.42*
	(0.16)	(0.23)	(0.25)	(0.25)	(0.25)
Loan Term: 6 months		-1.75***	-1.72***	-1.78***	-1.66***
		(0.48)	(0.47)	(0.47)	(0.48)
Loan Term: 12 months		0.22	0.26	0.17	0.32
		(0.53)	(0.53)	(0.54)	(0.55)
Repay Once		-2.00***	-1.63***	-1.62***	-1.39***
		(0.22)	(0.16)	(0.15)	(0.13)
Ever Clear			-2.77***	-2.77***	-2.77***
			(0.33)	(0.33)	(0.34)
Exist Loan			1.20***	1.19***	1.13***
			(0.18)	(0.18)	(0.17)
Ever Overdue			8.34	9.39	9.12
			(6.93)	(6.92)	(6.97)
Has Large Deposit			-0.95***	-0.93***	-0.83***
			(0.07)	(0.08)	(0.07)
Log(Age)			-0.30**	-0.39***	-0.01
			(0.13)	(0.14)	(0.12)
Male			0.01	0.01	0.01
			(0.08)	(0.08)	(0.07)
County			-0.55***	-0.43***	-0.44***
			(0.06)	(0.07)	(0.07)
Rural			-0.54***	-0.43***	-0.48***
			(0.09)	(0.09)	(0.09)
Interest Rate					6.06***
					(0.98)
Log(Loan Size)					-0.26***
					(0.04)
Origination Month FEs	Yes	Yes	Yes	No	No
Industry × Origination Month FEs	No	No	No	Yes	Yes
City × Origination Month FEs	No	No	No	Yes	Yes
Cluster Variable	Origination Month	Origination Month	Origination Month	Origination Month	Origination Month
Adjusted *R*-squared	0.00	0.01	0.02	0.03	0.03
Observations	542,559	542,559	542,559	542,559	542559

Table 5: The COVID-19 Shock

This table presents the regression analysis on the repayment risk around the COVID-19 shock. The data cover a 10% random sample of borrowers and their loans originated from January 2020 through March 2020. 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. All the loans matured at least 30 days before May 31, 2021, the ending date of the loan performance data. The dependent variable is 100 times the indicator on whether a loan is ever overdue 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. Post COVID-19 Shock is an indicator that is equal to one if the loan was originated in February and March 2020, and zero if it was originated in January 2020. Borrower characteristics variables include indicators on Ever Clear, Exist Loan, Ever Overdue, Has Large Deposit, Log(Age), Male, County, and Rural. All variables are defined in Appendix A. Loan origination month fixed effects, industry × loan origination month fixed effects, and city × loan origination month fixed effects are included and indicated in the corresponding columns. 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 FEs	Yes	Yes	No	No
Industry × Origination Month FEs	No	No	Yes	Yes
City × Origination Month FEs	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 Fast Repayment

This table presents the analysis on the repayment speed of loans in the main sample. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. 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. All the loans matured at least by May 31, 2021, the ending day of the loan performance period. Panel A presents the distribution of the ratio of payback time to loan maturity. Panel B presents a regression analysis on payback speed. The dependent variable is the ratio of payback time to loan maturity. 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. All variables are defined in Appendix A. Industry × loan origination month fixed effects and city × loan origination month fixed effects are included and indicated 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 Payback to Maturity

	Number of Loans	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

	Payback to Maturity	
Big Tech	-0.40***	-0.46***
	(0.01)	(0.01)
Online	-0.01	0.06***
	(0.01)	(0.01)
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: >= 12 months	-0.12***	-0.06
	(0.04)	(0.04)
Repay Once	-0.13***	-0.09***
	(0.01)	(0.00)
Ever Clear		-0.35***
		(0.01)
Exist Loan		0.11***
		(0.01)
Ever Overdue		0.25***
		(0.04)
Has Large Deposit		-0.05***
		(0.00)
Log(Age)		0.06***
		(0.01)
Male		-0.01***
		(0.00)
County		-0.01***
		(0.00)
Rural		-0.03***
		(0.00)
Interest Rate	-0.01	-0.03
	(0.06)	(0.04)
Log(Credit Limit)	-0.00	-0.00
	(0.00)	(0.00)
Industry × Origination Month FEs	No	Yes
City* Origination Month FEs	No	Yes
Cluster Variable	Origination month	Origination month
Adjusted *R*-squared	0.07	0.23
Observations	611885	611885

Table 7: Convenience and Interest Expense

This table presents the analysis of interest expense and each borrower's number of loans in the main sample. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. 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. All the loans matured at least by May 31, 2021, the ending day of the loan performance period. Panel A presents the distribution of interest expense per loan and Panel B presents the distribution of loan number taken by each borrower during our sample period.

Panel A: Interest Expense Per Loan

	No. Loans	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 8: Loan Characteristics of Overlapped Borrowers

This table presents the analysis of the loan characteristics on the overlapped sample of borrowers who borrowed 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 uncollateralized business loans from 6,684 unique borrowers. Panel A presents the summary statistics of variables in this overlapped sample. The ratio of payback time to loan maturity is computed based on loans that matured before May 31, 2021, the ending day of the loan performance period. All the other variables in the panel are based on the full sample of 58,481 loans. Panel B presents the 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 presents the regression analysis on the sizes and payback speeds of loans from different lending programs. The indicator variable Online (Regular) indicates Bank X online (regular) loan. The benchmark group is big tech loans without credit available from Bank X at the time of borrowing as defined above. The second column on the ratio of payback time over contract maturity is based on loans that matured before May 31, 2021. All variables are defined in Appendix A. Borrower fixed effects and loan origination month fixed effects are included. Standard errors in parentheses are clustered at loan origination month. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Panel A: Summary Statistics

	No. of Borrowers	No. of Loans	Interest Rate	Credit Limit	Loan Size	Repay Once	Maturity	Payback to Maturity	No. of Loans Per Borrower
Big Tech	6,684	42,548	14.5%	97,762	15,097	22.9%	10.0	41.4%	6.4
Online	4,929	12,768	8.7%	169,447	82,916	75.3%	9.8	77.5%	2.6
Regular	1,829	3,165	9.0%	179,186	125,293	66.1%	12.8	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 Borrowers	Number of Loans	Interest Rates on Big Tech Loan	Interest rates on Bank X Credit Limit	Loan Size	Remaining Bank X Credit Limit	Maturity	Payback to Maturity
With Credit Limit from Bank X	4669	24302	14.7%	8.3%	14493	171632	9.9	39.8%
Without Credit Limit from Bank X	4356	18246	14.3%	9.1%	15900	9840	10.1	44.3%

Panel C: Regression Analysis of Loan Characteristics

	Log(Loan Size)	Payback to Maturity
Online	1.46***	0.22***
	(0.02)	(0.01)
Regular	1.90***	0.23***
	(0.05)	(0.02)
Big Tech × Bank X Credit Available	-0.12***	-0.02***
	(0.01)	(0.00)
Loan Term: 6 months	0.39***	-0.03**
	(0.02)	(0.01)
Loan Term: 12 months	0.62***	-0.09***
	(0.02)	(0.01)
Loan Term: >=12 months	0.99***	0.07**
	(0.04)	(0.03)
Repay Once	0.08***	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
Origination Month FEs	Yes	Yes
Cluster Variable	Origination month	Origination month
Adjusted R-squared	0.63	0.65
Observations	58481	41824

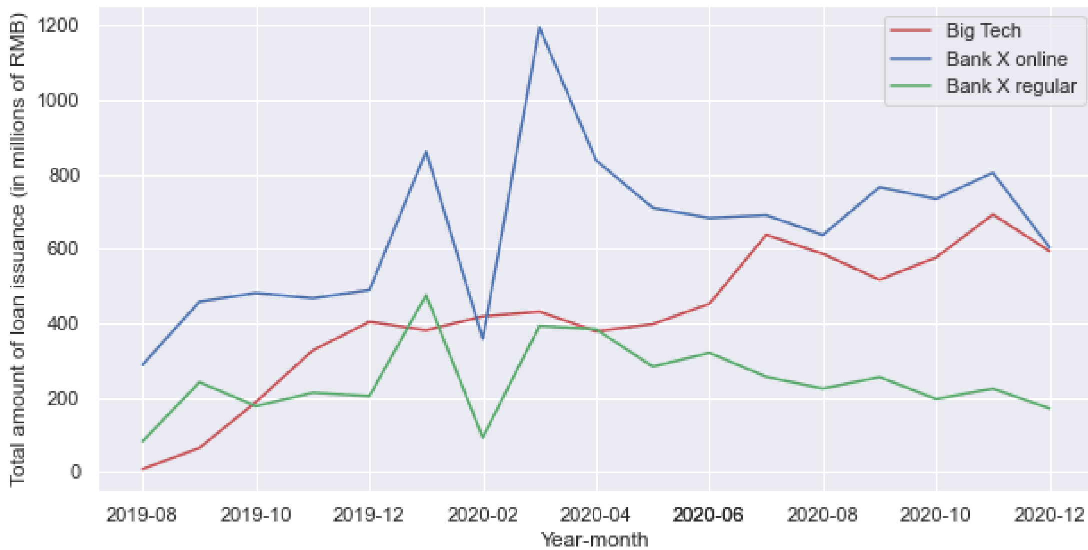
Table 9: Payment Overdue of Overlapped Borrowers

This table presents the regression analysis of the payment overdue on the overlapped sample of borrowers who borrowed both big tech loans and at least one type of Bank X loan over the period of August 2019 through December 2020, with all loans maturing at least 30 days before May 31, 2021, and not exceeding 12 months in duration. The analysis differentiates between borrowers with big tech and Bank X regular loans (Columns 1 and 2), and those with big tech and Bank X online loans (Columns 3 and 4). The dependent variable is 100 times the indicator on whether a loan is ever overdue at least 30 days. 'Big Tech' is an indicator variable set to 1 for big tech loans. 'Bank X Credit Available' indicates if a borrower had a cheaper and larger credit limit from Bank X at the time of borrowing the big tech loan. All variables are defined in Appendix A. Borrower fixed effects and loan origination month fixed effects are included and indicated in the corresponding specifications. Standard errors in parentheses are clustered at loan origination month. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

	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 FEs	No	Yes	No	Yes
Origination Month FEs	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

Figure 1: Credit Supply Over Time

This figure presents the total loan amounts (in millions of RMB) over time in the main sample. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. The sample includes 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.



Appendix A: Variable definitions

Variable	Definition
Big Tech	Indicator variable that equals to one if the loan is a big tech loan.
Online	Indicator variable that equals to one if the loan is a Bank X online loan.
Regular	Indicator variable that equals to one if the loan is a Bank X regular loan.
Interest Rate	The interest rate of this lending.
Ever Overdue >= 30 days	Indicator variable that equals to one if the loan is ever overdue by at least 30 days on any payment.
Borrower Overdue	Indicator variable at the borrower level, which is equal to one if the borrower became overdue at least 30 days *ex post* on *any* loan from *any* lending program, regardless whether it is a big tech loan or a Bank X's regular loan or online loan.
Payback to Maturity	The ratio of payback time to scheduled loan maturity.
Post COVID-19 Shock	Indicator variable that equals to one if the loan was issued in February 2020 or afterwards.
Bank X Credit Available	Indicator variable that equals to one if the borrower had a cheaper and larger remaining Bank X credit limit available at the time of taking a big tech loan.
Use up credit limit	Indicator variable that equals to one if the borrower uses up all the remaining credit limit.
Maturity	The loan's maturity period in month.
Loan Term: 6 months	Indicator variable that equals to one if the loan's maturity period is 6 months.
Loan Term: 12 months	Indicator variable that equals to one if the loan's maturity period is 12 months.
Loan Term: >= 12 months	Indicator variable that equals to one if the loan's maturity period is longer than 12 months.
Repay Once	Indicator variable that equals to one if the loan contract requires the borrower to repay the principal and interest rate all together at the end of loan's maturity period.
Ever Clear	Indicator variable that equals to one if the borrower paid off at least one loan from the corresponding lending program in the past.
Exist Loan	Indicator variable that equals to one if the borrower has at least one other loan outstanding from the corresponding lending program at the time of borrowing.
Ever Overdue	Indicator variable that equals to one if the borrower was ever overdue by at least 30 days on at least one loan from the corresponding lending program in the past.

Has Large Deposit	Indicator variable that equals to one if the borrower has at least RMB 10,000 in the deposit account at Bank X.
Age	Borrower's age at the time of borrowing.
Log(Age)	Logarithm of borrower age.
Male	Indicator variable that equals to one if the borrower is male.
Undergrad	Indicator variable that equals to one if the borrower's education level above an undergraduate degree.
High School	Indicator variable that equals to one if the borrower's education level above high school.
City	Indicator variable that equals to one if the borrower is from a city area.
County	Indicator variable that equals to one if the borrower is from a county area.
Rural	Indicator variable that equals to one if the borrower is from a rural area.
Log(Loan Size)	Logarithm of the size of the loan in RMB.
Log(Credit Limit)	Logarithm of credit limit in RMB by the corresponding lending program.
Log(Remaining Limit)	Logarithm of the remaining credit limit in RMB of the corresponding lending program at the time of borrowing.
Log(Avg. credit limit)	Logarithm of the average credit limit of the corresponding lending program for the borrower.
Log(Avg. interest rates)	Logarithm of the average interest rate of loans from the corresponding lending program for the borrower.
Log(Avg. loan size)	Logarithm of the average size of loans from the corresponding lending program for the borrower.
Log(No. loans)	Logarithm of the total number of loans from the corresponding lending program for the borrower.

Internet Appendix

In this Internet appendix, we present two distinct sets of evidence demonstrating the informational advantages held by the big tech lender. These are illustrated through the analysis of both the sample of overlapped borrowers and the main sample of borrowers.

A. The Sample of Overlapped Borrowers

In this section, we investigate the loans extended to overlapped borrowers, with a focus on whether the loan terms set by the big tech lending program initially have a greater correlation with the borrowers' subsequent loan performance.

Table A1 dives into this aspect by comparing various loan parameters – including credit limit, interest rate, loan size, and the number of loans – between two groups of borrowers. One group consists of those who eventually become delinquent for at least 30 days on at least one loan (whether it's a big tech loan or from Bank X), and the other comprises those who never have any overdue payments. As delinquency is measured at the borrower level, rather than the borrower-lending program level, this approach allows us to account for potential differences in post-origination monitoring between the lending programs, thereby concentrating on the distinctions in initial borrower screening.

In this analysis, we consider only the loans that were originated before the first overdue payment for each borrower to eliminate the impact of any overdue payment on subsequent loan origination and terms. For each borrower in each lending program, we calculate the average values of the credit limit, interest rate, loan size, and the number of loans. The regression analysis is then conducted at the borrower-lending program level. We include borrower fixed effects to control for individual differences, thereby underscoring the distinct approaches of the lending programs. A key coefficient in this analysis is the interaction between the big tech loan indicator and the borrower overdue indicator, which provides insights into whether the initial screening by the lending program is more closely linked to subsequent loan performance.

In Table A1, we segment the analysis based on the types of loans utilized by the borrowers. The first four columns focus exclusively on those borrowers who have obtained both big tech loans and regular loans from Bank X within the sample period. In contrast, the final four columns are specifically for borrowers who have taken both big tech loans and online loans from Bank X.

Columns 1 and 5 of the table present a noteworthy observation: for borrowers who eventually face financial distress, big tech loans are consistently smaller in size compared to those from both Bank X's regular and online lending programs. This trend suggests that the big tech lending program is more prudent in determining loan sizes. On the other hand, columns 2 and 6, which examine the number of loans issued, reveal no significant disparities among the lending programs. This indicates that the frequency of borrowing is relatively consistent between borrowers who become overdue and those who do not, regardless of the source of the loan. Taken together, these results indicate that a smaller total amount of big tech loans were originated to borrowers in financial distress later.

Columns 3 and 4 compare how credit limits and interest rates correlate with borrower distress between the big tech lending program and Bank X's regular lending program. There are no significant differences in credit limit and interest rate. However, columns 7 and 8, which compare the big tech lending program to Bank X's online lending program, paint a different picture. In cases of borrowers who later experience financial distress, the big tech lending program tends to set smaller credit limits and impose higher interest rates. This finding suggests that the big tech lending program may possess an information advantage over Bank X's online program, enabling it to more accurately predict the risk of borrower distress. This contrasts the similar correlation observed with Bank X's regular lending program, which might rely on more qualitative and subjective information in its lending decisions.

Overall, the findings from Table A1 suggest that the terms set for big tech loans to overlapped borrowers correlate more closely with their subsequent loan performance than the terms of Bank X's regular and online loans. This pattern indicates that the big tech lending program is effectively utilizing its informational advantages. It goes beyond just offering high interest rates and convenience, employing a more nuanced approach to screen its borrowers.

B. The Main Sample

For the three lending programs encompassed in our study, a common practice by the lender involves approving a credit line with a specified interest rate for each borrower. A critical aspect of this lending process is the information asymmetry between the lender and the borrower. The borrower might possess more detailed or accurate information about their potential future financial distress, which could lead to behaviors like excessive risk-taking after accessing credit.

To explore this aspect, we conduct a specific test. We aim to determine whether there is a positive conditional correlation between two key variables: one being a dummy variable indicating whether a borrower had reached their credit limit at the time of borrowing, and the other a dummy variable signifying whether the loan subsequently becomes overdue for at least 30 days. A positive and significant conditional correlation between these variables may reflect that borrowers, on average, possess private information about their likelihood of facing financial distress at the time they take out the loans. This private information could influence their decision to borrow up to their credit limit.

We apply this conditional correlation test separately to each of the three lending programs. The procedure involves conducting a pair of Probit regressions for each program. The first Probit regression has a dependent variable that is a dummy indicating whether the loan payment is overdue by more than 30 days. The second regression's dependent variable is a dummy for whether the borrower utilized their entire credit limit at the time of borrowing. These Probit regressions share the same set of independent variables, which include various loan contract terms, borrower characteristic variables, and dummy variables for the borrower's industry, province, and the loan origination month. This approach allows us to test for a positive correlation between the residuals of these regressions, thereby providing insights into whether borrowers use private information about their future financial risk when borrowing up to their credit limit, or if they engage in riskier behaviors post-borrowing.

In Table A2, the first pair of columns presents the results for the big tech loans. The focal point of these results is the correlation of residuals and the corresponding test statistic provided at the end of the columns. Interestingly, the findings reveal a small but negative conditional correlation of -0.004 between the usage of the entire credit limit by the borrower and the subsequent delinquency of the loan (overdue by at least 30 days). This negative correlation suggests the presence of advantageous selection rather than adverse selection in the sample of big tech loans.

The next pair of columns in Table A2 details the results for Bank X’s online loans. Here, the correlation coefficient is positive, yet it is statistically insignificant, implying an absence of adverse selection in these loans. The results for Bank X’s regular loans are reported in the final two columns of Table 10. In this case, there is a positive and significant correlation coefficient of 0.04, which indicates the presence of adverse selection among Bank X’s regular loans.

Overall, the data points to clear evidence of adverse selection in Bank X's regular loans, contrasting with the advantageous selection observed in the big tech loans.[30] These outcomes align with what we observed in the overlapped borrower sample. Furthermore, the lack of evidence for adverse selection in the big tech loans is in contrast to the findings of Chava et al. (2021), which identified that fintech lenders in the United States face more severe adverse selection issues than traditional banks. This disparity highlights the potential differences in lending environments and borrower behaviors across different financial sectors and regions.[31]

References

Chava, Sudheer, Rohan Ganduri, Nikhil Paradkar, and Yafei Zhang (2021), Impact of marketplace lending on consumers' future borrowing capacities and borrowing outcomes, Journal of Financial Economics 142(3), 1186-1208.

Pelosi, Marco (2021), Advantageous selection in fintech loans, SSRN Working Paper No. 3786766.

Vallee, Boris, and Yao Zeng (2019), Marketplace lending: A new banking paradigm? The Review of Financial Studies 32(5), 1939-1982.

[30] 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.

[31] In a related study, Vallee and Zeng (2019) show offsetting effects of public information production on the adverse selection faced by P2P lenders in marketplace lending platforms.

Table A1: Loan Characteristics and Payment Overdue

This table examines the association between whether the borrower is overdue and the characteristics of loans from different lending programs. The data is organized into subsamples, with dependent variables aggregated at the borrower-lending program level, resulting in two observations per borrower in each column. The 'Borrower Overdue' indicator variable reflects whether a borrower is overdue on any loan, irrespective of whether it's from a big tech loan or Bank X's regular or online loans. In cases of overdue borrowers, only loans issued before the first overdue date are considered in the analysis. 'Big Tech' is an indicator variable set to 1 for big tech loans. Columns 1-4 use Bank X regular loans as the benchmark, while columns 5-8 use Bank X online loans. All variables are defined in Appendix A. Borrower fixed effects and fixed effects of the origination month of the first loan from each lending program for each borrower are included. Standard errors in parentheses are clustered at loan origination month. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

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

Table A2: Adverse Selection

This table presents the correlation test of adverse selection for each lending program in the main sample. The data cover a 10% random sample of borrowers and their loans originated from August 2019 through December 2020. The sample includes 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. All the loans matured at least 30 days before May 31, 2021, the ending date of the loan performance data. 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. All variables are defined in Appendix A. All the columns are estimated using a Probit model. 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
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)
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)
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	