FinTech Credit and Entrepreneurial Growth

Harald Hau
University of Geneva, CEPR, and Swiss Finance Institute[1]

Yi Huang
Fanhai International School of Finance, Fudan University, and CEPR[2]

Chen Lin
The University of Hong Kong[3]

Hongzhe Shan
University of Geneva and Swiss Finance Institute[4]

Zixia Sheng
New Hope Financial Services[5]

Lai Wei
Lingnan University[6]

Abstract

Based on automated credit lines to about two million vendors trading on Alibaba's online retail platform, and a discontinuity in the credit decision algorithm, we document that a vendor's access to FinTech credit boosts its sales growth, transaction growth, and the level of customer satisfaction gauged by product, service, and consignment ratings. These effects are more pronounced for vendors characterized by greater information asymmetry about their credit risk and with less collateral, which reveals the information advantage of FinTech credit over traditional credit technology.

JEL Classification: G20, G21, O43

Keywords: FinTech, Big-tech, credit constraints, micro credit, entrepreneurship, firm growth, service quality, customer satisfaction

[1] Geneva Financial Research Institute, 42 Bd du Pont d'Arve, 1211 Genève 4, Switzerland. E-mail: prof@haraldhau.com. Web page: http://www.haraldhau.com.
[2] Fanhai International School of Finance, Fudan University, Harbour Ring Plaza, No.18 Middle Xizang Road, Huangpu District, Shanghai, China. Email: huang_y@fudan.edu.cn
[3] The University of Hong Kong, Pokfulam, Hong Kong, China. Email: chenlin1@hku.hk
[4] Geneva Financial Research Institute, 42 Bd du Pont d'Arve, 1211 Genève 4, Switzerland. E-mail: hongzhe.shan@unige.ch.
[5] CEO of New Hope Financial Services. Former Head of Risk Management and Banking at Ant Group. Email: shengzx@hotmail.com
[6] Lingnan University, Hong Kong China. Email: laiwei2@ln.edu.hk

Conflict-of-interest disclosure statement

Chen Lin

Chen Lin benefited from a research grant by the National Natural Science Foundation of China (No. 72192841).

Harald Hau

Harald Hau benefited from a research grant by the Swiss National Science Foundation (SNSF).

Yi Huang

Yi Huang benefited from financial research support by the Graduate Institute of International and Development Studies, Geneva and financial research support by Fudan University.

Hongzhe Shan

Hongzhe Shan benefited from a research grant by the Swiss National Science Foundation (SNSF).

Zixia Sheng

Zixia Sheng worked as Head of Risk Management and Banking at Ant Group until September 2018. Thereafter, he took up a new position as CEO of New Hope Financial Services, which is not related to the Ant Group.

Lai Wei

Lai Wei benefited from a research grant by the Hong Kong Research Grant Council (No. T35-710/20-R).

Acknowledgments and Disclaimer

We thank seminar participants at Ant Group, Asian Bureau of Finance and Economic Research, the Bank for International Settlements, Bocconi University, the Brookings Institute, the European Winter Finance Summit, the Federal Reserve Board of Governors, the Geneva Finance Research Institute, the Geneva International Macroeconomics and Financial Workshop, the Graduate Institute Geneva (IHEID), Harvard University, the International Monetary Fund, London Business School, London School of Economics, the NBER Chinese Economy Working Group Meeting, the NBER Corporate Finance Program Meeting, the World Bank, Stanford Graduate School of Business, Tsinghua University, the University of Bristol, and the University of Zurich for their comments. We thank Richard Baldwin, Ata Can Bertay, Nick Bloom, Hui Chen, Geng Li, Emily Breza, Stijn Claessens, Anthony DeFusco, Hanming Fan, Hongbin Gao, Giacomo De Giorgi, Alex Xi He, Sabrina Howell, Ergys Islamaj, Ayhan Kose, Lingfang Li, Ye Li, Ernest Liu, Dong Lou, Christopher Malloy, Maury Obstfeld, Cheng Ouyang, Ugo Panizza, Eswar Prasad, Richard Portes, Jun "QJ" Qian, Wenlan Qian, Yingyi Qian, Hélène Rey, Jean-Charles Rochet, Andy Rose, Hong Ru, Stephen Schaefer, Piao Shi, Hyun Song Shin, Kjetil Storesletten, René Stulz, Tao Sun, Fabio Trojani, Harald Uhlig, Alexander Wagner,Vikrant Vig, Pengfei Wang, Shang-Jin Wei, Da Zhi, and two anonymous referees for their comments. Special thanks go to Long Chen, Darrell Duffie, Zhiguo He, Bengt Holmström, Yiping Huang, and Wei Xiong and for their feedback on an earlier draft. We are grateful to colleagues at Ant Group, AliResearch, and Luohan Academy for their support, and to Xiaomin Guo, Yadong Huang, and Sibo Liu for their excellent research assistance. Lin acknowledges the financial support from a research grant by the National Natural Science Foundation of China (No. 72192841). Hau acknowledges the financial support from the Swiss National Science Foundation (SNSF). Huang acknowledges the financial research support by the Graduate Institute of International and Development Studies, Geneva and financial research support by Fudan University. Wei acknowledges the financial support from a research grant by the Hong Kong Research Grant Council (No. T35-710/20-R).

The authors highlight that the data and analysis reported in this paper could contain errors and their use is not suitable for company valuation or for deducing conclusions about the business success and/or commercial strategy of Ant Group. Our data access was granted through the New Blue Program (now the Open Data Program of the Luohan Academy) at the Ant Group. All statements made reflect the private opinions of the authors and do not express any official position of Ant Group and its management. The analysis was undertaken in strict observance of Chinese privacy laws.

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. Ant Group did not exercise any influence on the content of this paper, but did require data confidentiality.

1. Introduction

Credit technology has undergone a dramatic transformation with the advent of new data sources in both developed and emerging economies. Yet, little is known about the structural impact of this “FinTech” revolution on the prospects for entrepreneurship and small firm growth. Development economists have often voiced the conviction that credit constraints for small and micro firms are particularly pernicious in emerging economies, but various methodological and data issues mean that such beliefs are conjectural and have no solid empirical support.[7]

In this paper, we study automated online credit in China. Based on the data generated by billions of transactions in Taobao, Alibaba’s e-commerce marketplace for retail products, the financial firm Ant Group (formerly Alipay) is able to construct automated credit ratings and provide small loans to a large number of online vendors. Exogenous thresholds in the credit allocation algorithm allow a discontinuity design suitable for causal inference about the growth effects of credit access. The vast geographic scope of the data and its high measurement quality for outcome variables in various dimensions, including online sales, transaction volumes, and customer-contributed product and service ratings, circumvent many of the data shortcomings in the empirical development literature.

Loan distribution via the internet represents one of the fastest-growing segments of China’s financial sector, with outstanding loans growing from only 4 billion USD in 2013 to 156 billion USD in 2016 and an estimated 764 billion USD by 2020.[8] Loans to micro, small, and medium-size enterprises (MSMEs) amount to roughly 40% of the online loan market, with consumer lending accounting for the remainder. Ant Group is only one of a large number of firms active in this market: Other new providers of small firm credit include Amazon in the U.S. and Tencent in China. Common to these FinTech companies are new information sources, such as detailed real-time sales data for automated credit evaluations, an online distribution channel that dispenses with traditional bank branch networks, and more effective contract

[7] See, for example, a report by the International Finance Corporation (IFC, 2017) stating that 40% of micro, small, and medium businesses in developing countries have an unmet financing need of 5.2 trillion USD every year. These claims are extrapolated from survey data and do not inform about potential growth effects of credit access.
[8] These figures are based on an industry report by Goldman Sachs Global Investment Research, “Future of Finance: The Rise of China FinTech,” August 7, 2017.

enforcement strategies. Can these new credit technologies unlock latent entrepreneurial growth potentials beyond the reach of traditional bank credit?[9]

The first part of this paper provides a descriptive analysis of the heterogeneous entry decisions of Taobao vendors to operate online. We explore the regional factors that could account for the heterogeneous patterns of online entrepreneurial activities and infer the possibility that firms are underserved by bank credit and thus initiate online (shop) presence for easier access to (FinTech) credit. The previous literature on banking in China (Allen, Qian, and Qian, 2008; Qian, Strahan, and Yang, 2015) has pointed out various credit market frictions. For example, the overall level of banking development and bank credit supply is extremely heterogeneous across China's city-level prefectures and supply is determined to some extent by an administrative credit allocation process in which most banks are state-owned and the five largest account for 37.2% of the total bank assets as of 2016.[10] Moreover, bank credit tends to be tilted towards the state sector because of aligned political objectives of state-owned enterprises (SOEs) and "soft-budget" constraints of SOE borrowers (Lin and Tan, 1999; Bai, Lu, and Tao, 2006; Ru, 2018).

As FinTech credit can potentially overcome these frictions, it could induce greater online entrepreneurial activities of MSMEs that are crowded out by SOEs from the local credit market. We provide evidence that supports this hypothesis. A higher state bank density at the city level correlates positively with the total entry rate of Taobao vendors in regions where SOEs account for a large fraction of total output. These firms also enjoy a higher total amount of online credit. The results are consistent with the argument that the banking sector not only fails to alleviate credit frictions for small entrepreneurs, but actually accentuates them through the redirection of local savings to state sector investments. State-owned banks create a metaphorical "black hole" when it comes to entrepreneurial credit, which absorbs local savings and channels it mostly to SOE investments. FinTech credit can compensate such local credit supply shortages

[9] We use the term FinTech rather than TechFin simply because it is more commonly used. However, the latter term is more appropriate following the terminology suggested by Zetzsche et al. (2017): "TechFins rely on large-scale data sets [...] developed in their primary course of business and then put them to use in financial services." This is a good description of Ant Finance's business model, which is based on access to Alibaba's e-commerce transaction data. Lu, Liu, and Xiong (2022) also distinguish between FinTech credit and big-tech credit and mention Alibaba's Ant Group as a typical example of big techs offering financial services.

[10] Source: China Banking and Insurance Regulatory Commission, https://www.cbirc.gov.cn/. The so-called Big Five banks are Bank of China, Bank of Communications, China Construction Bank, Industrial and Commercial Bank of China, and Agricultural Bank of China.

for the private sector and thus helps to integrate China's geographically fragmented credit market for small private e-commerce vendors.

The main contribution of this paper is to produce quantitative evidence for the causal effect of FinTech credit on entrepreneurial growth and development in the e-commerce sector. This causal link between finance and firm growth represents a fundamental but methodologically challenging question for both the finance and development literature. We exploit a discontinuity in the credit approval algorithm to separate similar firms with and without credit access and study the causal growth effect of credit access in the world's largest emerging economy. The analysis is possible because Ant Group granted us (confidential) access to end-of-the-month records of all e-commerce firms/vendors trading on Taobao during the period from September 2014 to July 2016. The sample of all active Taobao vendors comprises 35.5 million firm-months for 3.4 million firms or vendors throughout China. During the sample period, Ant Group approves a credit line (i.e., the Taobao credit facility) for 2.89 million firms, thereby offering online credit for a total of 26.8 million firm-months.[11]

Based on daily transaction data from the Taobao e-commerce platform provided by Alibaba and other financial data sources, Ant Group first subjects these firms to a detailed credit evaluation. Specifically, Ant uses its algorithm-based credit-scoring model to automate the provision of credit lines based on a cut-off score, which enables us to employ a regression discontinuity design (RDD) to make causal inferences on the effect of access to FinTech credit. A unique feature of our credit data is that they comprise the full sample of e-commerce platform vendors: We observe firm performance for all credit eligible and non-eligible vendors. Compared to previous work on small-firm loans (Fracassi et al., 2016), our data structure avoids any sample selection on credit demand factors.

We focus on two types of growth-related performance measures. The first are sales and transaction growth, which are direct proxies for firms' growth outcomes. We are able to observe sales growth and transaction growth without measurement error for a very large sample of online vendors over monthly intervals. We find that sales and transactions spike by an incremental 18% and 13%, respectively, over an average month following credit approval.[12]

[11] Ant Group provides a variety of other types of credit to particular user groups of Alibaba's e-commerce platforms. This paper only focuses on the Taobao vendor credit line, which is the economically most significant loan category.

[12] By construction, our growth measures gauge the rate of change in sales or transactions from the month before to the month after credit approval. We divide the estimate by two to obtain the monthly effect.

Such large growth estimates support previous estimates in the development literature for the role of credit constraints as an important impediment to growth in emerging economies (Banerjee and Duflo, 2014).[13]

The second type of measures are customer-contributed product and service ratings, which gauge firms' investment in customer capital. Over the past few decades, firm investment has undergone a dramatic shift from tangible to intangibles expenditure, which has become a crucial source of firm growth and long-term value. Intangible capital is believed to contribute more than half of the output per hour, and to constitute the largest systematic source of growth in the U.S. (Lev, 2001; Corrado and Hulten, 2010; Bernanke, 2011).[14] Among the various components of intangible investment, including brands, human capital, and research and development (R&D), customer capital is arguably the most important and has attracted intensive discussion in recent literature (e.g., Gourio and Rudanko, 2014a,b).[15] Customer capital consisting of strong customer relationships and loyalty represents a sustainable competitive advantages and source of long-term firm value. We can trace the customer capital formation of Taobao vendors using multi-dimensional customer-contributed ratings, which come at high frequency and granular level. This helps to address the empirical challenge that the existing literature faces in measuring customer capital (Dou, Ji, Reibstein, and Wu, 2021). We find that each of the three ratings increases significantly following credit approval. Firms with credit access on average obtain higher product, service, and consignment ratings than firms without credit access, by 0.0541, 0.0544, and 0.0551 points, respectively. This amounts to about 24% of the standard deviation of these ratings which are expressed on a scale from 0 to 1. In robustness checks, we show that the results on sales growth, transaction growth and customer ratings all hold for longer measurement periods after credit access. The results are also robust to using higher-order polynomials, different functional forms and alternative bandwidths in the empirical specifications.

[13] Banerjee and Duflo (2014) estimate a growth rate of 75% for credit constrained firms after inclusion in a government- sponsored lending program in India. However, a small sample size of only 152 firms and uncertain outcome measurement impair a robust inference. For recent overviews, see Banerjee, Karlan, and Zinman (2015) and Beck, Demirgüç-Kunt, and Maksimovic (2018).

[14] This trend also picks up in other major economies around the world (Haskel and Wesstlake, 2018).

[15] According to a study by Binder and Hanssens (2015) using more than 6,000 mergers and acquisitions (M&As), customer capital accounts for about 20% of enterprise value, which is much more than the value of brands and exceeding R&D based on the latest statistics. Similarly, using information disclosed after M&As, Liang and Yeung (2018) find that customer-related intangible assets on average account for 18% of the targets' pre-merger market capitalization, which is way above the value of brand and exceeds that of R&D in recent years.

The statistical power of a large sample with extensive coverage of firms in different regions and industries allows us to document the heterogeneous growth effect of FinTech credit for different firm types. Firm differences enable us to explore the competitive advantage of FinTech credit along three dimensions that are theoretically motivated by the banking literature and concern pre-lending screening and collateral use, credit distribution costs, and post-lending monitoring and enforcement. Our analysis mainly focuses on the information advantage of FinTech credit in credit screening and monitoring, but we also discuss briefly suggestive evidence on the other channels.

The business model of FinTech credit is mainly based on the analysis of e-commerce transaction data and the competitive information advantage arising from these data. The closest economic analogy to this financial innovation could be improvements in consumer credit analysis in the 1980s and 1990s based on extensive credit card data. Livshits, Mac Gee, and Tertilt (2016) provide an insightful empirical discussion of this episode. They also develop an equilibrium model with asymmetric information about heterogeneous default risk and fixed costs of contract distribution. Their framework predicts that improved credit technologies mostly extend the extensive margin of credit. Hau et al. (2019) obtain similar predictions based on a simpler model and confirm empirically that use of FinTech credit is most active among weak creditors with low credit scores. This provides additional supportive evidence on the competitive advantage of new credit technologies for high-risk creditor types.[16]

In this paper, we demonstrate the heterogeneous benefits of FinTech credit by showing that FinTech credit approvals generate relatively higher sales and transaction growth as well as higher customer ratings for younger firms and firms operating in industries with higher information asymmetry.[17] We also find that FinTech credit approval has a much more

[16] As MSMEs usually have sparse credit history, possess mostly “soft” rather than “hard” information (i.e., information not easy to quantify), and lack collateral, they are subject to information asymmetries and represent high credit risk, and can hardly fit into bank lending models under stringent capital requirement (Petersen and Rajan, 1994; Berger and Udell, 1995).

[17] FinTech lenders usually have the following advantages: (1) they can access high-frequency, high-dimension, and high-coverage real-time information about small firms, including granular digital footprints and various networks; and (2) they can process information efficiently, for example, converting soft information into hard information without losing much crucial content (Berg, Burg, Gombovic, and Puri, 2020; Liberti and Petersen, 2018; Liu, Lu, and Xiong, 2022). These information advantages help them automate their credit allocation models so that their credit allocation decisions are less likely to be subject to human heuristics or biases compared to traditional bank lending decisions that are influenced by sentiment, subjective judgment, and cultural backgrounds of the loan officers (Cortes, Duchin, and Sosyura, 2016; Fisman, Paravisini, and Vig, 2017). Information advantages also make FinTech lenders less reliant on collateral because data can be regarded as a new type of collateral for FinTech lending (He, 2021). Our data also show that Ant Group tailors its credit supply to borrower characteristics, rather than to local credit market conditions, like the level of local credit competition. Such

significant impact on firms with less valuable collateral. This suggests that FinTech lenders depend less on collateral to mitigate information asymmetries and moral hazard problems (Aghion and Bolton, 1992). All of this is consistent with an information advantage for FinTech lenders.

The short-term nature of FinTech credit and its high interest rates (with a median value of 17%) raise concerns about how platform entrepreneurs can truly benefit. First, we note that firms can benefit from the approval of FinTech credit lines even if they do not take up the credit offer itself. Credit lines allow firms to access pre-committed debt capacity, which hedges against future liquidity shocks and relaxes their precautionary saving motives to hold cash today (e.g., Holmstrom and Tirole, 1998; Acharya et al., 2014, 2020). Firms with credit lines can then prioritize the use of cash holdings to fund growth opportunities when they need capital. Therefore, the mere accessibility of FinTech credit can have a direct, first-order impact on firms' investment decisions that boost sales and build up customer capital.

Second, Taobao vendors that operate in the retail segment are characterized by short seasonal spikes in inventory demand. Exceptionally high working capital needs therefore tend to last only for short periods of time so that even high interest rates are not prohibitive. According to Liu, Lu, and Xiong (2022), firms that borrow from the Ant Group have very fast repayment cycles. The 25th percentile and median repayment time is only 0.04 and 0.28 of the scheduled loan maturity, that is one week and six weeks for a six-month loan, respectively. Therefore, the net borrowing costs are much lower than the full annual costs based on the quoted (high) interest rate, with an effective average (median) interest expense to loan size ratio at the 5% (2.7%) level.[18] Furthermore, the high interest rate can serve as a mechanism to screen the borrowers with real liquidity needs and fast repayment abilities, and this helps address adverse selection problem and reduce loan risk.[19] In other words, the combination of high product turnover rates and low overall capital requirements in the online retail sector

geographic homogeneity in credit supply is usually not fulfilled in bank data where local interest rate setting is common. This implies that two online vendors with the same characteristics would obtain exactly the same credit offer regardless of their respective locations throughout China. Also note that Ant Group is a private company, and its credit policy has no political objectives, whereas traditional banks could tilt loans toward specific purposes and industries because they are controlled by local, city, provincial, or national government (Deng et al. 2015).

[18] Consistent with the short-term liquidity needs and high variability in inventory demand, Liu, Lu, and Xiong (2022) document a much more frequent borrowing by Ant's borrowers than bank borrowers, with an average (a median) of 6 (3) times over their 17-month sample period.

[19] Liu, Lu, and Xiong (2022) find evidence of advantageous selection that firms taking up more credit from the Ant Group tend to have a lower default rate compared with bank credit borrowers.

enable vendors to make fast repayments, thereby sustaining a relatively high (annualized) interest rate while achieving entrepreneurial growth.

The third part of the analysis seeks to understand the mechanisms by which FinTech credit fosters growth. We find that firms with a new credit line increase advertising spending, supply a greater variety of products, and convert more customers from simply visiting the webpage to placing orders. These results provide additional evidence that firms can implement certain policies relatively quickly to boost sales and customer experience. We note that the data currently available do not allow us to distinguish between sales diversion from other vendors and a genuine increase in (aggregate) consumer demand. Thus, it is not feasible to infer any macroeconomic growth and aggregate welfare contribution of Ant Group credit. Yet the improvement in customer experience is likely to represent a genuine welfare benefit.

2. Literature

An important research question in the development literature concerns the role of credit market frictions as a growth impediment for small firms. Some of the most recent contributions use natural experiments in pursuit of better causal identification. Berg (2018) exploits a rating cut-off in loan approval for SMEs and applies the RDD method to document the effect of loan rejections on the cash holdings of firms. Barrot and Nanda (2017) use the acceleration of receivable payments for small government contractors after the introduction of Quickpay and document employment effects of macroeconomic significance. Banerjee and Duflo (2014) estimate large sales and profit elasticities for firms in India's targeted lending programs – suggesting credit constraints for many small and medium-size enterprises. Other recent work emphasizes heterogeneous treatment effects contingent on entrepreneurial skills (Banerjee et al., 2018). Unfortunately, many randomized experiments on the impact of microcredit face statistical power problems due to a small sample size (Banerjee et al., 2015), which makes it difficult to pin-point the precise magnitude of economic effects. The large sample size in our study of online vendors, the exact measurement of monthly online sales growth, and customer-contributed, granular customer ratings help us to obtain stronger statistical results. Using uniform electronic records from the Taobao platform, our study also overcomes issues of accounting (in-)accuracy that are inherent in data sourced from small heterogeneous firms in developing countries.

With few exceptions, previous research is largely mute on the distinct dimensions of FinTech's competitive advantage and its heterogenous benefits across firm types.[20] The scope and accuracy of the Chinese data allow us to explore heterogeneity in the causal effect of access to FinTech credit across firms and characterize various channels through which FinTech platforms can expand entrepreneurial credit to the benefit of small businesses. These results provide suggestive evidence on the advantages of FinTech credit versus traditional bank credit and shed light on a growing literature that identifies substitution effects between FinTech and traditional bank credit.[21] We also note that the information advantages of FinTech credit, as evident in the information complementarities between online sales activity and FinTech credit provision, operate not only in the segment of small business credit, but extend to the domain of consumer credit. For example, Ouyang (2023) identifies a positive causal effect of cashless payment adoption by consumers on their access to consumer credit. Consistent with our arguments for an information advantage of FinTech credit, Ouyang (2023) shows that information from payment flows facilitates credit evaluation and provision with benefits concentrated among financially underserved customers.

More broadly, our findings provide implications for and supplement the literature on the real effect of FinTech adoption. For instance, Agarwal et al. (2019, 2022) suggests that the adoption of mobile payment technology exerts a major impact on customer acquisition and business creation of small firms, and boosts credit card spending of consumers, which is in line with our findings that small FinTech business credit enables firms to improve customer satisfaction, promoting entrepreneurship and firm growth. Furthermore, this paper adds to our understanding particularly about the role of FinTech credit, as a subset of broader FinTech innovations, in empowering small businesses. Frost, Gambacorta, Huang, Shin, and Zbinden

[20] Causal evidence of the positive effects of FinTech credit on growth and development is still limited. Fracassi et al. (2016) provide evidence of improved business growth and survival under eligibility for microloans from a non-profit lender in Texas. However, particular borrower profiles can self-select into the applicant pool, and it is more difficult to assert external validity in this case. Our experimental design differs in that a credit line is offered to all qualified Chinese online vendors independently of whether or not they seek credit. This allows us to benchmark the incremental performance of firms with access to FinTech credit against firms without it.

[21] Tang (2019) takes the implementation of the FAS 166/167 regulation as an exogenous negative shock to bank credit supply, and finds bank credit is replaced by P2P lending. Balyuk (2019) shows that a firm's P2P lending improves its access to complementary bank credit. Roure, Pelizzon and Thakor (2018) study peer-to-peer (P2P) lending in Germany and show that it is more inclusive than traditional bank credit. Di Maggio and Yao (2021) compare traditional bank to FinTech credit, and show that the latter features higher default rates. In the context of small business lending, Balyuk, Berger, and Hackney (2020) show credit substitution between bank and FinTech credit based on banks' stress-test exposure as a source of exogenous credit supply variation. Gopal and Schnabl (2022) show that small business lending from finance companies and FinTech lenders substitutes for the reduction in bank lending caused by the 2008 financial crisis. Erel and Liebersohn (2020) analyze competition between banks and FinTech providers in the context of the U.S. Paycheck Protection Program.

(2019) analyse the drivers and implications of FinTech in finance around the world. Their findings suggest that FinTech credit plays a larger role in regions with a less competitive banking industry and provide some preliminary evidence on its information advantages and effect on product offerings. Using proprietary data in China, Liu, Lu, and Xiong (2022) show that FinTech lenders have unique advantages in serving the under-banked borrowers, particularly for their short-term liquidity needs inside the big-tech lender's ecosystem. This is consistent with our findings that vendors have a financing motive underlying their entry decisions to operate on the online platform. They also show that FinTech loans exhibit advantageous selection in that the default rates are lower for those using up the credit limits. They suggest that high interest rates serve as a mechanism to screen the borrowers capable of making a fast repayment over short periods. This is consistent with our observation that most vendors draw on their credit line in a selective manner, and that they often consider FinTech credit as a form of liquidity insurance that relaxes their precautionary saving motives and cash holdings to fund growth opportunities.

Moreover, our contribution is special in its focus on FinTech credit in China – a country historically characterized by severe credit supply frictions for private-sector firms. Our analysis reveals that the intensity of state-owned bank branches correlates with a higher entry rate of Taobao vendors and the provision of more FinTech credit by Ant Group. This suggests that state-owned bank branches exacerbate local credit scarcity for entrepreneurs as they both refrain from local private-sector lending and also absorb local bank deposits. In this way, we contribute to a growing literature on the geographic segmentation of China's credit market (Dobson and Kayshap, 2006; Roach, 2009; Boyreau-Debray and Wei, 2004 and 2005; Brandt and Zhu, 2007; Dollar and Wei, 2007; Firth, Lin, Liu, and Wong, 2009).[22] Our analysis also has a bearing on discussion about the role of credit constraints for China's growth.[23]

---

[22] Most recently, Huang, Pagano, and Panizza (2019) provide evidence on China's credit market segmentation based on the crowding out of private investment by local government debt. Hau and Ouyang (2019) show how China's geographically segmented credit markets generate local credit scarcity and corporate underinvestment if local real estate booms absorb a large share of local savings. Gao, Ru, Townsend, and Yang (2017) provide an interesting discussion of Chinese bank deregulation aimed at reducing the segmentation of the local credit market.

[23] The role of informal lending channels and their efficiency in channelling funding to China's fast-growing private firm sector has been the subject of much debate (Tsai, 2002; Allen, Qian and Qian, 2008; Linton, 2008). Allen, Qian, and Qian (2005) argue that informal networks use a screening and monitoring technology that makes the lack of access to traditional banking a lesser concern for private Chinese firms – hence their fast growth over the last two decades. However, Ayyagari, Demirgüç-Kunt, and Maksimovic (2010) find evidence to the contrary in firm surveys: Private sector SMEs with access to bank credit appear to grow faster than private firms that rely on informal lending channels, even after controlling for the selection bias of such a comparison. The growth effect

Finally, credit access can provide an important competitive advantage, and the lack of it may increase firm risk. Barrot (2016) looks at the French trucking industry to show that legal restrictions on the amount of trade credit that trucking can provide to customers benefitted mostly small credit-constrained firms and lowered their default risk. Chen, Huang, Lin, and Sheng (2021) show that access to FinTech credit reduces firm volatility and the firm exit probability. Our results supplement their findings as we show that Ant Group enhances firm competitiveness by providing credit for them to boost sales and customer satisfaction that matter for firm survival.

3. FinTech Credit in China

3.1. Alibaba and Ant Group

Founded in 1999, Alibaba now is the largest e-commerce and FinTech conglomerate in China. It owns three major online shopping platforms called Alibaba (B2B), Tmall (B2C), and Taobao (C2C). By 2016, the gross merchandise value (GMV) (or total trading volume) in the two online retail platforms Tmall and Taobao exceeded 3 trillion RMB a year, which amounts to 4% of Chinese GDP. In 2002, Alibaba began to collect data from its e-commerce platforms in pursuit of better credit information. Alipay was launched in 2004 to provide improved payment services for online transactions. In collaboration with the China Construction Bank and the Industrial and Commercial Bank of China from 2006 to 2010, Alipay began to grant selected loans and developed its credit rating system, databases, and risk management systems. By 2010, Alipay was in a position to provide automated firm credit based on algorithms using the transaction and financial data obtained from Alibaba's online platforms. By 2014, Alipay had become the world's largest mobile and online payment platform and accounted for approximately half of all online transactions in China.[24] In 2015, Alipay was re-branded as Ant Financial Service Group. It continues to use the transaction data from Alibaba's retail platform to provide automated small business credit. In November 2020, Ant Group was set to raise 34.5 billion USD in what would have been the world's largest IPO at the time, valuing the company at 313 billion USD. On the eve of the IPO, the Chinese regulators suspended the process.

---

of FinTech credit documented in this paper suggests that informal credit is a highly imperfect substitute for formal credit even for very small firms in China.

[24] See Bobsguide, February 12, 2014: http://www.bobsguide.com/guide/news/2014/Feb/12/alipay-surpasses-paypal-as-leading-mobile-payments-platform/

Table 1, Column (1), documents the evolution of the annual trading volume on Taobao for each year ending in February from 2012 to 2016. Trading grew by roughly 74% a year over this four-year period. The trading activity generates commercial data on millions of small businesses or vendors, which can be employed to alleviate the credit constraints of the most successful entrepreneurs. The rapid growth of Alibaba's online retail is often attributed to the creation of escrow accounts managed by Alipay. Securing online payments through escrow accounts represented an astute operating mode in a retail market characterized by low consumer confidence in the reliability of online counterparties.

Table 1, Columns (2)-(3), describes the evolution of Taobao firm loans in terms of the number of eligible firms and the number of vendors using these loans as of February of each year from 2012 to 2016. Column (4) shows the aggregate amount of all eligible credit (credit lines), which grew by 82% a year from February 2012 to February 2016 in line with the overall growth in trading activity on Taobao. Column (5) reports the outstanding balance of credit used as of the corresponding year-month, which aggregates to approximately 17% of total available credit line by Ant Group. The aggregate Taobao firms' credit taken reached roughly 8.7 billion RMB in February 2016. This amounts to only 0.037% of the total micro and small firm credit supplied by China's banking system.[25] From a macroeconomic perspective, Ant Group's credit volumes in 2016 were still small and (as yet) had no structural impact on China's overall credit market.

[Table 1 about here]

3.2. Ant Group's Credit Approval Process

Ant Group can make its credit approval process more informative by sourcing firm performance data from Alibaba's online retail platform. The key element of the credit evaluation process is a linear credit scoring model, which combines historical default data on firm credit with sales and financial data mostly sourced from the online retail platforms. The credit score assigned by Ant Group is similar to the FICO score used by many large U.S. banks to evaluate borrower quality (e.g., Keys et al., 2010). A large number of variables enter the model, but the most important concern the recent sales record of a firm recorded on the online

[25] A research team at the Central University of Finance and Economics summarized data obtained from the CBRC for their China Micro, Small and Medium Enterprise (MSME) report (Shi, 2016) and evaluated the aggregate outstanding micro and small enterprise (MSE) loans of China's banking system at 23.46 trillion RMB.

retail platforms. The credit scoring model summarizes the credit evaluation in a continuous score ranging from 380 to 680. For most of the months covered by our data, Ant Group set a credit allocation rule that generally approves credit at the beginning of each month if the credit score exceeds the threshold value of 480. The choice of the 480-cutoff was motivated by a Value-at-Risk (VaR) model, where a maximal cumulative default probability was picked.

Ant Group evaluates credit eligibility on a monthly basis in an automated process. Vendors judged eligible for the credit are automatically informed via the Taobao web interface about the value of their credit line. To use this credit, they fill out a single online contract form, which takes approximately three minutes. The credit is available immediately, and the credit terms are similar to those of a credit card. The maturity of credit is usually 12 months, of which a minimum of 1/12 has to be repaid each month counting from the date the credit is drawn. If the credit score of the vendor drops below the credit score threshold of 480, the credit line is likely to be withdrawn. The earliest this can occur is one month after the initial credit approval. Withdrawal of the credit line implies that no new credit is available, but the existing balance of credit taken remains and has to be repaid over the remaining maturity.

The data we obtained from Ant Group have a few features that condition our empirical design. First, in parallel to the credit scoring model, Ant Group applies additional "hard" criteria, which exclude firms from credit approval even if the vendor's credit score exceeds the threshold of 480. Most frequently, these cases concern previous default on bank or trade credit according to national credit data. Also excluded are vendors penalized for poor service on Taobao or other Alibaba platforms. Vendor relationships with "dubious suppliers", like those involved in product counterfeiting or fraud, can also result in credit exclusion. Other rare exclusions concern "conflict of interest" rules: For example, employees of Ant Group or their family members cannot obtain credit. Unfortunately, we do not have access to all the information implying an unconditional denial of credit. Thus, vendors subject to an unconditional credit exclusion (outside the credit scoring model) generate so-called "no-show cases" for our analysis.

Second, we observe a vendor's credit score and credit approval information only for the last day of the month. As Ant Group generally bases the credit allocation decision in a month t on the beginning-of-month information, we proxy credit score at the beginning of month t using credit score at the end of month $t-1$. Generally, this does not pose a problem as Ant Group imposes a stability mechanism that keeps a firm's credit status mostly unchanged during a month. But occasionally credit decisions are also taken within the month (for example, if new firm information arrives), and the (outdated) credit scores on our record then become an incorrect predictor of access to credit. This generates so-called “cross-over” cases, namely observations on vendors with a credit score below 480 at the end of month $t-1$, which nevertheless record a credit approval during month t.

Figure 1, Panel A shows the distribution of monthly credit scores for 2 million Taobao firms from November 2014 to June 2015. For any given credit score, the green bars denote the number of firms with credit approval, and the (incremental) red bars above represent the number of firms without credit approval. At the credit score of 480, Figure 1, Panel A shows the discrete jump in the probability of credit approval. The existence of both “no-show” and “cross-over” cases in Figure 1 requires a fuzzy random discontinuity design (FRDD) to infer the causal effect of credit approval on firm outcomes.[26]

The discontinuity of credit approval at a particular credit score threshold provides a unique statistical opportunity to explore the causal effects of credit on firm performance for a large sample of firms around this discontinuity. A key assumption of the RDD is that agents cannot precisely manipulate the forcing variable (i.e., the credit score) near the cutoff (Lee and Lemieux, 2010). The calculation method for the credit score is unknown to the online vendors; neither do they observe their credit scores. This implies that Taobao vendors cannot easily game their credit eligibility. This assertion is supported by the smoothly rising distribution of vendors around the 480-score shown in Figure 1, Panel A. We find no evidence for any clustering of firms with credit approval just above or below the credit score of 480. Moreover, the “manipulation test” by Cattaneo, Jansson, and Ma (2017) does not suggest any discontinuity of density in the credit score variable; the test yields a p-value of 0.8796, and cannot reject the null hypothesis of no manipulation. Lastly, the removal of 480-threshold rule after June 2015 suggests that it was an ad hoc feature of the credit allocation process.

Moreover, the repeated (monthly) nature of credit approval decisions allows us to include month fixed effects in our analysis and thus filter cyclical growth effects from our analysis. While the data structure seems intermittent, the average duration of credit store and credit status of a firm extends beyond one month following a credit approval decision. On average, for firms

---

[26] Our empirical strategy of identifying the growth effects of credit is predicated on this jump in the probability of credit approval. The credit score as the forcing variable (with the credit discontinuity) is likely to be endogenous to outcome variables like sales growth – but only in a continuous (or “smooth”) manner that can be controlled for by conditioning on the credit score itself. Helpful introductions to the methodology include Imbens and Kalyanaraman (2012), Lee and Lemieux (2010), and McCrary (2008).

with credit scores in the range from 480 to 500 in a given month, more than 85% of them will continue to score above 480 in the next month, and about 52% will score above 480 in the next three months consecutively. If we further condition on firms obtaining credit access in a given month when their scores fall into the range from 480 to 500, 72% will continue to have the credit access in the next month, and about 46% will maintain the credit access in the next three months consecutively. We plot the fraction of firms staying above 480 (retaining credit access) over a consecutive number of months after a treatment event in Figure A1 of the Appendix. While the credit approval decisions are generally repeated at a monthly frequency, most firms with credit access in a given month receive a persistent treatment beyond one month. Therefore, we require a treated firm to retain its access to credit from the current month t to the end of next month $t+1$, and a control firm not to have access to credit during the same period (i.e., no credit access is observable to us at either the end of month t or the end of month $t+1$). Then, we measure incremental growth effects from the month prior to the approval of credit line (i.e., month $t-1$) to two months afterwards (i.e., month $t+1$).[27]

[Figure 1 about here]

4. Data Issues

4.1. Samples

Our analysis mainly uses two samples: (1) a city-level aggregated sample for analyzing the association between various regional factors and the entry rate of online vendors into the Taobao trading platform; and (2) a firm-month-level sample for analyzing the causal firm performance effect of FinTech credit.

The city-level sample is aggregated from all the Taobao vendors with location information, which is available for about one-third of the full population of Taobao vendors. Specifically, we use the establishment date of the vendors to infer the year of platform entry. Given that a vendor rarely withdraws from the Taobao platform once registered, we can reconstruct the growth path of the Taobao platform from different cities over the decade from 2005 to 2015. To supplement the analysis of entry decisions, we construct another aggregated sample on the total amount of monthly credit offered by Ant Group to Taobao vendors at the city level in

[27] By requiring a treated (control) firm to retain its credit approval (no credit) status over the stipulated period, we can mitigate the attenuation bias introduced by status-switching cases.

2015. Here, we explore whether the entry pattern of Taobao firms also correlates with the availability and use of online credit offered by Ant Group.

The main data concern monthly statistics on vendors selling in Alibaba's online retail platform Taobao during the period of November 2014 to June 2015. This sample starts in November 2014, which is the first month when all outcome variables are made available to us by Ant Group. The sample stops in June 2015, after which Ant Group updated its construction of credit scores, changed its credit approval standard, and since then the discontinuity at 480 no longer exists.[28] We focus on the active merchants and group them into treated and control groups. A firm is treated if it is granted access to a credit line from the current month t to the end of next month *t+1*. A control firm has no access to credit during the same period (i.e., no observable access at either the end of month t or the end of month *t+1*). Furthermore, by requiring all the dependent variables to be present, we end up with a sample of 7,420,423 observations from 1,717,780 firms, which is the largest valid sample for our analysis of the performance effect of FinTech credit. Within this sample, 1,196,887 observations from 547,491 firms are located in a credit score range of [460, 500]. The data in this local range are selected for the (fuzzy) random discontinuity design.

4.2. City-Level Variables

For the city-level analysis, we first construct two measures of the entry rate of Taobao firms. *Ln(# New TB Firms)* denotes the natural logarithm of the total number of Taobao firms entering the platform from a given city over the years from 2005 to 2015. We then merge this panel with various indicators on local macro conditions in 2005, the initial year of the entry measures. Whenever the respective variable is unavailable in 2005, we use its earliest available value after 2005. The macro indicators include GDP per capita (*PCGDP*) as a measure of local economic development, *Population* as a size measure for the city, *Digital Development Index*, the aggregate index from the Peking University Digital Financial Inclusion Index of China developed by Guo et al. (2020), as a proxy of local coverage and depth of local digital services, the balance of loans of all the financial institutions in a city over its GDP (*Loan/GDP*) that gauges the overall development of the banking system, the number of state-owned bank branches for every 10,000 citizens (*State Bank Intensity*), which proxies for state presence in local bank credit supply, and *SOE Output Share* as a proxy for the credit demand of SOEs,

[28] In December 2014, the 480 cutoff was briefly suspended, so we therefore exclude this month.

which is constructed using the output data in the annual survey of industrial firms in China.[29] We also calculate the total amount of monthly credit line offered by Ant Group (or used by Taobao vendors) at the city-level in 2015 and take the natural logarithm to get *Ln(Credit Line)* (or *Ln(Credit Use)*). The corresponding macroeconomic variables for this analysis are measured in 2015 (or the latest year the data are available before 2015). The summary statistics of the aggregated measures are presented in Table 2, Panel A.

4.3. Firm Panel Variables

The variables used in our FRDD analysis can be categorized into three groups. The first group is related to the credit status of a firm. We define *Credit Score* as the score generated by the credit-scoring model of Ant Group for a firm at the end of month $t-1$. Correspondingly, we define an indicator variable based on the credit score, which functions as our instrument. *IV (Credit Score≥480)* equals 1 if *Credit Score* is greater than or equal to 480 and 0 otherwise. The indicator variable, *Credit Approval*, measures a firm's observed approval status at the end of month t that stays valid until the end of $t+1$, and 0 if it has no credit line at either end of the two months. We also record the (time-weighted) amount of the credit used by the vendor and define it as *Credit Amount*.

The second group of variables are related to firms' growth outcomes. *Sales Growth* measures the sales growth of a firm from the month prior to credit allocation to the month afterwards, which is constructed as the log difference from month $t-1$ to $t+1$. *Transaction Growth* is similarly constructed based on a firm's transaction volume (i.e., the number of orders completed). We winsorize the value of both growth measures at the 1st and the 99th percentiles.

The third group of variables comprise three customer-contributed ratings from Taobao's Detailed Seller Ratings (DSR) system. The first metric is a product rating, which gauges customers' perceptions of product quality, such as whether the product description is accurate, and whether the product functions as expected. Thus, a merchant can increase its product rating by improving the design, quality, and function of the products. As most of the merchants on Taobao are retailers, they can procure better products from different suppliers swiftly, compared to manufacturing firms that need time to redesign their products. A merchant can also expand the product range available to customers to enrich their shopping experience.

[29] We use the registration type in the survey to identify SOEs. We did not include collectively owned firms as SOEs.

Furthermore, merchants can improve the way they display product information, such as incorporating more original, high-resolution images as well as greater detail about materials, place of origin, etc. The second metric is a service rating, which evaluates the quality of the interaction between the vendor and the customer. For example, it assesses whether a salesperson is responsive and helpful in customers' inquiries, whether they satisfy customers' particular needs, and their attitudes. Firms can invest in better customer hotlines (e.g., extended working hours), more service personnel, and greater customer support to improve this rating. The third metric is a consignment rating, which assesses the timeliness of product delivery and proper handling of the consignment. Since firms can always outsource the shipping and delivery services of their products, they can choose more reliable logistics providers (e.g., better packaging and faster delivery) to improve consignment quality. For each completed transaction, customers can input a rating from 1 to 5 under each metric, where 1 is the lowest and 5 is the highest.

For each rating metric, we construct the average value across all transactions in a firm-month, winsorize the value at the 1st and the 99th percentiles, and standardize it along the range of [0, 1] for ease of interpretation.[30] *Product Rating*, *Service Rating*, and *Consignment Rating* are thus defined as the standardized ratings of product quality, service rendering, and shipment quality, respectively. For our baseline analysis, we record the ratings in month *t+1*. Finally, we use a set of dummy variables for each main product category of the online shop (firm type or industry) based on Alibaba's vendor categorization. The five most prevalent vendor types are: Women's clothing (accounts for 15.1% of all online shops on Taobao), men's clothing (5.1%), cosmetics (4.4%), second-hand products (3.6%), and women's shoes (3.5%).

Table 2, Panel B presents the summary statistics of key variables in the local FRDD sample (i.e., credit scores in the local range of [460, 500]). These firms have an average *Credit Score* of 484.7, which represents a much higher credit risk compared to an average of 522.64 for firms comprising the full range of credit scores. These local-range firms obtain credit approval (*Credit Approval*=1) in 62% of all firm months, whereas more than 75% of all Taobao firms with internal ratings have access to credit in our sample period. The average (median) credit line obtained by a local-range firm amounts to 15,907 RMB (10,000 RMB) or proximately 2,532 USD (1,592 USD) at the contemporaneous exchange rate. The average (median) monthly

[30] We use the smallest and the largest value to transform the rating linearly using the following formula: Standardized rating=(original rating–min)/(max–min).

sales are only 32,337 RMB (9,800 RMB) or proximately 5,148 USD (1,560 USD) for these particular Taobao firms.

[Table 2 about here]

5. Credit Market Determinants Affecting E-commerce Entrepreneurship

First, we examine whether local credit market frictions are related to firms' decisions to enter the Taobao platform, and whether this decision correlates with the prospect of online credit from the Ant Group. In a geographically segmented credit market, the availability of traditional bank credit can vary by vendor location, particularly for small and new businesses with high credit risk. The availability of traditional bank credit is shaped by two forces. First, the overall level of banking development and bank credit supply (as captured by the aggregate *Loan/GDP* ratio) is extremely heterogeneous across China's city-level prefectures and is determined to some extent by an administrative credit allocation process in which state-owned banks play a dominant role (as captured by *State Bank Intensity*). Second, as the "soft-budget" constraints of SOEs tend to alleviate banks' concerns about their default risk, and state-owned banks and SOEs even have aligned political objectives, a large state sector in the local economy (as proxied by *SOE Output Share*) can further divert credit away from entrepreneurs. As a result, state-owned banks absorb local savings and channel it into lending to SOEs (or other large firms), which may actually aggravate the credit scarcity for local entrepreneurs. Thus, state-owned banks function like a "black hole" for local savings and actively reduce local private firm credit. On the other hand, the uniform China-wide credit supply by Ant Group can help to complete and integrate an otherwise fragmented credit market. Therefore, the larger the credit supply frictions and distortions in a particular location, the more we expect entrepreneurs to enter the Taobao platform as a source of liquidity. This is consistent with Liu, Lu, and Xiong (2022), who argue that FinTech lenders have a unique advantage in serving the under-banked borrowers – particularly for their short-term liquidity needs inside the big-tech lender's ecosystem.

We test this financing motive of online presence by regressing various platform entry measures defined in Section 4.2 onto proxies for the local economic and credit conditions. Table 3 shows the results, where Columns (1) features the (log) number of new Taobao firms, *Ln(#New TB Firms)*, as the dependent variable. We use *State Bank Intensity*, *SOE Output Share*, and their interaction term as the main explanatory variables, and also include city-level GDP per capita (*PCGDP*), *Population*, *Digital Development Index*, and *Loan/GDP* as control variables. All the control variables are measured in values for 2005 or the earliest year available if later than 2005. Consistent with a financing motive of platform presence, the coefficient for the interaction term *State Bank Density* × *SOE Output Share* is significantly positive. This suggests that a state-centric local economic and financial structure correlates positively with the online presence of local retail firms – potentially to compensate for the more severe credit constraints of private entrepreneurs. For a city with a *State Bank Density* greater by one standard deviation (0.64) and an average *SOE Output share* of 15%, we predict ceteris paribus a 17% larger entry rate for online vendors, which represents an economically large variation.[31] In terms of other regional indicators, we find that the overall entry rate of online vendors is positively associated with the development of credit infrastructure (as captured by *Loan/GDP*), local economic development (*GDPPC*), the population size, and digital development.

To further check whether the platform entry of retail vendors in regions with greater credit frictions is motivated by accessibility to online credit, we regress (1) the total amount of credit offered by Ant Group to vendors based in each city, and (2) the total amount of outstanding balance of the credit used by these vendors on the same set of macroeconomic indicators.[32] Table 3, Columns (2)-(3), focus on a cross-sectional snapshot in 2015, which is the latest full year for which aggregate city-level credit information is available to us. We find that cities with a higher combination of *SOE Output Share* and *State Bank Density*, are associated with a higher amount of online credit offered and drawn. Thus, online vendors in locations where private bank credit is more constrained can access and use more extensive FinTech credit lines.

[Table 3 about here]

6. FinTech Credit and Entrepreneurial Growth

In this section, we explore whether FinTech credit has a causal effect on sales growth, transaction growth, or customer ratings of product and service quality. As discussed in Section

---

[31] Deduced from a coefficient of 1.6282 in Table 2, Column (1), as exp(1.6282×0.64×0.15) – 1 = 0.17.

[32] As mentioned above, we have location data for only about one-third of the vendors, thus the aggregate amount of local online credit line or credit taken is not representative of the total credit lines extended to or used by vendors in each city. The aggregate data in 2015 is based on the average of monthly snapshots of the amount of eligible credit lines and outstanding balance of credit used as of the end of each month in 2015.

4.2, *Sale Growth* and *Transaction Growth* are defined as log differences between their respective monthly values in periods $t+1$ and $t-1$. *Product Rating*, *Service Rating*, and *Consignment Rating* are defined as the standardized ratings of product quality, service rendering, and shipping efficiency in period t+1, respectively. To establish causality, we apply a fuzzy regression discontinuity design (FRDD), as described in Section 3.2, which exploits the fact that firms passing the credit score threshold of 480 in Ant Group's internal credit rating model substantially increase their chance of credit approval. Figure 1, Panel B plots the percentage share of firms in the FRDD sample that become eligible for credit as a function of their credit score. Using a bin size of two points in credit score, and after fitting a linear function to the (left and right side) probability distribution, we see a probability increase of credit eligibility by approximately 30% at the credit score discontinuity of 480. As passing the threshold does not perfectly determine the allocation of credit to firms (i.e., the probability of credit access does not jump from 0 to 1 when the credit score exceeds 480), we cannot simply compare the outcomes of interest on each side of the threshold to estimate the treatment effect. Instead, we use the ratio between the difference in the expected outcomes and the change in the probability of credit approval around the cut-off to recover the treatment effect (Imbens and Lemieux, 2008; Lee and Lemieux, 2010). Econometrically, the treatment effect can be estimated using the 2SLS model under a standard instrumental variable framework (Hahn et al., 2001).

6.1. Graphical Illustration on the Discontinuity Effect

First, we demonstrate graphically the effect of the credit approval discontinuity on vendors' growth outcomes. We sort firms with *Credit Scores* in the range [470, 490] into 10 bins of similar credit scores where each bin is two credit score points wide. In Figure 2, Panels A and B draw the average *Sales Growth* and *Service Rating*, respectively, for firms in each credit score bin as red dots for the bins below the discontinuity threshold of 480 and as green dots for the bins above the threshold. The average *Sales Growth* of firms in bins just above the threshold of 480 is about 14% higher than for those in credit score bins just below. Within the same interval, the probability of credit access increases by approximately 33 percentage points. Thus, a rough estimate of the imputed incremental sales growth effect for firms acquiring credit access is 42% (=0.14/0.33) on average (for the two-month period) from the month before to the month after credit approval, which is an economically significant increase in online sales. Similarly, the average *Service Rating* of firms jumps from approximately 0.57 to 0.59 when they move from the bin below 480 to the one above. Thus, a rough estimate of the treatment effect of credit approval on service rating is 0.06 (=0.02/0.33) [or 26% of one standard deviation], which is recovered by the ratio between the jump in service rating and that in the treatment probability.

[Figure 2 about here]

6.2. Baseline Effects of Credit Approval

Next, we implement the FRDD through 2SLS regression analysis. In the first stage, we estimate the probability of credit access using equation (1). *Credit Approval* is an indicator variable equal to 1 if a firm has observable credit access at the end of month *t* to the end of month *t+1*, and zero otherwise; let *IV* denote a second indicator variable equal to 1 if the credit score of a firm at the beginning of month *t* is greater than or equal to 480, and zero otherwise. Let *S* represent the standardized credit score defined as the distance between a credit score and the cutoff value (i.e., $S_{i,t} = Credit\ Score_{i,t} - 480$). We allow for polynomial functions S^k up to an order of *K* as potential controls and denote by $\gamma^k, with\ \ k = 1,2, \dots, K,$ the corresponding coefficient. Such polynomials capture the "smooth" underlying relation between firm characteristics and a firm's credit score around the discontinuity at $S_{i,t} = 0$. We also include firm-type fixed effects, φ_j, to control for time-invariant firm and industry characteristics, and time-fixed effects, φ_t, to eliminate any common macro effect. Standard errors are clustered at the firm-type level to allow for statistical inferences robust to serial error correlation within a firm category.

$$Credit\ Approval_{i,t} = \alpha + \rho IV_{i,t} + \sum_{k=1}^{K} \gamma^k S_{i,t}^k + \varphi_j + \varphi_t + \varepsilon_{it} \ (1)$$

Any (F)RDD faces a trade-off between the precision and potential bias of estimation in the choices of regression bandwidth and polynomial orders, respectively. A large bandwidth draws on more sample observations, but can also require higher-order polynomials if the underlying forcing variable (S) has a non-linear effect on outcomes. On the other hand, for a small bandwidth around the cut-off, a simple linear approximation could be sufficient, but fewer sample observations are available for estimation. In our main specification, we use a local linear regression (i.e., the polynomial term in the standardized credit scores has an order of one, *K=1*) over a small range of credit scores from 460 to 500 (i.e., a bandwidth of 20 on each side of the cutoff). Nevertheless, we assess the robustness of the results to smaller local ranges of credit scores and alternative regression specifications in Section 9. We then predict the probability of credit approval using the estimates obtained in equation (1) and denote it by $\widehat{Credit\ Approval}_{i,t}$.

In the second stage, we regress each dependent variable on the predicted probability of credit approval, $\widehat{Credit\ Approval}_{i,t}$ as stated in equation (2), where the dependent variables are *Sales Growth*, *Transaction Growth*, or one of the three customer ratings. Following Imbens and Lemieux (2008), we use the same bandwidth and order of polynomials in both stages of the regression. The coefficient for $\widehat{Credit\ Approval}_{i,t}$ (i.e., $\boldsymbol{\tau}$) provides an estimate of the local average treatment effect of access to credit as long as the assumption of local randomization holds.

$$Dep_{i,t+1} = \beta + \tau \widehat{Credit\ Approval}_{i,t} + \sum_{k=1}^{K} \lambda^k S_{i,t}^k + \varphi_j + \varphi_t + \varepsilon_{it} \quad (2)$$

Table 4 summarizes the causal effects of access to FinTech credit on vendor performance. Panels A and B presents the first and second stage results, respectively. In Panel A, the coefficient for the credit score instrument *IV* identifies the increase in the credit approval probability of passing the 480 threshold, which is about 29 percentage points. The Kleibergen-Paap F-statistics associated with these first-stage regressions are very large and imply that the dummy variable *IV* represents a strong instrument.

The second stage regression in Panel B features five different dependent variables for vendor performance, namely *Sales Growth*, *Transaction Growth*, *Product Rating*, *Service Rating*, and *Consignment Rating*. These baseline specifications include only a linear term (K=1) in the control variable $S_{i,t}$.

We find that credit approval significantly improves all five measures of entrepreneurial performance. In particular, vendor sales for the bimonthly measurement period around credit approval increases by an average 36.31%. Similarly, transaction volume grows by 26.91% over the two-month measurement period. Column (3) reveals that FinTech credit increases the customer rating on product quality (*Product Rating*) by 0.054, which amounts to 24% of its standard deviation. We find similar results for *Service Rating* and *Consignment Rating*. Overall, credit approval by the retail platform provides an economically significant boost to the commercial performance of small e-commerce firms. As mentioned above, our findings are mainly based on the access to credit lines rather than actual drawdowns. This is because a credit line can theoretically change the investment behavior of the online vendor even if the credit is not used. For example, precautionary concerns about liquidity might deter productive investment and the credit line provides effective insurance against liquidity risk.[33]

[Table 4 about here]

7. Dimensions of the FinTech Advantage

In this section, we provide evidence mainly on FinTech lenders' information advantages over traditional banks by exploring heterogenous benefits to credit approval across different vendor types. We expect the vendor benefits from the FinTech credit approval to be larger if information or other frictions constrain access to traditional bank credit. Thus, incremental realized vendor growth reveals the incremental improvement of the credit technology that FinTech represents.

7.1. Information Channel

FinTech lenders can access high-frequency, high-dimension, and high-coverage real-time information of small firms, including granular digital footprints (e.g., payment, order flows, behavioral portraits of firm owners, etc.) and various networks (e.g., social, business, etc.). They can also process information efficiently, such as converting soft information into hard information without losing crucial content (Berg, Burg, Gombovic, and Puri, 2020; Liberti and Petersen, 2018; Liu, Lu, and Xiong, 2022).[34] These information advantages enable them to better assess the credit risk of online retail firms, which as a group represent high risk borrowers for the traditional banking sector in the absence of much verifiable performance information. We use two measures to gauge the information advantages of FinTech lenders.

An extensive banking literature interprets firm age as a proxy for information frictions in bank lending as younger firms represent an evaluation challenge with respect to credit risk (Beck et al., 2006; Zarutskie, 2006). Petersen and Rajan (2005) suggest that firm age can proxy for latent credit quality. Hadlock and Pierce (2010) show that firm age represents a pertinent

[33] Using an approval cutoff on loan applications by SMEs, Berg (2018) find that a loan rejection would cause low liquidity firms, out of pre-cautionary saving motives, to increase cash holdings to more than the requested loan amount; and they also experience smaller asset growth and lower investment after the loan rejection.
[34] Financial statements and past credit records are typical sources of hard information, which is easy to quantify and convert into metrics; characters, attitudes, and other behavioral traits of a firm owner are soft information that is difficult to measure and transmit to a third party (Strahan, 2017; Liberti and Petersen, 2018).

firm characteristic to deduce credit constraints reported in corporate filings. For our empirical analysis, we rank firms by their age and defined *Age Rank* on a unit interval.[35]

We acknowledge that firm age may covary with other influences that could condition the performance boost of credit access. Following Levine, Lin, and Wei (2017), we use the dispersion of growth prospects across firms in any industry as an alternative measure of credit risk opacity and information asymmetry. In particular, we measure firms' sales growth to construct the dispersion measure. Intuitively, a wider dispersion of firms' growth within an industry indicates a greater evaluation challenge for credit risk as the other firms in the same industry do not serve as good benchmarks. By contrast, the FinTech lender with its granular information at higher frequency from online digital sales and payment platforms can overcome this opacity. We define the variable *High Dispersion* as an indicator variable that equals 1 if the standard deviation of sales growth of all firms in an industry prior to the credit allocation is above the cross-industry median, and zero otherwise.

We expect FinTech credit approval to trigger a larger performance boost for younger vendors (i.e., vendors with a lower age rank) or vendors operating in industries with high growth dispersion. Accordingly, we augment the 2SLS equation system by including an interaction term with a proxy for the information advantage of the FinTech lender (*InfoAdv* = *Age Rank* or *High Dispersion*) in each stage. Formally,

$$Credit\ Approval_{i,t} = \alpha + \rho IV_{i,t} + \delta_1 InfoAdv_{i,t} + \delta_2 IV_{i,t} \times InfoAdv_{i,t} + \sum_{k=1}^{K} \gamma^k S_{i,t}^k + \varphi_j + \\ + \varphi_t + \varepsilon_{it} \tag{3a}$$

$$Credit\ Approval_{i,t} \times InfoAdv_{i,t} = \alpha + \rho IV_{i,t} + \delta_1 InfoAdv_{i,t} + \delta_2 IV_{i,t} \times InfoAdv_{i,t} + \\ + \sum_{k=1}^{K} \gamma^k S_{i,t}^k + + \varphi_j + \varphi_t + \varepsilon_{it} \tag{3b}$$

$$Dep_{i,t+1} = \beta + \tau \widehat{Credit\ Approval}_{i,t} + \gamma_1 InfoAdv_{i,t} + \gamma_2 \widehat{Credit\ Approval_{i,t}} \times InfoAdv_{i,t} + \\ + \sum_{k=1}^{K} \lambda^k S_{i,t}^k + \varphi_j + \varphi_t + \varepsilon_{it} \tag{4}$$

Equations (3a) and (3b) provide the first stage estimates for the credit approval probability and its gradient with respect to either *Age Rank* or *High Dispersion*, respectively. Equation (4) estimates the causal effect of both instrumented variables on various measures of vendor performance (*Dep*). Of particular interest is the coefficient γ_2, which captures the

[35] We define Age Rank as (Age – min) / (max – min), where max and min are the largest and smallest value of firm age in our sample.

heterogeneous performance effect of access to FinTech credit due to the information advantage of the FinTech lender.

In Table 5, Panels A and B report the second stage results for *Age Rank* and *High Dispersion*, respectively. As with the previous analysis, we use a local linear regression model over a local bandwidth of credit scores from 460 to 500. Again, we also control for the firm-type fixed effects and time fixed effects in the regressions and cluster the standard errors at the firm-type level.

As show in Panel A of Table 5, for all five vendor performance measures, the *Credit Approval* × *Age Rank* variable enters into all the regressions with a significant negative sign. This suggests that both sales and transaction growth and customer ratings improve more after credit approval for younger firms. Comparing two firms with *Age Rank* differing by one standard deviation within the FRDD sample (i.e., 0.13), we find that the younger firm experiences a sales (transaction) growth effect of access to credit that is 12 (8) percentage points larger over the two-month window following the credit approval.[36] Similarly, we estimate a stronger boost in the product, service, and consignment ratings for the younger firm, which corresponds to 13.8%, 10.2%, 9.8% of one standard deviation, respectively. Thus, FinTech credit from Ant Group is most beneficial to the performance of younger e-commerce firms near the credit approval threshold. This is consistent with a pronounced information advantage of FinTech lenders over traditional banks in this high credit risk segment of young firms.

Table 5, Panel B, further confirms the particular benefit of access to FinTech credit for firms in industries with high growth dispersion (*High Dispersion*), where information asymmetry tends to be larger and a credit risk analysis is particularly challenging for traditional banks. We find a positive coefficient for the interaction term *Credit Approval* × *High Dispersion* for all five vendor performance measures in Columns (1)-(5), which is again consistent with the information advantage of the FinTech lenders.

[Table 5 about here]

[36] The incremental effect over the two-month window for *Sales Growth* follows as $-0.9153\times(-0.13) = 12\%$.

7.2. Information as Collateral Substitute

A corollary to the information advantage enjoyed by FinTech lenders is their reduced reliance on collateral (Gambacorta, Huang, Li, Qiu, and Chen, 2020). Under traditional bank lending with asymmetric information, collateral plays a crucial role in mitigating adverse selection and moral hazard problems (Bester, 1985; Aghion and Bolton, 1992). Business upturns (downturns) increase (decrease) collateral values and lead to a lower (higher) agency cost of financing (Bernanke and Gertler, 1989) and a greater (lower) financing capacity (Holmstrom and Tirole, 1997; Vig, 2013). By contrast, FinTech lenders tend to have better information about borrowers, which improves their screening and monitoring capacity. Overall, FinTech lenders appear to rely less on collateral to mitigate default risk, which implies that access to FinTech credit is particularly beneficial to vendors with weak or no collateral.

We construct two proxies to test the greater collateral independence of FinTech credit. First, we categorize industries by durability (Araújo, Kubler, Schommer, 2012) and define an indicator variable, *High Durability*, equal to 1 for durable product industries and zero otherwise. *High Durability* industries include Computer Hardware, Furniture, Basic Building Materials, Automobiles, Motorcycles, Gold and Gems, Musical Instruments, Large Home/Factory Appliances, etc., whereas *Low Durability* industries include Apparels, Shoes, Cosmetics, Food and Beverages, Flower, Magazines, Cooking Appliances, Tableware, Cleaning Supplies, etc. Second, we use proxies for property ownership of the vendor constructed by the Ant Group itself. Real estate represents a crucial form of collateral, and shocks to real estate values have been shown to significantly impact firms' access to credit (e.g., Chaney, Sraer, and Thesmar, 2012; Adelino, Schoar, and Severino, 2015; Loutskina and Strahan, 2015). We define a dummy variable *Property Ownership* for firms tagged by Ant Group as having a very high probability of owning a real estate property (i.e., more than 90%). Since housing prices in China generally increase during our sample period, we assume real estate owning vendors to possess valuable collateral.

In Table 6, Panels A and B, we repeat the 2SLS regressions with the dummies for *High Durability* and *Property Ownership* as the relevant interaction terms with *Credit Approval*, respectively. As before, firm-type and time fixed effects are included. The dummy *High Durability* itself (without interaction) is absorbed by the firm-type fixed effects. We find that access to FinTech credit boosts both firm growth and customer ratings more substantially if firms operate in industries with less durable products (Panel A) and if vendors are less likely to possess real estate property (Panel B). This suggests that access to FinTech credit alleviates financial constraints particularly for those firms that lack collateral. Thus, greater collateral independence constitutes a competitive advantage for FinTech lender.

[Table 6 about here]

7.3. Other Channels

A second competitive advantage of FinTech credit resides in its low loan distribution costs. FinTech lenders typically provide transactional loans (rather than relationship loans) for a wide range of small borrowers at a low cost.[37] Based on the internal estimation of Ant Group, the average cost per loan generated is only 2.3 RMB ($0.368), of which 2 RMB goes to electricity bills and data storage hardware, whereas the micro-lending cost of other traditional lending institutions is about 2,000 RMB per transaction. There are fewer than 400 employees overseeing the credit services at Ant Group with an accumulated loan amount of 1.3 trillion RMB (USD 207 billion in 2015) and a potential client base of 8 million MSMEs.[38] Since FinTech lenders have almost zero fixed costs relative to banks in distributing a loan, the cost advantages matter inversely to the size of the credit line provided. Thus, we use the inverse of predicted credit line size as proxy for firms' (implicit) transaction costs if they had borrowed from a bank and name this measure *Distribution Cost*. We estimate the size of the credit line based on firm characteristics including size, age, and average distance to surrounding bank branches, and scale it by firm size. We conjecture that firms with a higher relative *Distribution Cost* benefit more from access to FinTech credit. As shown in Table A1 of the Internet Appendix, we indeed find that the growth effect of FinTech credit is more pronounced for firms with higher distribution costs.

The third distinguishing element of FinTech credit could be better contract enforcement. Unlike traditional banks, which rely heavily on the external legal environment for contract enforcement (La Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1997, 1998; Qian and Strahan, 2007), FinTech lenders can conduct real-time post-lending monitoring and use alternative approaches to enforce contracts and recover losses rather than through the court systems.[39]

---

[37] As the size of the fee is independent of the size of the loan for small businesses (i.e., a larger loan size implies a smaller unit cost), lowering the transaction costs can be particularly important to promote small business lending at a large scale (Petersen and Rajan, 1994; Liberti and Petersen, 2018).

[38] The risk management division is the largest of the credit team in Ant Group, responsible for maintaining the credit system at the back end, whereas banks rely more on loan managers at the front end, generating very different cost implications.

[39] For example, the early warning system of Ant Group, as part of the integrated credit platform, generates post-lending scores based on order conversion rate and other metrics to assess whether the borrower is likely to have

Therefore, FinTech lenders depend less on an external legal enforcement environment, which creates a competitive advantage in locations with low legal quality, where contracting frictions lead to a general undersupply of bank credit. We expect vendors to benefit more from FinTech lenders if they operate in regions with a weak legal enforcement environment.

We use the *Legal Quality Index* for 120 cities in China from the 2006 World Bank survey to measure the strength of regional legal and institutional development. The index represents a continuous measure ranging from 0 to 1, with a higher value indicating greater confidence in the local legal system and a stronger legal enforcement environment. We repeat the previous regressions with the *Legal Quality Index* as the new interaction term and provide the results in Table A2 of the Internet Appendix. Consistent with the hypothesis of reduced legal enforcement dependence of FinTech lender, we find that vendors operating in cities with a lower legal quality index experience a greater improvement in sales and transaction growth after their FinTech credit approval, as well as larger upticks in their customer ratings. While we are aware that the index could correlate with a variety of other factors influencing the local productivity of additional firm credit, we still find this evidence intriguing and potentially relevant for emerging markets often criticised for their poor legal environment.

8. Mechanisms of Vendor Performance Enhancement

In this section, we seek to understand the mechanisms by which access to FinTech credit allows vendors to boost their business performance. We pay particular attention to the short-term nature of the credit line and its high interest rate.

8.1. Liquidity Insurance Benefits

First, we highlight that the effect of FinTech credit on firm performance does not have to be realized via actual credit use. As mentioned above, credit lines can serve as liquidity insurance. Thus, access to FinTech credit can relax firms' precautionary saving motives and promote investment in growth opportunities. In this case, vendors draw on the credit line only

---

a credit deterioration in the coming months. Depending on the degrees of deterioration, alarms and actions will be triggered at different levels according to pre-defined algorithms (i.e., from watch list indexing, additional financial information request, to credit line suspension). When it comes to the enforcement stage, the credit system will initiate the debt-collection scheme so that robocalls with synthesized speech will be made to assess borrowers' willingness to repay. Based on their responses and the real operating data, algorithms automatically categorize the cases into liquidity and strategic default and trigger different actions to tackle them.

in the case of a negative liquidity shock. Consistent with such a liquidity insurance mechanism, we find that the average amount of credit drawn down only accounts for about 17% of total credit line approved. Furthermore, excluding those firms with actual drawdowns of credit and retaining only those with the option of credit still yields performance improving effects. In other words, the mere liquidity procurement through FinTech credit lines accounts for some firm growth and development effects.

8.2. Is FinTech Credit Cost Effective?

We argue that the average interest cost of approximately 17% for FinTech credit is not prohibitively high. We note that most Taobao vendors are operating in industries with high product turnover and turnover variability due to seasonality in customer demand. Credit for inventory finance may only be needed to meet peak demands and the fast turnover allows for swift repayment. The flexibility of the FinTech credit line relative to a fixed-term bank loan is therefore of particular benefit, and given rapid repayment, the net interest expense is modest despite the high interest rate (Liu, Lu, and Xiong, 2022). According to Liu, Lu, and Xiong (2022), firms that borrow from the Ant Group have very fast repayment rates. The 25th percentile and median repayment time is only 0.04 and 0.28 of the scheduled loan maturity, that is one week and six weeks for a six-month loan, respectively. The short-term nature of the loans makes the net borrowing costs much lower than the full annual costs implied by the quoted (high) interest rate. The effective average (median) interest expense to loan size ratio is only 5% (2.7%). Consistent with the short-term liquidity needs and highly variable inventory demand, Liu, Lu, and Xiong (2022) also find that these firms borrow more frequently with an average (a median) of 6 (3) times over their 17-month sample period. Furthermore, the high interest rate may serve as a mechanism to screen the borrowers with real liquidity needs and fast repayment abilities, and this helps address adverse selection problem and reduce loan risk.

8.3. Operational Changes

To understand how vendors achieve a swift improvement in sales and customer ratings, we explore a few additional indicators to infer operational changes feasible under access to FinTech credit. One potential channel is online advertisement, which can be implemented fairly quickly to gain attention from potential customers, expand customer demand, differentiate own products from the competition, or just divert demand from other vendors. We are able to observe a vendor's advertisement expenditure in the online marketplace Taobao and define *Ad Expense* as the natural logarithm of one plus his/her monthly advertisement expenditures.

A second managerial response to credit access concerns the opportunity to expand the product offering and quality. We construct three measures in this aspect. *Product Types* is defined as the natural logarithm of one plus the number of product types offered for sales by the vendor. Greater “breadth of product choice” can augment the customer experience (Matsa, 2011), and represents an important quality dimension of the online shop. The *Customer Conversion Rate* is defined as the number of shop visitors that complete transactions over the total number of online shop visitors (in hundreds) per month. To improve the latter, firms also need to improve not only product quality, but also service quality: It is common for a prospective customer to chat with the salesperson online to learn more details about the product, promotions, value-added services, and to have other inquires addressed. Therefore, investment in better customer hotlines, more (and better trained) service personnel, and stronger customer support (e.g., improved communication efficiency, extended service hours, and offering value-added services) can all influence a potential customer’s final purchase decisions. Moreover, firms can improve product display and make additional sales information more easily accessible on the interface. We expect such improvements to be implemented fairly quickly and to be reflected in a higher *Customer Conversion Rate*.

We then apply the same FRDD design as before to infer causal effects of FinTech credit approval on these various operating measures and report the second-stage results in Table 7. Column (1) documents a substantial increase of 27% in advertising expenditure upon access to FinTech credit. Product variety in Column (2) increases by 12%. Treated vendors also feature a higher proportion of online visits that are converted into purchases. Again, the economic magnitude is significant, with close to one additional customer converted out of every 100 visitors. Taken together, these results deliver coherent evidence on the operational changes online vendors undertake if they obtain FinTech credit. All these changes can rationalize the evidence of enhanced firm performance documented in Table 4. The evidence also tends to speak to a welfare-enhancing effect of FinTech credit. While it is unclear whether more advertising increases aggregate customer demand or simply diverts marginal customers from other vendors, we can consider higher service quality and customer satisfaction as welfare gains.

[Table 7 about here]

8.4. Firm Survival

Finally, the large growth effect could also be contributed by the difference between above/below threshold in the share of firms that go out of business. For firms with a liquidity problem, if they score just above 480 in a period, getting the loans could allow them to survive a few more months at least; whereas if they score just below 480, they go out of business almost immediately and will have a very negative sales growth recorded. Consistent with his expectation, we find that firms receiving access to credit indeed have a higher survival rate versus those without.

9. Robustness

We subject our analysis to a variety of robustness checks. First, we examine whether the positive vendor performance effects of access to credit persist over a longer time window. To implement the test, we require treated sample firms to have access to credit from month t until the end of month $t+2$, and the control firms to have no access to credit during the same period. Accordingly, we modify the definition of *Sales Growth* (*Transaction Growth*) as the difference between the natural logarithm of sales (transaction) in month $t+2$ and that in month $t-1$ (i.e., growth over a three-month window). Similarly, we measure the three customer ratings in month $t+2$.

Table 8 Panel A reports the second stage results for the same local linear specification as the baseline regression in Table 4. The coefficients capturing the effect of (predicted) credit approval on vendor performance are now larger for the extended three-month measurement period and remain statistically highly significant. Firms with continuous credit approval enjoy an 85% (55%) higher sales (transaction) growth than those without access to credit.[40] The results suggest that consecutive access to credit can exert a larger growth effect on firms, but could also introduce confounding selection effects, since repeated approval depends on good sales performance.

Additional robustness tests (reported in Table 8, Panel B) use the change rather than the level of customer ratings as the dependent variable. We calculate the change in each service

[40] The growth rate is 48% (29%) for sales (transactions) over a three-month period if we do not condition a treated (control) firm to retain its credit approval (no credit) status over the period (i.e., firms with switching credit status are included). This suggests that the switching cases can introduce an attenuation bias that leads to potential underestimation of the treatment effect.

quality measure from the month before the credit treatment to the month after, and we denote the differenced variables as Δ*Product Rating*, Δ*Service Rating*, and Δ*Consignment Rating*, respectively. The estimated effect for the *Credit Approval* variable remains statistically significant and economically comparable to the baseline findings. The robustness to the outcome specification in differences suggests that the increase in service quality is unlikely to be driven by the differences in the ratings for firms with and without access to credit prior to the credit allocation event.

We also conduct robustness tests for a variety of alternative specifications to the baseline regression in Table 4. In Table 8, Panels C, we verify that the results are qualitatively similar if we fit separate linear slopes to the left and the right of the discontinuity threshold. Panel D fits a second-order polynomial (instead of a linear function) to control for non-linear background effects. Panels E and F reduce the window size from [460,500] to [465,495] or [470,490], respectively. All these modifications are without much consequence for the economic magnitudes of estimated vendor performance effects.

Finally, we conduct a placebo test using falsified cutoffs to assign the credit. We focus on the validity of credit assignment in the first stage and examine whether credit scores based on the falsified cutoffs can predict a similarly large jump in the probability of access to FinTech credit. Following Bradley et al. (2017), we run a simulation for 1,000 times to obtain 1,000 random falsified cutoffs other than 480. For each cutoff, we redefine *IV* as an indicator variable that equals 1 if the credit score is at or above its random value. We standardize the credit scores around the random cutoffs and redefine the linear term in *S*. Then, we re-estimate the first stage regressions using a local linear model with firm-type and time fixed effects.[41] Everything else is defined in the same way as in the baseline analysis and we store the estimates on the coefficient of *IV* from each firm-stage simulation. Based on the summary statistics of the 1,000 placebo estimates, we find that the average jump in the probability of credit approval is -0.0005, and is statistically insignificant. The median is -0.001 and the 25^{th} (75^{th}) percentile is -0.019 (0.003) – all values far below the size of the estimated jump for the correct cutoff (i.e., 29%). The results strengthen the validity of our setting and the 2SLS approach.[42]

[41] We use a bandwidth of 10 credit score units to reduce the overlap of the local range with the true cutoff. The results remain robust to using a bandwidth of 20 credit score units instead.
[42] We do not continue with the second-stage regressions based on the predicted access to credit using the falsified cutoffs because it suffers from a weak instrument problem and would lead to very imprecise estimates (Jiang, 2017).

[Table 8 about here]

Finally, we explore whether a short-term credit approval exerts a longer-term effect on firm performance. Here, we measure *Sales Growth* and *Transaction Growth* from the month before to six months after the credit approval event. *Product Rating*, *Service Rating*, *Consignment Rating*, and three additional operational indicators, namely, *Ad Expense*, *Product Types*, and *Customer Conversion Rate*, are measured in the sixth month after the credit approval event. As shown in Table 9, the performance improvements of credit access remain economically large over the six-month horizon.

[Table 9 about here]

10. Conclusion

In this paper, we examine how access to FinTech credit boosts the performance of small e-commerce firms in China. Evidence on these issues can inform the policy debate about the growth contribution and welfare benefits of new credit technologies based on new extensive customer data (He, Huang, and Zhou, 2021). We hope to contribute to a constructive fact-based regulatory response to the emerging FinTech sector.

Based on Ant Group's credit approval records for millions of firm-months and granular vendor performance data, we show that access to FinTech credit has an economically significant positive causal performance effect on Chinese e-commerce firms. By exploiting a discontinuity in the probability of credit approval at a particular threshold value of the internal credit score, we provide evidence that credit approval implies a large development boost to sales, transactions, and customer satisfaction gauged by customer ratings on products and services. On average *Sales Growth* and *Transaction Growth* spike by an incremental 36% and 26%, respectively, in the two-month period following credit approval. The increase in each dimension of customer ratings accounts for about 24% of the sample standard deviation of these ratings. Such large estimates support previous conjectures in the development literature that credit constraints constitute a pivotal growth impediment in emerging economies (Banerjee and Duflo, 2014).

We identify various dimensions characterizing the competitive advantage of FinTech credit over traditional bank credit based on the heterogeneity of the observed vendor growth. In accordance with the information advantage of FinTech lenders, we find that the strongest benefits of access to online credit accrue to younger firms and vendors without collateral. These firms pose particular challenges to the credit analysis within traditional banks and therefore are often excluded from commercial credit. Other evidence hints at the role of lower distributional costs and better contract enforcement as additional competitive advantages of the FinTech lender.

Lastly, we document a variety of operational changes that FinTech credit allows online vendors to undertake. We find that credit approval is followed by a substantial increase in advertisement expenditure, an increase in product variety, and a higher conversion rate of visiting customers into purchasing customers. Most of these operational changes pursue a better customer experience and amount to welfare benefits for the online consumer.

Overall, our analysis reveals significant growth and development constraints for small private firms in China due to credit market frictions. An expansion of FinTech credit can help to equalize the growth prospects of small e-commerce vendors by creating more equal credit conditions, which should contribute to China's private sector growth. While our results on the growth effects of credit access pertain to the e-commerce segment of China's retail sector, it is very plausible that the real costs of China's credit market frictions are quantitatively larger in more capital-intensive sectors.

Moreover, our findings provide a forward-looking estimate on the effect of platform lending on entrepreneurial growth for other developing economies, where the logistical infrastructure and internet penetration are still less developed. While China is leading in mobile market penetration according to cellular subscription data compiled by the World Bank, we note that many other emerging economies are catching up and also witness a fast development of high-speed internet. [43,44] This holds the promise for similar entrepreneurial growth in their respective retail sectors through better credit technologies.

[43] Data on mobile cellular subscription are available from: https://data.worldbank.org/indicator/IT.CEL.SETS.P2?most_recent_value_desc=true

[44] Data on fixed broadband subscription data are available from: https://data.worldbank.org/indicator/IT.NET.BBND.P2?most_recent_value_desc=true

References

[1] Acharya, V., S. T. Bharath, and A. Srinivasan. 2007. Does Industry-Wide Distress Affect Defaulted Firms? Evidence from Creditor Recoveries. Journal of Financial Economics 85(3):787-821.

[2] Acharya, V., H. Almeida, F. Ippolito, and A. Perez. 2014. Credit lines as Monitored Liquidity Insurance: Theory and Evidence. Journal of Financial Economics112 (3):287-319.

[3] Acharya, V., H. Almeida, F. Ippolito, and A. P. Orive. 2020. Bank lines of credit as contingent liquidity: Covenant violations and their implications. Journal of Financial Intermediation 44:100817.

[4] Adelino, M., A. Schoar, and F. Severino. 2015. House Prices, Collateral, And Self-Employment. Journal of Financial Economics 117 (2):288-306.

[5] Agarwal, S., W. Qian, Y. Ren, H.T. Tsai, and B.Y. Yeung. 2022. The Real Impact of FinTech: Evidence from Mobile Payment Technology. Working Paper.

[6] Agarwal, S., W. Qian, B.Y. Yeung, and X. Zou. 2019. Mobile Wallet and Entrepreneurial Growth. AEA Papers and Proceedings, 109: 48-53.

[7] Aghion, P., and P. Bolton. 1992. An Incomplete Contracts Approach to Financial Contracting. The Review of Economic Studies 59(3):473-494.

[8] Allen, F., J. Qian, and M. Qian. 2005. Law, Financial, and Economic Growth in China. Journal of Financial Economics 77:57-116.

[9] Allen, F., J. Qian, and M. Qian. 2008. China’s Financial System: Past, Present and Future. In: Brandt, L., and T. Rawski (eds.), China's Great Economic Transformation, Cambridge University Press.

[10] Araújo, A., F. Kubler, and S. Schommer. 2012. Regulating Collateral-Requirements When Markets Are Incomplete. Journal of Economic Theory 147(2):450-476.

[11] Ayyagari, M., A. Demirgüç-Kunt, and V. Maksimovic. 2010. Formal versus Informal Financial: Evidence from China. Review of Financial Studies 23(8): 3048-3097.

[12] Bai, C.-E., J. Lu, and Z. Tao. 2006. The Multitask Theory of State Enterprise Reform: Empirical Evidence from China. The American Economic Review 96(2):353-357.

[13] Balyuk, T. 2019. Financial Innovation and Borrowers: Evidence from Peer-To-Peer Lending. Rotman School of Management Working Paper, (2802220).

[14] Balyuk, T., A. N. Berger, and J. Hackney. 2020. What is Fueling FinTech Lending? The Role of Banking Market Structure (June 23, 2020).

[15] Banerjee, A.V., E. Breza, E. Duflo, and C. Kinnan. 2018. Do Credit Constraints Limit Entrepreneurship? Heterogeneity in the Returns to Microfinance, Buffett Institute Global Poverty Research Lab Working Paper No. 17-104.

[16] Banerjee, A.V., and E. Duflo. 2014. Do Firms Want to Borrow More? Testing Credit Constraints Using a Directed Lending Program, The Review of Economic Studies 81(2): 572--607.

[17] Banerjee, A.V., D. Karlan, and J. Zinman. 2015. Six Randomized Evaluations of Microcredit: Introduction and Further Steps, American Economic Journal: Applied Economics 7(1): 1-21.

[18] Barrot, J.-N. 2016. Trade Credit and Industry Dynamics: Evidence from Trucking Firms, Journal of Financial 71(5): 1975-2015.

[19] Barrot, J.-N., and R. Nanda. 2017. Can Paying Firms More Quickly Affect Aggregate Employment? MIT Working Paper.

[20] Beck, T., A. Demirguc-Kint, L. Laeven, and V. Maksimovic. 2006. The Determinants of Financing Obstacles. Journal of International Money and Finance 25: 932-952.

[21] Bernanke, B. S., 2011, Promoting Research and Development – the Government's Role. Speech at the Conference on "New Building Blocks for Jobs and Economic Growth", Washington DC, 16 May 2011.
[22] Bernanke, B., and M. Gertler. 1989. Agency Costs, Net Worth, and Business Fluctuations. The American Economic Review 79(1):14-31.
[23] Berg, T. 2018. Got Rejected? Real Effects of Not Getting a Loan. The Review of Financial Studies 31(12):4912-4957.
[24] Berg, T., V. Burg, A. Gombović, and M. Puri. 2020. On the Rise of FinTechs: Credit Scoring Using Digital Footprints. The Review of Financial Studies 33(7):2845-2897.
[25] Berger, A. N., and G. F. Udell. 1995. Relationship Lending and Lines of Credit in Small Firm Finance. The Journal of Business 68(3):351-381.
[26] Bester, H. 1985. Screening vs. Rationing in Credit Markets with Imperfect Information. The American Economic Review 75(4):850-855.
[27] Binder, C., and D. M. Hanssens, 2015, Why Strong Customer Relationships Trump Powerful Brands, Harvard Business Review.
[28] Boyreau-Debray, G., and S.-J. Wei., 2004. Can China Grow Faster? A Diagnosis on the Fragmentation of the Domestic Capital Market. International Monetary Fund, IMF Working Papers 04/76.
[29] Boyreau-Debray, G., and S.-J. Wei. 2005. Pitfalls of a State-Dominated Financial System: The Case of China? NBER Working Paper No. 11214.
[30] Bradley, D., I. Kim, and X. Tian. 2017. Do Unions Affect Innovation? Management Science 63(7):2251-2271.
[31] Brandt, L., and X. Zhu. 2007. China's Banking Sector and Economic Growth. In: China's Financial Transition at a Crossroads, edited by Charles W. Calormiris. Columbia University Press.
[32] Cattaneo, M. D., Jansson, M., and X. Ma. 2018. Manipulation Testing Based on Density Discontinuity. The Stata Journal 18(1), 234-261.
[33] Chaney, T., D. Sraer, and D. Thesmar. 2012. The Collateral Channel: How Real Estate Shocks Affect Corporate Investment. The American Economic Review 102(6):2381-2409.
[34] Chen, T., Y. Huang, C. Lin, and Z. Sheng. 2022. Finance and Firm Volatility: Evidence from Small Business Lending in China, Management Science 68(3):2226-2249.
[35] Corrado, C. A., and C. R. Hulten. 2010. How Do You Measure a "Technological Revolution"? The American Economic Review 100(2):99-104.
[36] Cortés, K., R. Duchin, and D. Sosyura. 2016. Clouded judgment: The role of sentiment in credit origination. Journal of Financial Economics 121(2):392-413.
[37] Deng, Y., Morck, R., Wu, J., and Yeung, B. 2015. China's Pseudo-Monetary Policy. Review of Finance 19(1), 55-93.
[38] Deyoung, R., A. Gron, G. Torna, and A. Winton. 2015. Risk Overhang and Loan Portfolio Decisions: Small Business Loan Supply before and during the Financial Crisis. The Journal of Finance 70(6):2451-2488.
[39] Di Maggio, M., and V. Yao. 2021. Fintech borrowers: lax-screening or cream-skimming? Review of Financial Studies, 34(10): 4565-4618.
[40] Dollar, D., and S.-J. Wei. 2007. Das (Wasted) Kapital: Firm Ownership and Investment Efficiency in China. NBER Working Paper No. 13103.
[41] Dou, W. W., Y. Ji, D. Reibstein, and W. Wu. 2021. Inalienable Customer Capital, Corporate Liquidity, and Stock Returns. The Journal of Finance 76 (1):211-265.
[42] Erel, I., and J. Liebersohn. 2020. Does FinTech Substitute for Banks? Evidence from the Paycheck Protection Program. NBER Working Paper No. w27659.
[43] Firth, M., C. Lin, P. Liu, and S. Wong. 2009. Inside the Black Box: Bank Credit Allocation in China's Private Sector. Journal of Banking and Finance 33: 1144-1155.

[44] Fisman, R., D. Paravisini, and V. Vig. 2017. Cultural Proximity and Loan Outcomes. American Economic Review 107(2):457-492.
[45] Fracassi, C., M.J. Garmaise, S. Kogan, and G. Natividad. 2016. Business Microloans for U.S. Subprime Borrowers, Journal of Finanical and Quantitative Analysis 51(1): 55-83.
[46] Frost, J., L. Gambacorta, Y. Huang, H.S. Shin, and P. Zbinden. 2019. BigTech and the Changing Structure of Financial Intermediation. BIS Working Paper No. 798.
[47] Gambacorta, L. Y. Huang, Z. Li, Q. Han, and S. Chen. 2020. Data vs Collateral. BIS Working Paper No. 881.
[48] Gao, H., H. Ru, R. M. Townsend, and X. Yang. 2017. Rise of Bank Competition: Evidence from Banking Deregulation in China. Working Paper.
[49] Goldman Sachs Global Investment Research. 2017. Future of Finance: The Rise of China FinTech. Industry Report.
[50] Gopal, M., and P. Schnabl. 2022. The Rise of Finance Companies and FinTech Lenders in Small Business Lending, Review of Financial Studies, forthcoming.
[51] Gompers, P. A., W. Gornall, S. N. Kaplan, and I. A. Strebulaev. 2020. How do venture capitalists make decisions? Journal of Financial Economics 135(1):169-190.
[52] Gourio, F., and L. Rudanko. 2014. Customer Capital. The Review of Economic Studies 81(3):1102-1136.
[53] Guo, F., J. Wang, F. Wang, T. Kong, X. Zhang, and Z. Cheng, 2020, Measuring China's Digital Financial Inclusion: Index Compilation and Spatial Characteristics, China Economic Quarterly 19(4), 1401-1418.
[54] Hadlock, C. J., Pierce, J. R., 2010. New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. Review of Financial Studies 23: 1909-1940.
[55] Hahn, J., P. Todd, and W. Van der Klaauw. 2001. Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design. Econometrica 69 (1):201-209.
[56] Hau, H., Y. Huang, H. Shan, and Z. Sheng. 2019. How FinTech Enters China's Credit Market. AEA Papers and Proceedings 109: 60-64.
[57] Hau, H., and D. Ouyang. 2019. Capital Scarcity and Industrial Decline: Evidence from 172 Real Estate Booms in China. SFI Working Paper No. 18-38.
[58] He, Z., J. Huang, and J. Zhou. 2021. Open Banking: Credit Market Competition When Borrowers Own the Data. University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2020-168.
[59] Holmström, B., and J. Tirole. 1997. Financial Intermediation, Loanable Funds, and the Real Sector. The Quarterly Journal of Economics 112(3):663-691.
[60] Holmström, B., and J. Tirole. 1998. Private and Public Supply of Liquidity. Journal of Political Economy 106(1):1-40.
[61] Huang, Y., M. Pagano, and U. Panizza. 2020. Local Crowding Out in China, Journal of Finance 75(6): 2855-2898.
[62] Imbens, G. W., and T. Lemieux. 2008. Regression discontinuity designs: A guide to practice. Journal of Econometrics 142(2):615-635.
[63] Imbens, G. W., and K. Kalyanaraman. 2012. Optimal Bandwidth Choice for the Regression Discontinuity Estimator. Review of Economic Studies 79: 933-959.
[64] International Finance Corporation. 2017. MSME Finance Gap Report 2017, Washington.
[65] Jiang, W. 2017. Have Instrumental Variables Brought Us Closer to the Truth. The Review of Corporate Finance Studies 6(2):127-140.
[66] Keys, B. J., Mukherjee, T., Seru, A., & Vig, V. (2010). Did Securitization Lead to Lax Screening? Evidence from Subprime Loans. Quarterly Journal of Economics 125(1), 307-362.
[67] La Porta, R., F. López de Silanes, A. Shleifer, and R. Vishny. 1997. Legal Determinants of External Finance. The Journal of Finance 52(3):1131-1150.

[68] La Porta, R., F. López de Silanes, A. Shleifer, and R. Vishny. 1998. Law and Finance. Journal of Political Economy 106:1113-1155.
[69] Lee, D. S., and T. Lemieux. 2010. Regression Discontinuity Designs in Economics. Journal of Economic Literature 48(2):281-355.
[70] Lev, B. 2001. Intangibles: Management, Measurement, and Reporting. Washington, DC: Brookings Institution Press.
[71] Levine, R., C. Lin, and L. Wei. 2017. Insider Trading and Innovation. Journal of Law and Economics 60(4): 749-800.
[72] Liang, C., P. E. Yeung, 2018, On the Reliability, Informativeness, and Information Transfers of Recognized Customer-Related Intangibles, Working Paper.
[73] Liberti, J. M., and M. A. Petersen. 2018. Information: Hard and Soft. The Review of Corporate Finance Studies 8(1):1-41.
[74] Lin, J. Y., and G. Tan. 1999. Policy Burdens, Accountability, and the Soft Budget Constraint. American Economic Review 89 (2):426-431.
[75] Linton, K. C. 2008. Access to Capital in China: Competitive Conditions for Foreign and Domestic Firms. Journal of International Commerce and Economics 1: 27-49.
[76] Livshits, I., J. C. Mac Gee, and M. Tertilt. 2016. The democratization of credit and the rise in consumer bankruptcies. Review of Economic Studies 83(4): 1673-1710.
[77] Lee, D. S., and T. Lemieux. 2010. Regression Discontinuity Designs in Economics. Journal of Economic Literature 48: 281-355.
[78] Liu, L., G. Lu, and W. Xiong. 2022. The Big Tech Lending Model. Working Paper.
[79] Loutskina, E., and P. E. Strahan. 2015. Financial Integration, Housing, and Economic Volatility. Journal of Financial Economics 115(1):25-41.
[80] Matsa, D. A. 2011. Competition and Product Quality in the Supermarket Industry. The Quarterly Journal of Economics 126(3):1539-1591.
[81] McCrary, J. 2008. Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. Journal of Econometrics 142: 698-714.
[82] Opler, T. C., and S. Titman. 1994. Financial Distress and Corporate Performance. The Journal of Finance 49 (3):1015-1040.
[83] Ouyang, Shumiao. 2023. Cashless Payment and Financial Inclusion. Working Paper.
[84] Petersen, M. A., and R. G. Rajan. 1994. The Benefits of Lending Relationships: Evidence from Small Business Data. The Journal of Finance 49(1):3-37.
[85] Petersen, M.A., and R. G. Rajan. 1995. The Effect of Credit Market Competition on Lending Relationships. The Quarterly Journal of Economics 110(2):407-443.
[86] Qian, J., P. E. Strahan, and Z. Yang. 2015. The Impact of Incentives and Communication Costs on Information Production and Use: Evidence from Bank Lending. Journal of Finance 70(4): 1457-1493.
[87] Qian, J., and P. E. Strahan. 2007. How Laws and Institutions Shape Financial Contracts: The Case of Bank Loans. The Journal of Finance 62(6):2803-2834.
[88] Roach, S. 2009. China's Great Contradiction. In: The Next Asia, edited by Stephen Roach. John Wiley and Sons.
[89] Roure, C., L. Pelizzon, and A. V. Thakor. 2019. P2P lenders versus banks: Cream skimming or bottom fishing?. SAFE Working Paper No. 206.
[90] Ru, H. 2018. Government Credit, a Double-Edged Sword: Evidence from the China Development Bank. The Journal of Finance 73 (1):275-316.
[91] Shi, J. P. 2016. China MSME Finance report. Mintai Institute of Finance and Banking and Central University of Finance and Economics, available at DOI: 10.13140/RG.2.2.21772.10880
[92] Strahan, P. E. 2017. Are Concentrated Banks Better Informed Than Diversified Ones? Journal of Accounting and Economics 64(2):278-283.

[93] Tang H. 2019. Peer-to-peer lenders versus banks: substitutes or complements?. The Review of Financial Studies 32(5): 1900-1938.
[94] Tsai, K. 2002. Black-Alley Banking: Private Entrepreneurs in China. Ithaca, NY: Cornell University Press.
[95] Vig, V. 2013. Access to Collateral and Corporate Debt Structure: Evidence from a Natural Experiment. The Journal of Finance 68 (3):881-928.
[96] Zetzsche, D., R. P. Buckley, D. W. Arner, and J. N. Barberis. 2017. From Fintech to Techfin: the Regulatory Challenges of Data-Driven Finance, Working Paper Series No. 6, EBI.

Table 1 Evolution of Firm Credit

As of the end of February for each year from 2012 to 2016, Column (1) reports the evolution of the annual trading volume in the e-commerce trading platform Taobao; Columns (2) and (3) report the number of firms eligible for Taobao credit and those vendors using at least some of the online credit, respectively; and we report the total amount of eligible credit lines in Column (4), and the outstanding balance of credit used in Column (5), respectively.

	Taobao	Firm Credit			
	Annual Trading Volume (GMV)	Number of Firms		Eligible Credit Lines	Outstanding Credit Used
	(in billion RMB)	Eligible	Use Credit	(in 100 million RMB)	
As of	(1)	(2)	(3)	(4)	(5)
Feb 2012	824	95,645	11,842	47.2	5.1
Feb 2013	1173	310,946	33,968	116.7	13.8
Feb 2014	1597	751,920	152,685	263.0	44.2
Feb 2015	1877	1,103,183	231,512	429.2	75.1
Feb 2016	2202	883,294	310,486	516.9	86.7

Table 2 Summary Statistics

This table presents the summary statistics on the variables used in two main regression samples. Panels A and B report summary statistics on all variables in the city-level and FRDD sample, respectively.

	N	P10	P50	Mean	P90	SD
Panel A. City-level Sample						
No. New TB Firms	267	103	542	3887.44	8361	12774.03
Credit Line (in ¥10,000)	273	62.15	838.35	9932.22	18210.44	38790.36
Credit Use (in ¥10,000)	273	12.13	144.64	1920.20	3758.10	7291.76
Loan/GDP (%)	267	41.89	59.93	71.28	115.65	36.85
State Bank Density	267	0.36	0.72	0.88	1.50	0.64
SOE Output Share	267	0.01	0.08	0.15	0.41	0.17
PCGDP (in ¥10,000)	267	0.55	1.13	1.72	3.43	2.19
Population (in million)	267	1.41	3.54	4.11	7.41	2.42
Digital Development Index	267	92.29	105.74	124.73	212.3	47.73
Panel B. Local FRDD Sample						
Sales Growth	1196887	-2.48	-0.35	-0.44	1.49	2.02
Transaction Growth	1196887	-2.48	-0.47	-0.48	1.43	1.61
Product Rating	1196887	0.27	0.60	0.57	0.85	0.22
Service Rating	1196887	0.28	0.62	0.59	0.87	0.23
Consignment Rating	1196887	0.27	0.61	0.58	0.86	0.23
Credit Score	1196887	467.72	486.90	484.70	497.80	11.02
Credit Approval	1196887	0	1	0.62	1	0.48
Credit Line	1196887	0	10000	15907.16	18,000	57647.37
Age Rank	1196848	0.04	0.12	0.16	0.34	0.13
High Dispersion	1196205	0	1	0.75	1	0.43
High Durability	1196887	0	0	0.12	1	0.33
Property Ownership	1196887	0	0	0.20	1	0.40
Ln (1+Ad Expense)	1196887	0	0	2.94	8.46	3.71
Ln (1+ Product Types)	1196887	2.20	3.78	3.79	5.50	1.35
Customer Conversion Rate	1196887	1.08	5.18	7.44	16.07	7.56

Table 3. Macro Factors Affecting China's E-Commerce Entrepreneurship and FinTech Credit
This table presents the cross-sectional regression results on the macro factors influencing the aggregate entry rate and FinTech credit access of Taobao firms at the city level. *# New TB Firms* denotes the total number of newly registered Taobao firms from 2005 to 2015 in a city, where only firms with city information available are counted. *Credit Line* measures the total amount of eligible credit lines approved by Ant Financial for all Taobao firms (with location information) in a city as of an average month in 2015. *Credit Use* is the total outstanding balance of credit drawn by all Taobao firms (with location information) in a city as of an average month in 2015. Independent variables are measured in the earliest year available during 2005-2015 for the entry regression or with the latest information for the 2015 credit access regression. *PCGDP* is the GDP per capita of a city in 10,000 RMB. *Digital Development Index* is a province level variable developed by Guo et al. (2016). *Loan/GDP* is the amount of commercial loans over GDP in a city in percentage points. *State Bank Density* is the number of state bank branches over the total population (in 10,000) in a city. *SOE Output Share* is the share of output contributed by SOEs in a city, where SOE is defined following the registration type in the Annual Survey of Industrial Firms in China. We report t-statistics based on robust standard errors in parenthesis. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	*Ln(# New TB Firms)*	*Ln(Credit Line)*	*Ln(Credit Use)*
	(1)	(2)	(3)
State Bank Density × SOE Output Share	1.6282***	1.7612***	1.4501*
	(2.96)	(2.59)	(1.84)
State Bank Density	0.2125	-0.0090	0.0339
	(1.30)	(-0.03)	(0.11)
SOE Output Share	-0.2368	-0.7390	-0.4487
	(-0.80)	(-1.39)	(-0.36)
Loan/GDP (%)	0.0046***	0.0018	0.0019
	(2.73)	(0.79)	(0.76)
PCGDP (in millions)	0.2417***	0.1403***	0.1346***
	(2.97)	(3.28)	(2.83)
Population (in millions)	0.3679***	0.3303***	0.3390***
	(13.63)	(3.89)	(3.93)
Digital Development Index	0.0460***	0.0509***	0.0522***
	(9.92)	(9.08)	(8.86)
R2	0.742	0.623	0.602
N	267	279	279

Table 4. FinTech Credit Access and Firm Performance

This table shows the fuzzy RD estimates of FinTech credit access on firm performance. We use the 2SLS regression system in equations (1) and (2) to implement the design. In the first stage (Panel A), we regress the credit access dummy, *Credit Approval*, onto an indicator variable, *IV (Credit Score>=480)*, which equals 1 when the credit score is equal to or greater than 480, and 0 otherwise. In the second stage (Panel B), we regress the dependent variable onto the instrumented *Credit Approval*. We use the local linear regression model for the credit scores, which range from 460 to 500, and include firm-type and time fixed effects in both stages. The dependent variables are *Sales Growth* and *Transaction Growth* measured from one month before to one month after the credit allocation event, and *Product Rating*, *Service Rating*, and *Consignment Rating*, measured in the month after the credit allocation event, respectively. Firm-type and time-fixed effects are included. We report t-statistics based on standard errors clustered at the firm-type level in parentheses. The Kleibergen-Paap weak instrument statistic is presented in the last row of Panel B. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A. First Stage

Dependent Var.	*Credit Approval*
	(1)
IV (Credit Score>=480)	0.2872***
	(27.50)
Polynomials in Credit Score	Yes
Firm Type FE	Yes
Time FE	Yes
Adj. R2	0.334
N	1,196,887

Panel B. Second Stage

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval	0.3631***	0.2691***	0.0541***	0.0544***	0.0551***
(Instrumented)	(15.97)	(16.31)	(9.17)	(9.62)	(9.90)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.094	0.157	0.124	0.126	0.128
N	1,196,887	1,196,887	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.			756.2		

Table 5. FinTech Credit Access and Firm Performance: Information Channel

This table shows the heterogeneous effects of FinTech credit access on firm performance across firms with varying credit information quality. We use smaller firm age (Panel A) and higher industry dispersion of growth (Panel B) as proxies of information asymmetries facing traditional credit and information advantages of FinTech credit. *Age Rank* is the relative firm rank based on age, ranging from zero to one. *High Dispersion* is an indicator variable that equals 1 if a firm is operating in an industry, where the standard deviation of sales growth across all firms in the industry prior to the credit allocation event is above the industry median, and zero otherwise. In the first stage, we instrument *Credit Approval* and its interaction with the information advantage proxy as specified in equations (3a) and (3b). In the second stage, we regress performance measures on the instrumented variables in accordance with equation (4). The dependent variables are *Sales Growth*, *Transaction Growth*, *Product Rating*, *Service Rating*, and *Consignment Rating*, respectively. We use the local linear regression model for the credit scores, which range from 460 to 500, and include firm-type and time-fixed effects in both stages. We report t-statistics based on standard errors clustered at the firm-type level in parentheses. The Kleibergen-Paap weak instrument statistic is presented in the last row of each panel. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A. Heterogeneous Effect by Firm Age

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval × *Age Rank*	-0.9153***	-0.5972***	-0.2339***	-0.1806***	-0.1725***
(Instrumented)	(-5.69)	(-4.90)	(-10.98)	(-8.85)	(-8.54)
Credit Approval	0.4733***	0.3413***	0.0867***	0.0810***	0.0807***
(Instrumented)	(22.94)	(23.15)	(10.04)	(10.72)	(10.66)
Age Rank	0.9353***	0.5750***	-0.1630***	-0.2530***	-0.2656***
	(7.15)	(6.02)	(-9.36)	(-14.51)	(-13.35)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.095	0.158	0.154	0.167	0.170
N	1,196,848	1,196,848	1,196,848	1,196,848	1,196,848
Kleibergen-Paap F-stat.			430.9		

Panel B. Heterogeneous Effect by Industry Dispersion in Growth

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval × *High Dispersion*	0.1875*	0.1263*	0.0449***	0.0379***	0.0350***
(Instrumented)	(1.75)	(1.76)	(5.44)	(4.03)	(3.79)
Credit Approval	0.2183***	0.1710***	0.0196***	0.0253***	0.0282***
(Instrumented)	(2.51)	(2.86)	(5.08)	(5.57)	(6.19)
High Dispersion	-0.2399***	-0.2110***	-0.0313***	-0.0245***	-0.0230***
	(-2.50)	(-3.08)	(-4.65)	(-3.29)	(-3.12)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.094	0.158	0.124	0.127	0.129
N	1,196,205	1,196,205	1,196,205	1,196,205	1,196,205
Kleibergen-Paap F-stat.			355.7		

Table 6 FinTech Credit Access and Firm Performance: Information as Substitute for Collateral

This table shows the heterogeneous effects of FinTech credit access on firm performance across vendors with varying degrees of collateral availability. We use asset durability of an industry (Panel A) and the estimated real estate property ownership (Panel B) as proxy for collateral availability, respectively. *High Durability* is an indicator variable that equals 1 if a firm operates in industries featured with durable goods. *Probability Ownership* is an indicator variable that equals 1 if the estimated probability of the firm owner owning a real estate property is greater than 0.9. In the first stage, we instrument *Credit Approval* and its interaction with the collateral proxies (i.e., *High Durability* or *Property Ownership*) analogous to equations (3a) and (3b). In the second stage, we regress performance measures on the instrumented variables analogous to equation (4). The dependent variables are *Sales Growth*, *Transaction Growth*, *Product Rating*, *Service Rating*, and *Consignment Rating*, respectively. We use the local linear regression model for the credit scores, which range from 460 to 500, and include firm-type and time-fixed effects in both stages. We report t-statistics based on standard errors clustered at the firm-type level in parentheses. The Kleibergen-Paap weak instrument statistic is presented in the last row of each panel. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A. Heterogeneous Effect by Asset Durability

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval × *High Durability*	-0.0880***	-0.0736***	-0.0386***	-0.0283**	-0.0308***
(Instrumented)	(-2.17)	(-2.81)	(-3.26)	(-2.31)	(-2.55)
Credit Approval	0.3722***	0.3857***	0.0581***	0.0574***	0.0583***
(Instrumented)	(18.37)	(18.06)	(9.73)	(8.83)	(8.78)
High Durability (absorbed by Firm Type FE)					
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.094	0.157	0.124	0.127	0.129
N	1,196,887	1,196,887	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.			364.7		

Panel B. Heterogeneous Effect by Property Ownership

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval × Property Ownership	-0.0416**	-0.0248**	-0.0245***	-0.0178***	-0.0167***
(Instrumented)	(-2.14)	(-1.98)	(-4.19)	(-3.04)	(-2.64)
Credit Approval	0.3701***	0.2732***	0.0588***	0.0581***	0.0586***
(Instrumented)	(17.20)	(17.45)	(9.00)	(9.34)	(9.62)
Property Ownership	0.0537***	0.0365***	-0.0059	-0.0153***	-0.0191***
	(3.44)	(3.68)	(-1.29)	(-3.62)	(-3.74)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.094	0.157	0.125	0.129	0.131
N	1,196,887	1,196,887	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.			380.5		

Table 7. Mechanisms of Vendor Performance Enhancement

This table shows the FRDD estimates of credit access on other activities and performance of firms. We use the 2SLS regression system in equations (1) and (2) and report the results for the second stage, where the dependent variables are *Advertisement*, *Product Variety*, *Customer Conversion Rate* and *Product Collection Rate,* respectively. *Advertisement* is the natural logarithm of one plus the vendor's monthly expenditures on advertisement. *Product Variety* is the natural logarithm of one plus the number of product types for sales. *Customer Conversion Rate* is defined as the ratio of the number of customers that completed transactions over the total number of customers of a firm in a month (scaled by a factor of 100). We use local linear regression model for the credit scores, which range from 460 to 500, and include firm-type and time-fixed effects in both stages. We report t-statistics based on standard errors clustered at the firm-type level in parentheses. The Kleibergen-Paap weak instrument statistic is presented in the last row. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	*Advertisement* [Ln (1+Ad Expense)]	*Product Variety* [Ln (1+ Product Types]	*Customer Conversion Rate*
	(1)	(2)	(3)
Credit Approval	0.2679***	0.1233***	0.6979***
(Instrumented)	(6.68)	(4.99)	(5.56)
Polynomials in Credit Score	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj. R2	0.030	0.087	0.130
N	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.		756.2	

Table 8. Robustness Checks

This table presents robustness results to the baseline specification in Table 4 using alternative measures, samples, or specifications. All panels except Panel C use specifications analogous to equations (1) and (2). Panel A shows the effect of credit access on sales and service performance, where *Sales Growth* and *Transaction Growth* are measured from the month before to two months after the credit allocation event, and *Product Rating, Service Rating,* and *Consignment Rating* two months after the credit allocation event. Panel B uses the *change* in the ratings from the month before the credit allocation event to the month after as the dependent variable. Panel C uses a different linear functional form for the credit scores to the right and the left of the cutoff at 480. Panel D adopts a second-order polynomial (K=2) for the credit score controls. Panel E and F uses credit scores within the range [465, 495] and [470, 490] as alternative bandwidths, respectively. All other panels use a local range [460, 500] for credit scores. We report t-statistics based on standard errors clustered at the industry level in parentheses. The Kleibergen-Paap weak instrument statistic is presented in the last row of each panel. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A. Performance with Three Months' Consecutive Credit Access

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval	0.8470***	0.5519***	0.0843***	0.0853***	0.0844***
(Instrumented)	(24.10)	(23.32)	(13.52)	(14.49)	(14.77)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.049	0.079	0.139	0.138	0.144
N	931,599	931,599	881,387	881,387	881,387
Kleibergen-Paap F-stat.	840			896.4	

Panel B. Change of Service Ratings

Dependent Var.	Δ *Product Rating*	Δ *Service Rating*	Δ *Consignment Rating*
	(1)	(2)	(3)
Credit Approval	0.0323***	0.0325***	0.0349***
(Instrumented)	(21.36)	(21.40)	(21.36)
Polynomials in Credit Score	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj. R2	0.015	0.016	0.024
N	1,014,149	1,014,149	1,014,149
Kleibergen-Paap F-stat.		602.5	

Panel C. Differential Right and Left Slopes for the Credit Score Variable

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval	0.3812***	0.2815***	0.0464***	0.0454***	0.0471***
(Instrumented)	(16.45)	(16.61)	(7.61)	(8.31)	(8.78)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.094	0.157	0.123	0.127	0.129
N	1,196,887	1,196,887	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.			1089.0		

Panel D. Second-Order Polynomial for the Credit Score Variable

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval	0.3836***	0.2832***	0.0465***	0.0451***	0.0470***
(Instrumented)	(16.43)	(16.35)	(7.84)	(8.45)	(8.88)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.094	0.157	0.124	0.127	0.129
N	1,196,887	1,196,887	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.			1105.0		

Panel E. Alternative Bandwidth [465, 495]

Dependent Var.	Sales Growth	Transaction Growth	Product Rating	Service Rating	Consignment Rating
	(1)	(2)	(3)	(4)	(5)
Credit Approval	0.4159***	0.2957***	0.0513***	0.0506***	0.0515***
(Instrumented)	(14.43)	(12.91)	(10.08)	(11.68)	(12.13)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.094	0.156	0.093	0.099	0.099
N	862,893	862,893	862,893	862,893	862,893
Kleibergen-Paap F-stat			960.7		

Panel F. Alternative Bandwidth [470, 490]

Dependent Var.	Sales Growth	Transaction Growth	Product Rating	Service Rating	Consignment Rating
	(1)	(2)	(3)	(4)	(5)
Credit Approval	0.4544***	0.2999***	0.0488***	0.0437***	0.0454***
(Instrumented)	(10.13)	(8.29)	(9.95)	(9.26)	(9.69)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.094	0.156	0.068	0.077	0.076
N	553,711	553,711	553,711	553,711	553,711
Kleibergen-Paap F-stat.			849.0		

Table 9. FinTech Credit Access and Long-term Firm Performance

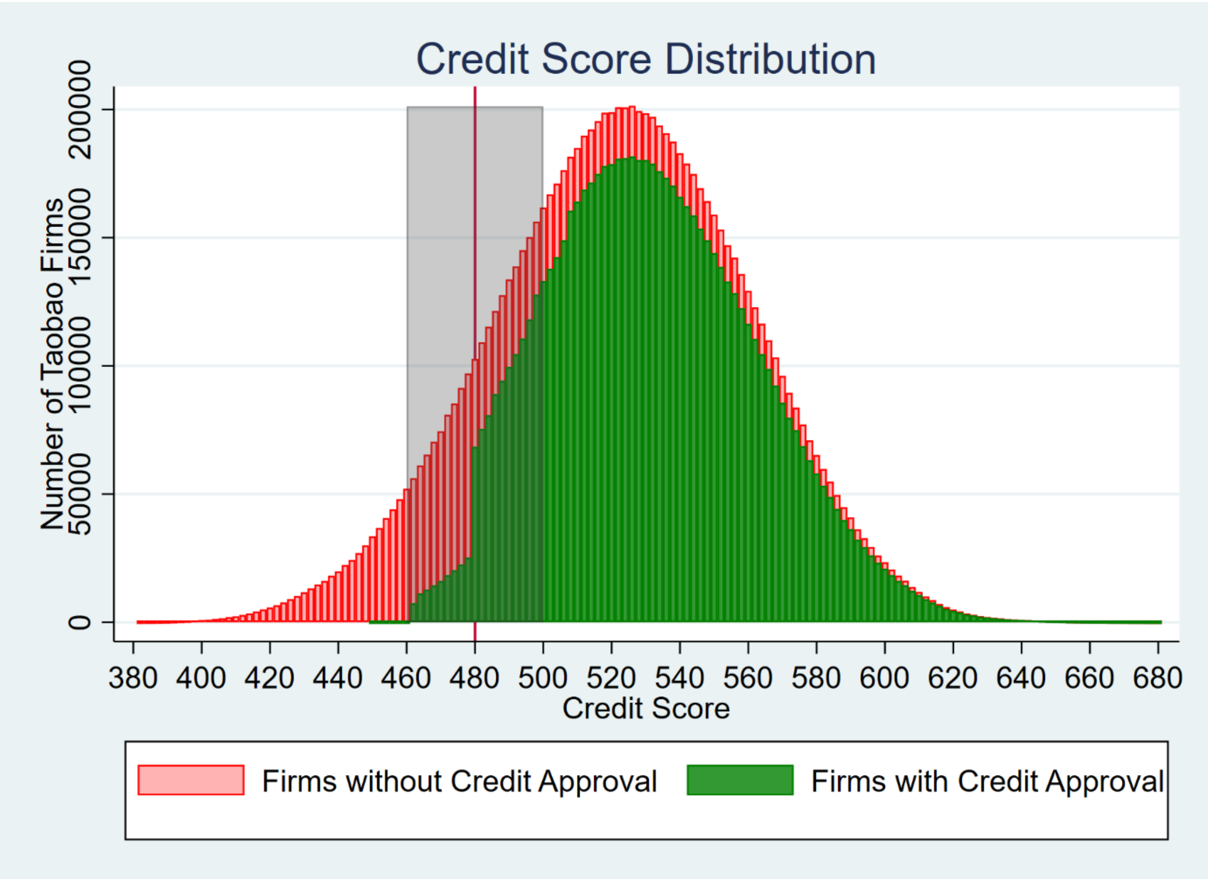
This table shows the long-term effects of FinTech credit access on firm performance in six months following the approval of credit. The dependent variables is *Sales Growth* and *Transaction Growth*, measured from the month before to six months after a credit allocation event, in column (1) and (2), respectively; it is *Product Rating*, *Service Rating*, *Consignment Rating*, *Advertisement*, *Product Variety*, and *Customer Conversion Rate*, defined in the sixth month following a credit allocation event, respectively. We use the local linear regression model for the credit scores, which range from 460 to 500, and include firm-type and time-fixed effects in both stages. We report t-statistics based on standard errors clustered at the firm-type level in parentheses. The Kleibergen-Paap weak instrument statistic is presented in the last row of each panel. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*	*Advertisement* [Ln (1+Ad Expense)]	*Product Variety* [Ln (1+ Product Types)]	*Customer Conversion Rate*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Approval	0.4816***	0.2460***	0.0479***	0.0494***	0.0512***	0.1401***	0.1920***	0.2352***
(Instrumented)	(8.15)	(5.97)	(7.40)	(7.91)	(8.88)	(4.63)	(6.06)	(9.89)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.047	0.049	0.086	0.084	0.090	0.144	0.064	
N	1,196,887	1,196,887	941,227	941,227	941,227	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.	756.2			600.3			756.2	

Figure 1. Credit Score Distribution and Credit Approval

Panel A plots the distribution of monthly credit scores for 2 million Taobao firms from November 2014 to June 2015. The green bars mark the Taobao firms with credit approval, and the (upper) red bars represent those without credit approval. The grey shaded region marks the sampling interval for the FRDD with the discontinuity at the credit score of 480. Panel B is the discontinuity plot for the probability of credit approval against credit scores. The vertical axis is the probability of credit access. The horizontal axis is the credit score in the local range of [470, 490]. Each dot on the figure represents the average probability that a credit line is granted to a firm located in the credit score range with a bandwidth of two. The probability is estimated by dividing the total number of firms with credit access by the total number of eligible firms in the same bin. A linear line is fit to the scattered dots on each side of the cutoff score (i.e., 480), surrounded by a 95% confidence interval in light grey lines.

(A) Credit Score Distribution



(B) Probability of Credit Approval

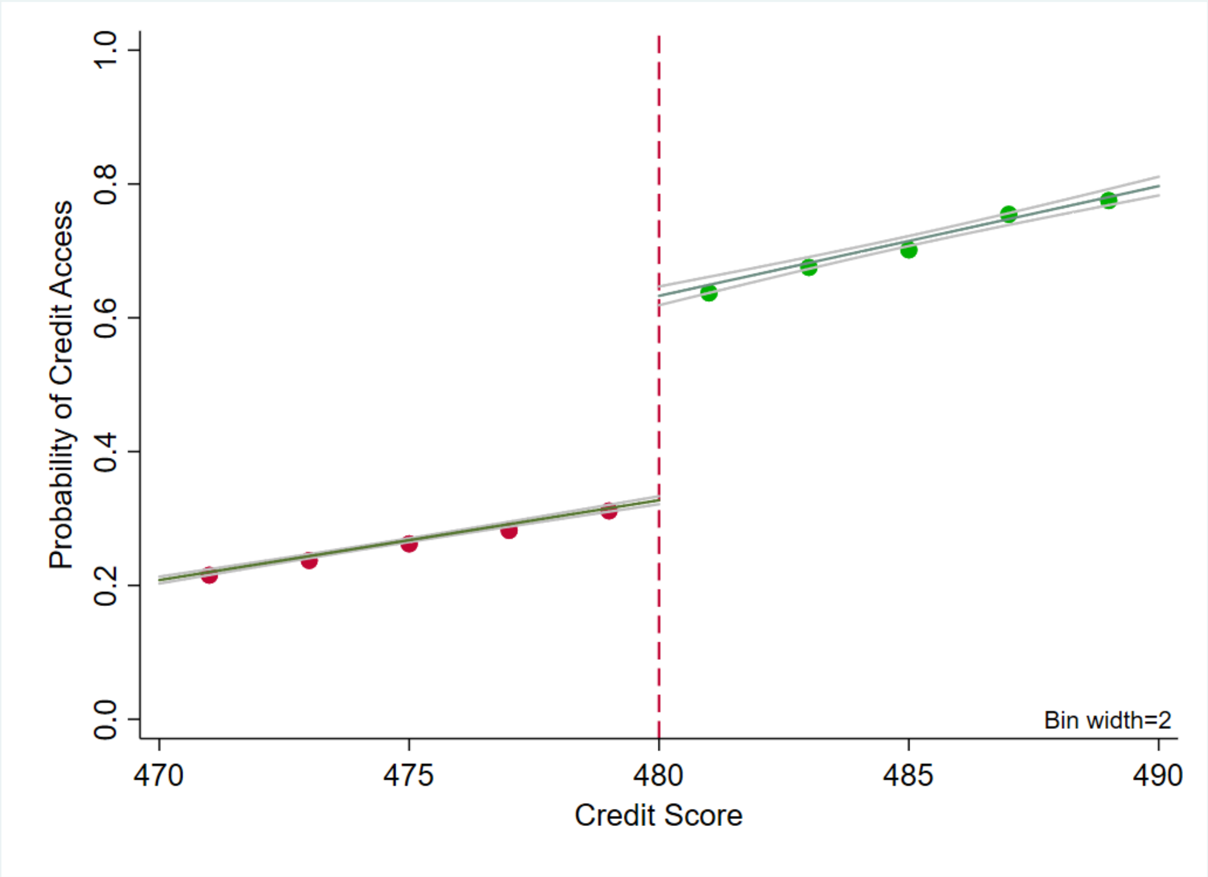
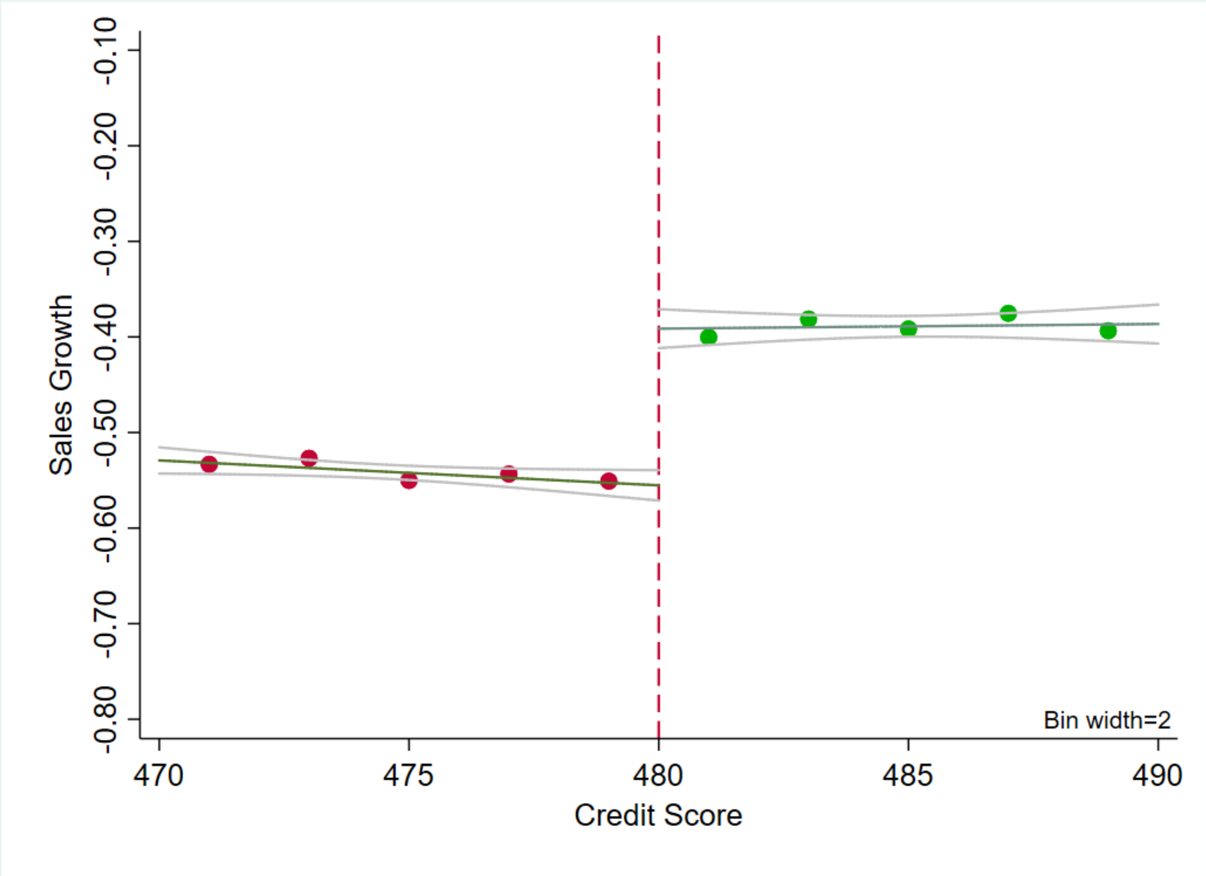


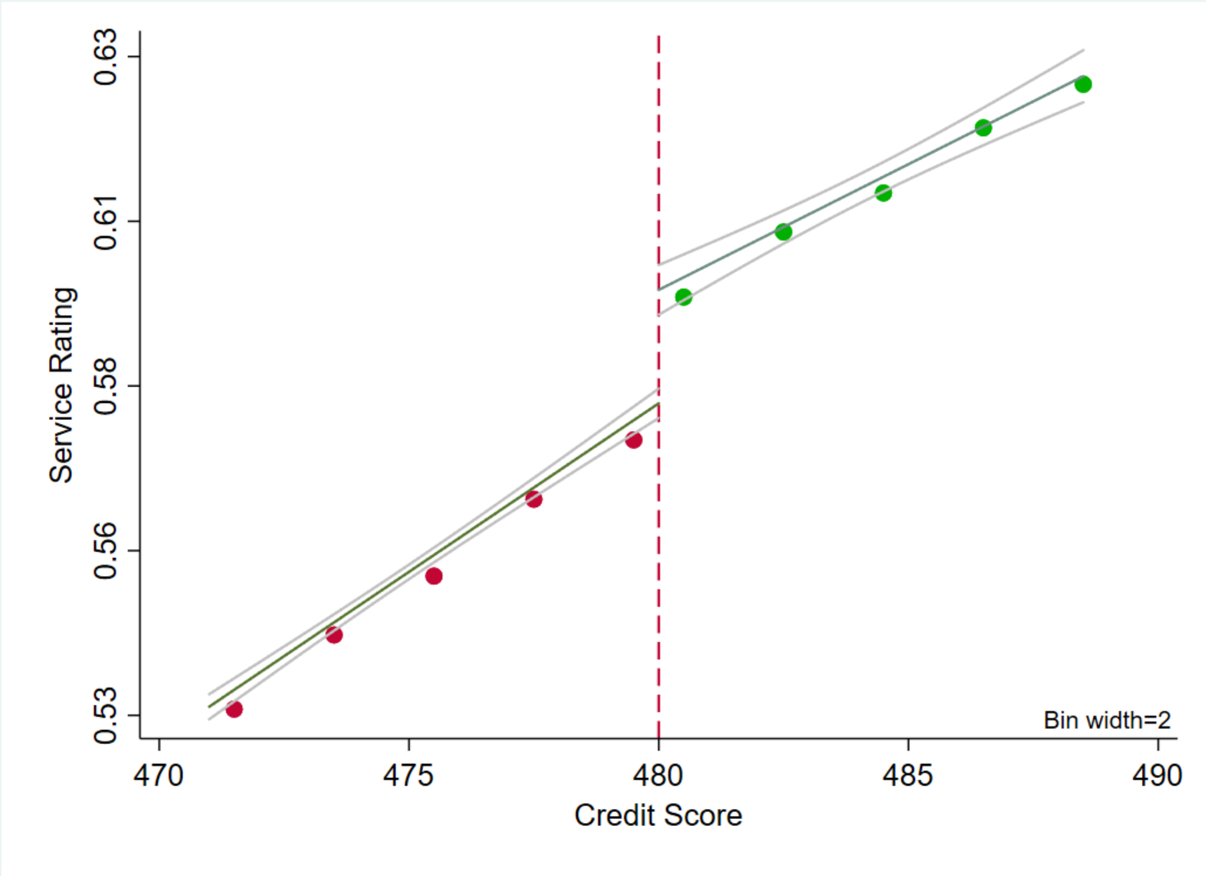
Figure 2. Discontinuity Plot on Outcome Variables

This figure presents discontinuity plots on firms' growth from month t-1 to t+1 and CSR ratings at month t+1 against credit scores in month t. The vertical axis is the value of *Sales Growth* and *Service Rating*. The horizontal axis is credit scores in the local range of [470, 490]. Each dot on the figure represents the average value of the respective outcome measure for firms located in the credit score range with a bandwidth of four. A linear line is fit to the scattered dots on each side of the cutoff score (i.e., 480), and surrounded by a 95% confidence interval in light grey lines.

(A) Sales Growth



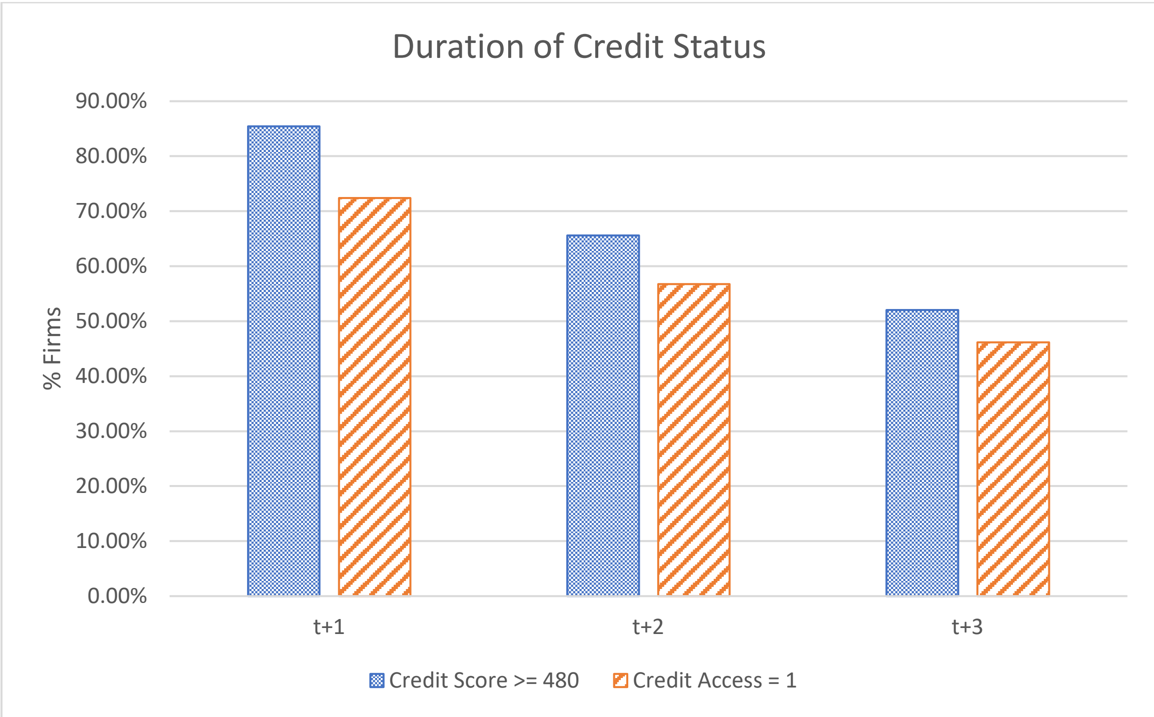
(B) Service Rating



Appendix

Figure A1. Duration of Credit Status

This figure plots the average percentage of firms with (1) credit score in the range of [480, 500] in month *t* that continues to score above 480 in month *t+1*, *t+2*, *t+3*, respectively, and (2) credit score in the range of [480, 500] and credit access in month t, and in addition maintain the access status at the end of month *t+1*, *t+2*, and *t+3*, respectively.



Internet Appendix

Table A1. FinTech Credit Access and Firm Performance: Distribution Cost Channel

This table shows the heterogeneous effects of FinTech credit access on firm performance across firms facing varying levels of distribution costs. *Distribution Cost* is proxied by the inverse of the predicted size of a firms' credit line. We report the second stage, which regresses vendor performance measures on the instrumented variables analogous to equation (4). The dependent variables are *Sales Growth*, *Transaction Growth*, *Product Rating*, *Service Rating*, and *Consignment Rating*, respectively. We use the local linear regression model for the credit scores, which range from 460 to 500, and include firm-type and month-fixed effects in both stages. We report t-statistics based on standard errors clustered at the firm-type level in parentheses. The Kleibergen-Paap weak instrument statistic is presented in the last row of each panel. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A.

	N	**P10**	**P50**	**Mean**	**P90**	**SD**
Distribution Cost	1196846	0.08	0.60	0.75	1.70	0.61

Panel B.

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval × *Distribution Cost*	0.2788***	0.2211***	0.0714***	0.0686***	0.0712***
(Instrumented)	(10.34)	(10.04)	(9.17)	(7.47)	(8.09)
Credit Approval	0.1973***	0.1364***	0.0138***	0.0158***	0.0152***
(Instrumented)	(8.30)	(8.18)	(3.60)	(4.49)	(4.45)
Distribution Cost	0.0797***	0.0762***	-0.0125*	-0.0138*	-0.0182**
	(2.76)	(3.81)	(-1.77)	(-1.88)	(-2.62)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.101	0.157	0.134	0.135	0.136
N	1,196,846	1,196,846	1,196,846	1,196,846	1,196,846
Kleibergen-Paap F-stat.			461.8		

Table A2. FinTech Credit Access and Firm Performance: Enforcement Channel

This table shows the heterogeneous effects of FinTech credit access on firm performance across regions of varying degrees of law enforcement quality. We use the city-level *Legal Quality Index* as proxy for the regional law enforcement quality. *Legal Quality Index* is obtained from the 2006 World Bank survey for 120 cities in China. It measures firms' average confidence level in the legal system of the region and ranges from 0 to 1. In the first stage, we instrument *Credit Approval* and its interaction with the channel variable following equation (3) and (4). In the second stage, we regress performance measures on the instrumented variables following equation (5). The dependent variables are *Sales Growth*, *Transaction Growth*, *Product Rating*, *Service Rating*, and *Consignment Rating*, respectively. We use the local linear regression model over the credit scores from 460 to 500 and include firm-type and time-fixed effects in both stages. We report t-statistics based on standard errors clustered at the firm-type level in parentheses. Kleibergen-Paap weak instrument statistic is presented in the last row of each panel. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively.

Panel A.

	N	**P10**	**P50**	**Mean**	**P90**	**SD**
Legal Quality Index	282010	0.69	0.79	0.79	0.98	0.12

Panel B.

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Credit Approval × *Legal Quality Index*	-0.2856*	-0.2370***	-0.1379**	-0.1280**	-0.1274***
(Instrumented)	(-1.67)	(-2.70)	(-2.42)	(-2.29)	(-2.42)
Credit Approval	0.6052***	0.4588***	0.1576***	0.1525***	0.1536***
(Instrumented)	(3.89)	(5.54)	(3.77)	(3.93)	(4.19)
Legal Quality Index	0.0740	0.0745	0.1406	0.1283	0.1230
	(0.52)	(0.85)	(1.35)	(1.34)	(1.34)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.089	0.156	0.106	0.111	0.114
N	282,010	282,010	282,010	282,010	282,010
Kleibergen-Paap F-stat.			312.3		