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FinTech Credit and Entrepreneurial Growth

HARALD HAU, YI HUANG, CHEN LIN, HONGZHE SHAN, ZIXIA SHENG, and LAI WEI*

ABSTRACT

Based on automated credit lines to 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 less collateral, which reveals the information advantage of FinTech credit over traditional credit technology.

*Harald Hau is with University of Geneva, CEPR, and Swiss Finance Institute. Yi Huang is with Fudan International School of Finance, Fudan University. Chen Lin is with Faculty of Business and Economics, The University of Hong Kong. Hongzhe Shan is with Pictet Asset Management. Zixia Sheng is with New Hope Financial Services. Lai Wei is with Faculty of Business, Lingnan University. We are grateful to the Editor Wei Xiong, the Associate Editor, and two anonymous referees for their constructive comments and suggestions. We are grateful to colleagues at Alibaba Group, Ant Group, AliResearch, Luohan Academy and other related institutions who helped with the data accessibility and processing, including but not limited to Long Chen, Zhenghua Li, Ivy Li and Shi Piao, and to Xiaomin Guo, Yadong Huang, and Sibo Liu for their excellent research assistance. Lin acknowledges financial support from the National Natural Science Foundation of China (No. 72192841). Hau and Shan acknowledge financial support from the Swiss National Science Foundation (SNSF). Huang acknowledges financial research support by the Graduate Institute of International and Development Studies, Geneva, and financial research support by Fudan University. Wei acknowledges financial support from the Hong Kong Research Grant Council (No. T35-710/20-R). Sheng worked as the 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. 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 at the Ant Group and the Open Data Program of the Luohan Academy. 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. Ant Group did not exercise any influence on the content of this paper but did require data confidentiality. We have read *The Journal of Finance* disclosure policy and have no conflicts of interest to disclose.

Correspondence: Harald Hau, University of Geneva, GFRI, Unipignon, 40 Boulevard du Pont d'Arve, 1211 Geneva 4, Switzerland.
Email: prof@haraldhau.com

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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 often argue 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.[1]

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 for 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 along 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 loans outstanding increasing from only 4 billion USD in 2013 to 156 billion USD in 2016 and an estimated 764 billion USD by 2020.[2] 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 providers of small-firm credit include Amazon in the United States 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 enforcement strategies. Can these new credit technologies unlock latent entrepreneurial growth potential beyond the reach of traditional bank credit?[3]

[1] 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 unmet financing needs of 5.2 trillion USD annually. These claims are extrapolated from survey data and do not shed light on the potential growth effects of credit access.

[2] These figures are based on an, August 7, 2017, industry report by Goldman Sachs Global Investment Research, entitled "Future of Finance: The Rise of China FinTech."

[3] 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.

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 likelihood that firms are underserved by bank credit and thus initiate online (shop) presence for easier access to (FinTech) credit. Previous literature on banking in China (Allen, Qian, and Qian (2008), Qian, Strahan, and Yang (2015)) highlights 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 bank credit supply is determined in part by an administrative credit allocation process in which most banks are state-owned and the five largest account for 37.2% of total bank assets as of 2016.[4] Moreover, bank credit tends to be tilted toward the state sector because of alignment in 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 lead to greater online entrepreneurial activities of MSMEs that are crowded out from the local credit market by SOEs. We provide evidence that supports this hypothesis. Higher density of state banks at the city level correlates positively with the total entry rate of Taobao vendors in regions in which SOEs account for a large fraction of total output. These firms also enjoy greater total online credit in aggregate. The results are consistent with the view that the banking sector not only fails to alleviate credit frictions for small entrepreneurs, but actually exacerbates them by redirecting local savings to state-sector investments—state-owned banks lead to a metaphorical "black hole" when it comes to entrepreneurial credit, absorbing local savings and channeling them mostly to SOE investments. FinTech credit can compensate such local credit supply shortages for the private sector and thereby integrate China's geographically fragmented credit market for small private e-commerce vendors.

The main contribution of this paper is to provide 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 literatures. 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 the 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 active Taobao vendors comprises 35.5 million firm-months for 3.4 million firms or vendors throughout China. During the

[4] 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.

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.[5]

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 cutoff 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 credit-noneligible vendors. Thus, 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 sets of growth-related performance measures. The first set of measures comprise 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 increase by an incremental 22% and 15%, respectively, over an average month following credit approval.[6] 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)).[7]

The second set of measures comprise customer-contributed product and service ratings, which gauge firms' investment in customer capital. Over the past few decades, firm investment has observed 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 United States (Lev (2001), Corrado and Hulten (2010), Bernanke (2011)).[8] 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 (2014)).[9] Customer capital

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

[6] 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.

[7] 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 robust inference. For recent overviews, see Banerjee, Karlan, and Zinman (2015) and Beck et al. (2018).

[8] This trend also holds in other major economies around the world (Haskel and Westlake (2018)).

[9] 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

consisting of strong customer relationships and loyalty represents a sustainable competitive advantage and source of long-term firm value. We can trace the customer capital formation of Taobao vendors using multidimensional customer-contributed ratings, which come at high frequency and a highly granular level. This helps us address the empirical challenge that existing literature faces in measuring customer capital (Dou et al. (2021)). We find that each of the three ratings increases significantly following credit approval. Firms with credit access realize on average 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 a standard deviation of these ratings, which are expressed on a scale from zero to one. In robustness checks, we show that the results on sales growth, transaction growth, and customer ratings all hold for longer measurement periods following credit access. The results are also robust to using higher-order polynomials, different functional forms, and alternative bandwidths in the empirical specifications.

The statistical power of a large sample with extensive coverage of firms in different regions and industries allows us to document heterogeneous growth effects of FinTech credit for different types of firms. 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 prelending screening and collateral use, credit distribution costs, and postlending monitoring and enforcement. Our analysis focuses mainly on the information advantage of FinTech credit in credit screening and monitoring, but we also briefly discuss suggestive evidence on the other channels.

The business model of FinTech credit is based mainly 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 finding provides additional supportive evidence on the competitive advantage of new credit technologies for high-risk creditor types.[10]

more than the value of brands and exceeds that of R&D based on the latest statistics. Similarly, using information disclosed after M&As, Liang and Yeung (2018) find that customer-related intangible assets account on average for 18% of the targets' premerger market capitalization, which is far above the value of brand and exceeds that of R&D in recent years.

[10] 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 thus do not fit into bank lending models that employ stringent capital requirements (Petersen and Rajan (1994), Berger and Udell (1995)).

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 greater information asymmetry.[11] We also find that FinTech credit approval has a much more significant impact on firms with less valuable collateral. These results suggest that FinTech lenders depend less on collateral to mitigate information asymmetries and moral hazard problems (Aghion and Bolton (1992)), consistent with an information advantage for FinTech lenders.

The short-term nature of FinTech credit and its high interest rates (median value of 17%) raise concerns about how platform entrepreneurs can truly benefit. We first 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 precommitted debt capacity, which hedges against future liquidity shocks and relaxes their precautionary saving motives to hold cash today (e.g., Holmström and Tirole (1998), Acharya et al. (2014), Acharya et al. (2020)). Firms with credit lines can then prioritize the use of cash holdings to fund growth opportunities when they need capital. The mere accessibility of FinTech credit can therefore have a direct first-order impact on firms' investment decisions that boosts sales and builds customer capital.

We also note that Taobao vendors who operate in the retail segment are characterized by short seasonal spikes in inventory demand. Exceptionally high working capital needs therefore tend to last for only 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 are only 0.04 and 0.28 of the scheduled loan maturity, which are one week and six weeks for a six-month loan, respectively. Net borrowing costs are therefore much lower than the full annual costs based on the quoted (high) interest

[11] FinTech lenders usually have two information advantages: (i) they can access high-frequency, high-dimension, and high-coverage real-time information about small firms, including granular digital footprints and various networks, and (ii) they can process information efficiently, for example, converting "soft" information into "hard" information without losing much content (Liberti and Petersen (2019), Berg et al. (2020), Liu, Lu, and Xiong (2022)). These information advantages help them automate their credit allocation models so that their credit allocation decisions are less likely 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 (Cortés, 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, Huang, and Zhou (2023)). 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 geographic homogeneity in credit supply is usually not fulfilled in bank data where a 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 the local, city, provincial, or national government (Deng et al. (2015)).

rate, with an effective average (median) ratio of interest expense to loan size of 5% (2.7%).[12] Furthermore, the high interest rate can serve as a mechanism to screen borrowers with real liquidity needs and fast repayment abilities, helping address the adverse selection problem and reduce loan risk.[13] In other words, the combination of high product turnover rates and low overall capital requirements in the online retail sector enables vendors to repay their loans quickly, thereby sustaining a relatively high (annualized) interest rate while achieving entrepreneurial growth.

In the third part of the analysis, we seek to understand the mechanisms through 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 the 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 or aggregate welfare contribution of Ant Group credit. Nevertheless, the improvement in customer experience is likely to represent a genuine welfare benefit.

The remainder of the paper proceeds as follows. Section I reviews relevant literature and highlights the contribution of the study. Section II provides background information about FinTech credit in China. Section III describes the data, sample, and variables. Section IV to VIII present the methodology and empirical findings. Finally, Section IX concludes.

I. 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 cutoff in loan approval for small and median enterprises (SMEs) and applies the RDD method to document the effect of loan rejections on firms' cash holdings. 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 the presence of credit constraints for many SMEs. Other

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

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

recent work emphasizes heterogeneous treatment effects contingent on entrepreneurial skills (Banerjee et al. (2018)). Unfortunately, many randomized experiments on the impact of microcredit might face statistical power problems due to a small sample size (Banerjee, Karlan, and Zinman (2015)), which makes it difficult to pinpoint the precise magnitude of economic effects. The large sample size in our study of online vendors, the objective measurement of monthly online sales growth, and customer-contributed, granular customer ratings help us to obtain powerful 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 a few exceptions, previous research is largely mute on the distinct dimensions of FinTech's competitive advantage and its heterogenous benefits across firm types.[14] The scope of the Chinese online vendor data allows 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.[15] 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 also 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

[14] 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 nonprofit lender in Texas. However, particular borrower profiles can self-select into the applicant pool, and thus, 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 Taobao vendors independent of whether they seek credit. This allows us to benchmark the incremental performance of firms with access to FinTech credit against firms without it.

[15] Tang (2019) takes the implementation of the FAS 166/167 regulation as an exogenous negative shock to bank credit supply and finds that bank credit is replaced by peer-to-peer (P2P) lending. Balyuk (2019) shows that a firm's P2P lending improves its access to complementary bank credit. Roure, Pelizzon and Thakor (2022) 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 (2022) show that credit substitution between bank and FinTech credit based on banks' stress-test exposure is 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.

from payment flows facilitates credit evaluation and provision with benefits concentrated among financially underserved customers.[16]

More broadly, our findings provide implications for and supplement the literature on the real effect of FinTech adoption. For instance, Agarwal et al. (2019) and Agarwal et al. (2022) suggest that the adoption of mobile payment technology exerts a major impact on customer acquisition and business creation of small firms, and boosts consumers' credit card spending, which is in line with our findings that small FinTech business credit enables firms to improve customer satisfaction, which promotes entrepreneurship and firm growth. Furthermore, this paper adds to our understanding in particular about the role of FinTech credit, as a subset of broader FinTech innovations, in empowering small businesses. Frost et al. (2019) analyze 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 information advantages of FinTech credit and its effect on product offerings. Using proprietary data in China, Liu, Lu, and Xiong (2022) show that FinTech lenders have unique advantages in serving underbanked borrowers, particularly for their short-term liquidity needs inside the big-tech lender's ecosystem. This result is consistent with our finding that vendors have a financing motive underlying their entry decision to operate on the online platform. They also show that FinTech loans exhibit advantageous selection in that default rates are lower for those vendors who use up their credit limits. These results suggest that high interest rates serve as a mechanism to screen borrowers capable of repaying their loans over short periods. This is consistent with our observation that most vendors draw on their credit line in a selective manner, often considering FinTech credit as a form of liquidity insurance that relaxes their precautionary saving motives and cash holdings to fund growth opportunities.

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 greater 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. These findings suggest that state-owned bank branches exacerbate local credit scarcity for entrepreneurs as they both refrain from local private-sector lending and absorb local bank deposits. We therefore also contribute to a growing literature on the geographic segmentation of China's credit market (Boyreau-Debray and Wei (2004, 2005), Dobson and Kashyap (2006), Brandt and Zhu (2007), Dollar and Wei (2007), Roach (2009), Firth et al. (2009)).[17] Our analysis also

[16] Agarwal, Qian, Seru, and Zhang (2020) infer the linkage between borrowers' identity as bureaucrats and the size of consumer credit line offered to them.

[17] Most recently, Huang, Pagano, and Panizza (2020) provide evidence on China's credit market segmentation based on the crowding out of private investment by local government debt. Hau and Ouyang (2018) 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

has a bearing on discussion about the role of credit constraints for China's growth.[18]

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 and shows that legal restrictions on the amount of trade credit that trucking can provide customers benefitted mostly small, credit-constrained firms, lowering their default risk. Chen et al. (2022) show that access to FinTech credit reduces firm volatility and the probability of firm exit. 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.

II. FinTech Credit in China

A. Alibaba and Ant Group

Founded in 1999, Alibaba is now the largest e-commerce and FinTech conglomerate in China. It owns three major online shopping platforms—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 to extract 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 select 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.[19] In 2015, Alipay was rebranded as Ant Financial Service Group. The firm continues to use transaction data from Alibaba's retail platform to

savings. Gao et al. (2019) provide an interesting discussion of Chinese bank deregulation aimed at reducing the segmentation of the local credit market.

[18] The role of informal lending channels and their efficiency in channeling funding to China's fast-growing private-firm sector have 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 screening and monitoring technologies that make the lack of access to traditional banking less of a 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 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.

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

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 that time, valuing the company at 313 billion USD; on the eve of the IPO, Chinese regulators suspended the process.

Appendix Table AI, column (1), documents the evolution of the annual trading volume on Taobao from 2012 to 2016.[20] Trading grew by roughly 28% 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 reduce 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 model in a retail market characterized by low consumer confidence in the reliability of online counterparties.

Appendix Table AI, columns (2) and (3) describe the evolution of Taobao firm loans in terms of the number of eligible firms and the number of vendors using these loans as of a single time point in 2012 to 2016. Column (4) shows the aggregate amount of eligible credit (credit lines), which grew 82% a year from 2012 to 2016. 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 amount of credit taken by Taobao firms 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.[21] 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.

B. Ant Group's Credit Approval Process

Ant Group is able to make its credit approval process 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 sourced mostly from online retail platforms. The credit score assigned by Ant Group is similar to the Fair Isaac Corporation (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 retail platforms. The credit scoring model summarizes the credit evaluation using a continuous score ranging from around 380 to around 680. For most of the months covered by

[20] We aggregate quarterly GMV from the second quarter of a year to the first quarter of the next year to obtain the annual GMV of the year.

[21] A research team at the Central University of Finance and Economics summarized data obtained from the China Banking Regulatory Commission for their China MSME report (Shi, 2016) and estimated the aggregate micro and small enterprise (MSE) loans outstanding of China's banking system to be 23.46 trillion RMB.

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 cutoff of 480 was motivated by a value-at-risk (VaR) model, where a maximal cumulative default probability was picked.

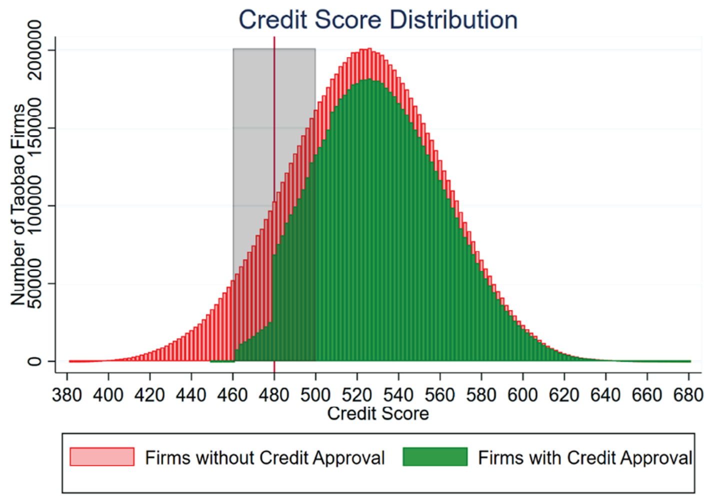
Ant Group evaluates credit eligibility on a monthly basis in an automated process. Vendors judged eligible for credit are automatically informed via the Taobao web interface about the value of their credit line. To use this credit, vendors fill out a single online contract form, which takes approximately three minutes. The credit is available immediately, and the credit terms are similar to those of a credit card. The maturity of the credit is usually 12 months, of which a minimum of 1/12 has to be repaid each month based on 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 that we obtained from Ant Group have a few features that condition our empirical design. First, in addition to the credit scoring model, Ant Group applies additional "hard" criteria that 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," such as 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 of the information implying an unconditional denial of credit. Thus, vendors subject to an unconditional credit exclusion (outside the credit scoring model) generate "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 month t on beginning-of-month information, we proxy the credit score at the beginning of month t using the 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 over the course of a month. However, occasionally credit decisions are taken within the month (e.g., if new firm information arrives), in which case the (outdated) credit scores in our record become an incorrect predictor of access to credit. This generates "cross-over" cases, whereby observations on vendors with a credit score below 480 at the end of month $t-1$ nevertheless record a credit approval during month t.

Figure 1, Panel A, shows the distribution of monthly credit scores for about 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

Panel (A) Credit Score Distribution



Panel (B) Probability of Credit Approval

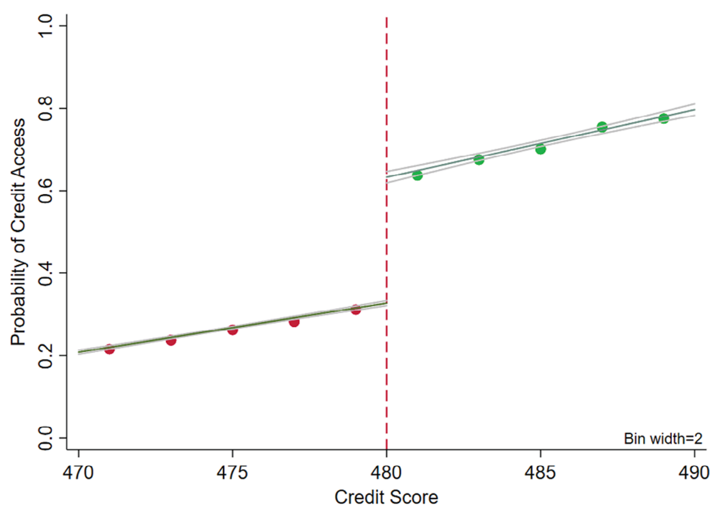


Figure 1. Credit score distribution and credit approval. Panel A plots the distribution of monthly credit scores for 2 million Taobao firms from November 2014 to June 2015. The green bars mark the Taobao firms with credit approval, and the (upper) red bars represent those without credit approval. The gray-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 gray lines. (Color figure can be viewed at wileyonlinelibrary.com)

approval. At the credit score of 480, Panel A shows a 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.[22]

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 RDD is that agents cannot precisely manipulate the forcing variable (i.e., the credit score) near the cutoff (Lee and Lemieux (2010)). The method used to calculate the credit score is unknown to the online vendors, nor do they observe their credit scores. This implies that Taobao vendors cannot easily game their credit eligibility. This claim 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 of Cattaneo, Jansson, and Ma (2018) 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 the 480-threshold rule after June 2015 suggests that it was an ad hoc feature of the credit allocation process.

The repeated (monthly) nature of credit approval decisions also 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 a firm's credit score and credit status extends beyond one month following a credit approval decision. On average, for firms with credit scores in the range of 480 to 500 in a given month, more than 85% will continue to score above 480 in the next month, and about 52% will score above 480 in the next three consecutive months. If we further condition on firms obtaining credit access in a given month when their scores fall between 480 and 500, 72% will continue to have credit access in the next month, and about 46% will maintain the credit access over the next three consecutive months. We plot the fraction of firms that stay above 480 (retain their credit access) over a consecutive number of months after a treatment event in Figure A1 of the Appendix. While credit approval decisions are generally repeated at a monthly frequency, most firms with credit access in a given month receive persistent treatment beyond one month. We therefore 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 $t+1$). We

[22] 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).

then measure incremental growth effects from the month prior to the approval of credit line (i.e., month $t-1$) to two months afterward (i.e., month $t+1$).[23]

III. Data

A. Samples

Our analysis uses mainly two samples: (i) 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 (ii) 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 vendors' establishment date 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 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 November 2014 to June 2015 period. 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 and changed its credit approval standard, after which the discontinuity at 480 ceases to exist.[24] We focus on 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 key variables to be nonmissing and firms to be located in a credit score range of [460, 500], we end up with a sample of 1,196,887 observations for 547, 491 firms. The data in this local range are selected for the FRDD for our analysis of the performance effect of FinTech credit.

[23] 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. We acknowledge the suggestions of the Associate Editor and one of the referees for inspiring this design.

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

B. City-Level Variables

For the city-level analysis, we begin by constructing a measure of the entry rate of Taobao firms. The first measure, *Ln*(*# New TB Firms*), denotes the natural logarithm of the total number of Taobao firms entering the platform from a given city over the period from 2005 to 2015. We then merge this cross-sectional data with various indicators on local macro conditions in 2005, the initial year of the entry measures. If 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 measure of city size, *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 for 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*) as a measure of the overall development of the banking system, the number of state-owned bank branches for every 10,000 citizens (*State Bank Intensity*) as a proxy for state presence in local bank credit supply, and *SOE Output Share* as a proxy for the credit demand of SOEs, which is constructed using the output data in the annual survey of industrial firms in China.[25] We also calculate the total aggregate 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 if it was before 2015). Summary statistics for the aggregated measures are presented in Table I, Panel A.

C. Firm Panel Variables

The variables used in our FRDD analysis can be categorized into three groups. The first group relates to the credit status of a firm. Our first such measure is *Credit Score*, the score generated by the credit-scoring model of Ant Group for a firm at the end of month $t-1$. Our second measure, an indicator variable based on the credit score, functions as our instrument: *IV (Credit Score≥480)* equals one if *Credit Score* is greater than or equal to 480 and zero otherwise. Our third measure, *Credit Approval*, is an indicator that equals one if a firm's observed approval status at the end of month t is valid at the end of $t+1$, and zero if the firm has no credit line at the end of either of the two months. Our fourth measure, *Credit Amount*, records the (time-weighted) amount of credit used by the vendor.

The second group of variables relates to firms' growth outcomes. The first, *Sales Growth*, measures the sales growth of a firm from the month prior to credit allocation to the month after, which is constructed as the log difference

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

Table I

Summary Statistics

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

	N	P10	P50	Mean	P90	*SD*
Panel A. City-Level Sample						
No. New TB Firms	267	103	542	3,887.44	8361	12,774.03
Credit Line (in ¥10,000)	273	62.15	838.35	9,932.22	18,210.44	38,790.36
Credit Use (in ¥10,000)	273	12.13	144.64	1,920.20	3,758.10	7,291.76
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	1,196,887	−2.48	−0.36	−0.44	1.49	2.02
Transaction Growth	1,196,887	−2.48	−0.47	−0.48	1.43	1.61
Product Rating	1,196,887	0.27	0.60	0.57	0.85	0.22
Service Rating	1,196,887	0.28	0.62	0.59	0.87	0.23
Consignment Rating	1,196,887	0.27	0.61	0.58	0.86	0.23
Credit Score	1,196,887	467.72	486.90	484.70	497.80	11.02
Credit Approval	1,196,887	0	1	0.62	1	0.48
Credit Line	1,196,887	0	10,000	15,907.16	18,000	57,647.37
Age Rank	1,196,848	0.04	0.12	0.16	0.34	0.13
High Dispersion	1,196,205	0	1	0.75	1	0.43
High Durability	1,196,887	0	0	0.12	1	0.33
Property Ownership	1,196,887	0	0	0.20	1	0.40
Ln (1 + Ad Expense)	1,196,887	0	0	2.94	8.46	3.71
Ln (1 + Product Types)	1,196,887	2.20	3.78	3.79	5.50	1.35
Customer Conversion Rate	1,196,887	1.08	5.18	7.44	16.07	7.56

from month $t - 1$ to $t + 1$. The second, *Transaction Growth*, is constructed similarly 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 comprises 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. A merchant can increase its product rating by improving the design, quality, and function of its products. As most of the merchants on Taobao are retailers, they can quickly procure better products from different suppliers, 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, and can improve the way they display product information, for instance, by 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 addressing customers' inquiries, whether they satisfy customers' particular needs, and whether they maintain a professional attitude. 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 [0, 1] range for ease of interpretation.[26] We thus define *Product Rating*, *Service Rating*, and *Consignment Rating* 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 employ 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, men's clothing, cosmetics, second-hand products, and women's shoes.

Table I, Panel B, presents summary statistics for 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 and obtain credit approval (*Credit Approval* $= 1$) in 62% of sample firm months. The average (median) credit line obtained by a local-range firm amounts to 15,907 RMB (10,000 RMB) or approximately 2,532 USD (1,592 USD) at the contemporaneous exchange rate. As a reference, the average (median) monthly sales is only 32,337 RMB (9,800 RMB) or approximately 5,148 USD (1,560 USD) for these particular Taobao firms.

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

IV. Credit Market Determinants Affecting E-Commerce Entrepreneurship

We first 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 given state-owned banks and SOEs often have similar 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 that local entrepreneurs face. Thus, state-owned banks function like a "black hole" for local savings and actively reduce local private firm credit. In contrast, the China-wide credit supply that Ant Group provide can help 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 prediction is consistent with Liu, Lu, and Xiong (2022), who argue that FinTech lenders have a unique advantage in serving the underbanked 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 the various platform entry measures defined in Section III.B. on proxies for local economic and credit conditions. Table II reports the results. In columns (1), the (log) number of new Taobao firms, *Ln(#New TB Firms)*, is the dependent variable. The main explanatory variables are *State Bank Intensity*, *SOE Output Share*, and their interaction, and the controls include city-level GDP per capita (*PCGDP*), *Population*, *Digital Development Index*, and *Loan/GDP*. All of the control variables are measured in 2005 or the earliest year available if later than 2005. Consistent with a financing motive of platform presence, the coefficient on the interaction term *State Bank Density* $\times$ *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 compensating for the more severe credit constraints of private entrepreneurs. For a city with *State Bank Density* one-standard-deviation greater (0.64) and an average *SOE Output Share* of 15%, we predict ceteris paribus a 17% larger entry rate for online vendors, which represents

Table II

Macro Factors Affecting China's E-Commerce Entrepreneurship and FinTech Credit

This table presents 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 in a city from 2005 to 2015, where only firms with city information available are counted. *Credit Line* measures the total amount of eligible credit lines approved by Ant Group 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 to 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. (2020). *Loan/GDP* is the ratio of commercial loans to GDP in a city in percentage points. *State Bank Density* is the ratio of the number of state bank branches to 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 the 10%, 5%, and 1% level, respectively.

Dependent Var.	*Ln(# New TB Firms)* (1)	*Ln(Credit Line)* (2)	*Ln(Credit Use)* (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)
N	267	273	273

an economically large effect.[27] In terms of other regional indicators, we find that the overall entry rate of online vendors is positively associated with credit infrastructure development (*Loan/GDP*), local economic development (*GDPPC*), 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 (i) the total amount of credit offered by Ant Group to vendors based in each city and (ii) the total outstanding balance of the credit used by these vendors

[27] This effect is deduced from a coefficient of 1.6282 in Table II, column (1), as $\exp(1.6282 \times 0.64 \times 0.15) - 1 = 0.17$.

on the same set of macroeconomic indicators.[28] Table II, columns (2) and (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 FinTech credit lines to a greater extent.

V. FinTech Credit and Entrepreneurial Growth

In this section, we explore whether FinTech credit has a causal effect on sales growth, transaction growth, and customer ratings of product and service quality. As discussed in Section III.B, *Sale Growth* and *Transaction Growth* are defined as log differences between their respective monthly values in periods $t+1$ and $t-1$, and *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 FRDD as described in Section II.B, 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 an increase in the probability of credit eligibility of approximately 30% at the credit score discontinuity of 480. Since that passing the threshold does not perfectly determine the allocation of credit to firms (i.e., the probability of credit access does not jump from zero to one when the credit score just 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 cutoff to recover the treatment effect (Imbens and Lemieux (2008), Lee and Lemieux (2010)). Econometrically, the treatment effect can be estimated using the two-stage least squares (2SLS) model under a standard instrumental variable framework (Hahn, Todd, and Klaauw (2001)).

A. Graphical Illustration of the Discontinuity Effect

We first demonstrate graphically the effect of the credit approval discontinuity on vendors' growth outcomes. We sort firms with *Credit Scores* in the range

[28] As mentioned above, we have location data for only about one-third of the vendors, and thus, the aggregate local online credit line or aggregate amount of online credit taken is not representative of the total credit lines extended to or used by vendors in each city. The aggregate data in 2015 are 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.

[470, 490] into 10 bins of similar credit scores, where each bin is two credit score points wide. Figure 2, Panels A and B, depict average *Sales Growth* and *Service Rating*, respectively, for firms in each credit score bin: red dots correspond to the bins below the discontinuity threshold of 480 and green dots to 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 that of firms in credit score bins just below the threshold. 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 bin 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 treatment probability.

B. Baseline Effects of Credit Approval

We next implement the FRDD through 2SLS regression analysis. In the first stage, we estimate the probability of credit access using equation (1):

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

where *Credit Approval* is an indicator variable equal to one if a firm has observable credit access at the end of month t to the end of month $t+1$, and zero otherwise, *IV* is an indicator variable equal to one if the credit score of a firm at the beginning of month t is greater than or equal to 480, and zero otherwise, and S is the standardized credit score calculated 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 order K as potential controls and denote by γ^k, $k = 1, 2, \ldots, K$, the corresponding coefficients. 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-group 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.

Any (F)RDD faces a trade-off between the precision and potential bias of estimation in the choices of regression bandwidth and polynomial order, respectively. On the one hand, a large bandwidth draws on more sample observations, but can require higher order polynomials if the underlying forcing variable (S) has a nonlinear effect on outcomes. On the other hand, for a small bandwidth around the cutoff, a simple linear approximation could be

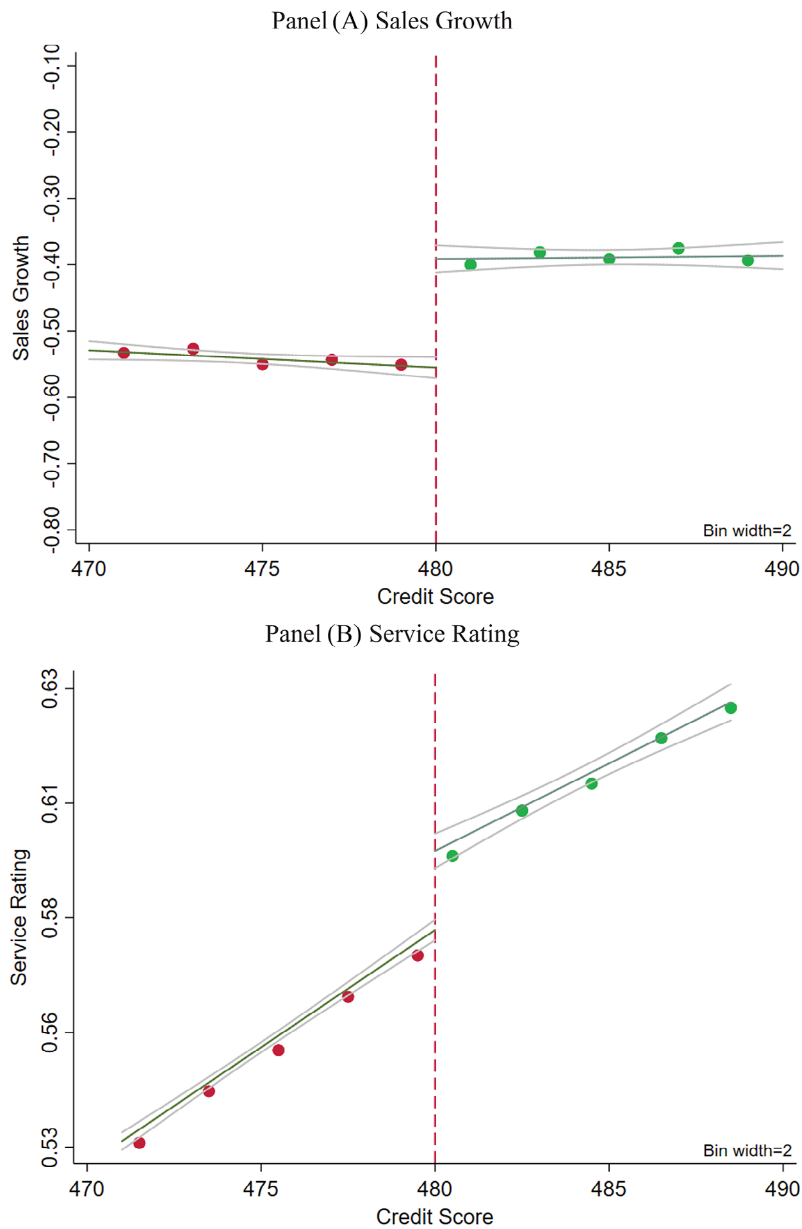


Figure 2. Discontinuity plot on outcome variables. This figure presents discontinuity plots of firm growth from month $t-1$ to $t+1$ and CSR ratings at month $t+1$ against credit scores in month t. The vertical axis is the value of *Sales Growth* and *Service Rating*. The horizontal axis shows credit 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 gray lines. (Color figure can be viewed at wileyonlinelibrary.com)

sufficient, but fewer sample observations are available for estimation. In our main specification, we use 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); in Section VIII, we assess the robustness of the results to smaller local ranges of credit scores and alternative regression specifications. We then predict the probability of credit approval using the estimates obtained in equation (1) and denote it by $\widehat{Credit\ Approval}_{i,t}$.[29]

In the second stage, we regress each dependent variable on the predicted probability of credit approval, $\widehat{Credit\ Approval}_{i,t}$,

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

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 on $\widehat{Credit\ Approval}_{i,t}$(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.

Table III summarizes the causal effects of access to FinTech credit on vendor performance. Panels A and B present the first- and second-stage results, respectively. In Panel A, the coefficient on 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 44%. Similarly, transaction volume grows by 31% over the two-month measurement period.[30] Column (3) reveals that FinTech credit increases the customer rating on product quality (*Product Rating*) by 0.054, which amounts to 24.5% of

[29] The FRDD analyses in the main tables are implemented using Ordinarily Least Square regressions in two separate stages. We also reproduce the results in the Internet Appendix using joint estimation of the two stages. The results are highly robust (i.e., identical coefficients with minor differences in the t-statistics). The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[30] Based on the coefficient of 0.3631 and 0.2691, respectively, we have $\exp(0.3631)-1 = 0.4378$ and $\exp(0.2691)-1 = 0.3088$.

Table III

FinTech Credit Access and Firm Performance

This table shows the FRRD 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*, on an indicator variable, *IV (Credit Score≥480)*, which equals one when the credit score is equal to or greater than 480, and zero otherwise. In the second stage (Panel B), we regress the dependent variable on 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. 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 the 10%, 5%, and 1% level, 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
N	1,196,887

Panel B. Second Stage

Dependent Var.	*Sales Growth* (1)	*Transaction Growth* (2)	*Product Rating* (3)	*Service Rating* (4)	*Consignment Rating* (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
N	1,196,887	1,196,887	1,196,887	1,196,887	1,196,887
Kleibergen-Paap *F*-stat.			756.2		

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 based mainly on the access to credit lines rather than on 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.[31]

VI. 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.

A. 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, for example, converting "soft" information into hard information without losing crucial content (Liberti and Petersen (2019), Berg et al. (2020), Liu, Lu, and Xiong (2022)).[32] 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 given little verifiable performance information.

We use two measures to gauge the information advantage of FinTech lenders. First, 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 (1995) suggest that firm age can proxy for latent credit quality. Hadlock and Pierce (2010) further show that firm age represents a pertinent firm characteristic to deduce credit constraints reported in corporate filings. For our empirical analysis, we rank firms by their age and define *Age Rank* on a unit interval.[33]

Because firm age may covary with other factors that could condition the positive performance effect of credit access, we also follow Levine, Lin, and

[31] Using an approval cutoff on loan applications by SMEs, Berg (2018) find that a loan rejection would lead low-liquidity firms, out of precautionary saving motives, to increase cash holdings by more than the requested loan amount. They further show that SMEs experience smaller asset growth and lower investment after loan rejection.

[32] 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 (2019)).

[33] 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.

Wei (2017) and use the dispersion in growth prospects across firms in a given 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, wider dispersion of firm growth within an industry indicates a greater difficulty in evaluating credit risk as the other firms in the industry do not serve as good benchmarks. By contrast, a FinTech lender's granular information at higher frequency from online digital sales and payment platforms can lower this opacity. We define the variable *High Dispersion* as an indicator that equals one 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 increase for younger vendors (i.e., vendors with lower age rank) or vendors operating in industries with high-growth dispersion. Accordingly, we augment the 2SLS system by including the interaction with a proxy for the information advantage of the FinTech lender (*InfoAdv* = *Age Rank* or *High Dispersion*) in each stage. Formally,

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

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

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

Equations (3a) and (3b) provide the first-stage estimates for the credit approval probability and its gradient with respect to *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 that captures the heterogeneous performance effect of access to FinTech credit due to the information advantage of the FinTech lender.

Table IV, 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

Table IV

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 dispersion of industry growth (Panel B) as proxies for 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 one if a firm is operating in an industry, in which 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*. We use the local linear regression model for 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 the 10%, 5%, and 1% level, 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
N	1,196,848	1,196,848	1,196,848	1,196,848	1,196,848
Kleibergen-Paap F-stat.			418.4		

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*	0.1910*	0.1297*	0.0456***	0.0381***	0.0353***
(Instrumented)	(1.80)	(1.83)	(5.64)	(4.05)	(3.84)
Credit Approval	0.2160***	0.1685***	0.0192***	0.0253***	0.0281***
(Instrumented)	(2.44)	(2.83)	(5.11)	(5.63)	(6.32)
High Dispersion	−0.2439***	−0.2139***	−0.0319***	−0.0248***	−0.0234***
	(−2.54)	(−3.11)	(−4.88)	(−3.35)	(−3.21)

(*Continued*)

Table IV—*Continued*

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)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	1,196,205	1,196,205	1,196,205	1,196,205	1,196,205
Kleibergen-Paap *F*-stat.			355.7		

500. Again, we also control for firm-type fixed effects and time fixed effects in the regressions and cluster the standard errors at the firm-type level.

As we show in Panel A of Table IV, for all five vendor performance measures, the *Credit Approval* × *Age Rank* interaction enters into all of the regressions with a significant negative sign. This suggests that sales and transaction growth as well as customer ratings improve more after credit approval for younger firms. Comparing two firms with a one-standard-deviation difference in *Age Rank* within the FRDD sample (i.e., 0.13), we find that the younger firm experiences 13 (8) percentage points larger effect of access to credit on sales (transaction) growth over the two-month window following the credit approval.[34] Similarly, we find stronger increases in product, service, and consignment ratings for the younger firm, equaling 13.8%, 10.2%, and 9.8% of a standard deviation, respectively. Thus, FinTech credit from Ant Group is most beneficial for the performance of younger e-commerce firms near the credit approval threshold. This result is consistent with a pronounced information advantage of FinTech lenders over traditional banks in the high-credit-risk segment of young firms.

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

[34] The incremental effect over the two-month window for *Sales Growth* is given as $\exp(-0.9153 \times (-0.13)) - 1 = 12.64\%$ and that for *Transaction Growth* follows as $\exp(-0.5972 \times (-0.13)) - 1 = 8.07\%$.

B. Information as Collateral Substitute

A corollary to the information advantage enjoyed by FinTech lenders is their reduced reliance on collateral (Gambacorta et al. (2023)). 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 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 *High Durability* as an indicator equal to one for durable product industries and zero otherwise. Industries in the high-durability category include Computer Hardware, Furniture, Basic Building Materials, Automobiles, Motorcycles, Gold and Gems, Musical Instruments, Large Home/Factory Appliances, etc., whereas industries in the low-durability category include Apparels, Shoes, Cosmetics, Food and Beverages, Flower, Magazines, Cooking Appliances, Tableware, Cleaning Supplies, etc. Second, we use proxies for the property ownership of the vendor constructed by Ant Group. 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 *Property Ownership* as an indicator that takes the value of one for firms recorded by Ant Group as having a very high probability (greater than 90%) of owning real estate property. Since housing prices in China generally increase during our sample period, we assume that vendors owning real estate possess valuable collateral.

In Table V, Panels A and B, we repeat the 2SLS regressions using *High Durability* and *Property Ownership*, respectively, as the relevant interaction terms with *Credit Approval*. As before, firm-type and time fixed effects are included. The dummy *High Durability* without interaction is absorbed by the firm-type fixed effects. We find that access to FinTech credit boosts both firm growth and customer ratings to a greater extent if firms operate in industries with less durable products (Panel A) and if vendors are less likely to possess real estate (Panel B). This result 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 lenders.

Table V

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 estimated real estate property ownership (Panel B) as proxies for collateral availability. *High Durability* is an indicator variable that equals one if a firm operates in a durable goods industry. *Probability Ownership* is an indicator variable that equals one if the estimated probability of the firm owner owning real estate 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*. We use the local linear regression model for 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 the 10%, 5%, and 1% level, 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***	0.2767***	0.0581***	0.0574***	0.0583***
(Instrumented)	(18.37)	(19.64)	(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
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)

(*Continued*)

Table V—*Continued*

Panel B. Heterogeneous Effect by Property Ownership					
Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*
	(1)	(2)	(3)	(4)	(5)
Polynomials in Credit Score	Yes	Yes	Yes	Yes	Yes
Firm Type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	1,196,887	1,196,887	1,196,887	1,196,887	1,196,887
Kleibergen-Paap *F*-stat.			380.5		

C. Other Channels

A second competitive advantage of FinTech credit relates to its low loan distribution costs. FinTech lenders typically provide transactional loans (rather than relationship loans) for a wide range of small borrowers at low cost.[35] Based on the internal estimates of Ant Group in 2017, 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 microlending cost of traditional lending institutions is about 2,000 RMB per transaction. Fewer than 400 employees oversee 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.[36] 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. Accordingly, we use the inverse of predicted credit line size as a proxy for firms' (implicit) transaction costs if they had borrowed from a bank and label 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 (if data available) and scale it by firm size. We conjecture that firms with a higher relative *Distribution Cost* benefit more from access to FinTech credit. As Table AII of the Appendix shows, we do find that the growth effect of FinTech credit is more pronounced for firms with higher distribution costs.

The third distinguishing feature of FinTech credit could be better contract enforcement. Unlike traditional banks, which rely heavily on the external legal environment for contract enforcement (La Porta et al. (1997, 1998),

[35] 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 transaction costs can be particularly important to promote small business lending at a large scale (Petersen and Rajan (1994), Liberti and Petersen (2019)).

[36] 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.

Qian and Strahan (2007)), FinTech lenders can conduct real-time postlending monitoring and use alternative approaches to enforce contracts and recover losses other than the court systems.[37] FinTech lenders therefore 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 zero to one, with a higher value indicating greater confidence in the local legal system and a stronger legal enforcement environment. We repeat the previous regressions with *Legal Quality Index* as the new interaction term and present the results in Table AIII of the Appendix. Consistent with the hypothesis of reduced legal enforcement dependence of FinTech lenders, we find that vendors operating in cities with a lower legal quality index experience greater improvement in sales and transaction growth after their FinTech credit approval, as well as larger upticks in their customer ratings. While we acknowledge that the index could correlate with a variety of other factors influencing the local productivity of additional firm credit, this evidence is nonetheless intriguing and potentially relevant for emerging markets often criticized for their poor legal environment.

VII. Mechanisms for Vendor Performance Enhancement

In this section, we seek to understand the mechanisms through 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.

A. Liquidity Insurance Benefits

We first highlight that the effect of FinTech credit on firm performance does not have to operate via actual credit use. As mentioned above, credit lines can serve as liquidity insurance with access to FinTech credit relaxing firms' precautionary saving motives and promoting investment in growth opportunities.

[37] For example, the early warning system of Ant Group, as part of the integrated credit platform, generates postlending scores based on order conversion rate and other metrics to assess whether the borrower is likely to have a credit deterioration in the coming months. Depending on the degree of deterioration, alarms and actions will be triggered at different levels according to predefined algorithms (e.g., from watch list indexing and 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 cases into liquidity and strategic default and trigger different actions to tackle them.

In this case, vendors draw on the credit line only 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 accounts only for about 17% of total approved credit lines. Furthermore, excluding those firms with actual drawdowns of credit and retaining only those with the credit option continues to yield performance-improving effects. In other words, mere liquidity procurement through FinTech credit lines accounts for some firm growth and development effects.

B. 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 operate 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 Ant Group have very fast repayment rates. The 25^{th} percentile and median repayment time is only 0.04 and 0.28 of the scheduled loan maturity, which equals 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, at an average (median) of six (three) times over their 17-month sample period. Furthermore, the high interest rate may serve as a mechanism to screen borrowers with real liquidity needs and fast repayment ability, helping address adverse selection and reduce loan risk.

C. Operational Changes

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

A second managerial response to credit access relates to the opportunity to expand their product offering and quality. We construct two measures of such response. The first, *Product Variety*, is defined as the natural logarithm

Table VI

Mechanisms of Vendor Performance Enhancement

This table shows the FRDD estimates of credit access on other firm activities and performance. 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*. *Adverting* is the natural logarithm of one plus the vendor's monthly expenditures on advertising. *Product Variety* is the natural logarithm of one plus the number of product types for sale. *Customer Conversion Rate* is the ratio of the number of customers that completed transactions to the total number of customers of a firm in a month (scaled by 100). We use the local linear regression model for 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 the 10%, 5%, and 1% level, respectively.

Dependent Var.	*Advertising* [Ln (1 + Ad Expense)] (1)	*Product Variety* [Ln (1 + Product Types] (2)	*Customer Conversion Rate* (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
N	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.		756.2	

of one plus the number of product types offered for sale by the vendor. Greater breadth of product choice can augment the customer experience (Matsa (2011)) and thus represent an important dimension of the online shop's quality. The second measure, *Customer Conversion Rate*, is defined as the ratio of the number of shop visitors that complete transactions to the total number of online shop visitors (in hundreds) per month. To improve the latter, firms need to improve not only product quality, but also service quality. It is common for a prospective customer to chat with a salesperson online to learn more about the product, promotions, and value-added services, and to address other questions. 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 more value-added services) can positively influence a potential customer's final purchase decision. Moreover, firms can improve product display and make additional sales information more easily accessible on the online interface. We expect such improvements to be implemented fairly quickly and to be reflected in a higher *Customer Conversion Rate*.

We 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 VI. Column (1) documents a substantial 31% increase in advertising expenditure upon access to FinTech credit. Column (2) shows that product variety increases by 13%.[38] And column (3) indicates that close to one out of every 100 visitors converts into an additional customer. Taken together, these results provide consistent evidence on the operational changes online vendors make when they have access to FinTech credit. All of these changes can rationalize the evidence of enhanced firm performance documented in Table III. The evidence also speaks to a possible welfare-enhancing effect of FinTech credit. While it is unclear whether more advertising increases aggregate customer demand or simply attracts marginal customers from other vendors, we consider higher service quality and customer satisfaction as welfare gains.

D. Firm Survival

Finally, the large growth effect could also be due in part to the difference between above-threshold and below-threshold firms in the share of firms that go out of business. For firms with a liquidity problem, if they score just above 480 in a single period, getting a loan could allow them survive a few more months at least, whereas if they score just below 480 and fail to obtain a loan, they will go out of business almost immediately and observe very negative sales growth. Consistent with this expectation, we find that firms that receive access to credit do indeed have a higher survival rate versus those without.

VIII. 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 firms to have access to credit from month t to the end of month $t+2$, and 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 VII, Panel A, reports the second-stage results for the same local linear specification as the baseline regression in Table III. The coefficients capturing the effect of (predicted) credit approval on vendor performance, that is, 0.85 (*Sales Growth*) and 0.55 (*Transaction Growth*), are now larger for the extended three-month measurement period and remain highly statistically significant.[39] These results suggest that continuous access to credit can have a larger growth

[38] Based on the coefficients in columns (1) and (2), we have $\exp(0.2679) - 1 = 0.3072$ and $\exp(0.1233) - 1 = 0.1312$, respectively.

[39] The coefficient is 0.48 (0.29) for sales (transactions) if we do not condition a treated (control) firm to retain its credit approval (no credit) status over the three-month period (i.e., firms with switching credit status are included). This suggests that the switching cases can introduce attenuation bias that leads to potential underestimation of the treatment effect.

Table VII

Robustness Checks

This table presents robustness results for the baseline specification in Table III 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* are measured 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 different linear functional forms for 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. Panels E and F use 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 the 10%, 5%, and 1% level, respectively.

Panel A. Performance with Three Months' Consecutive Credit Access

Dependent Var.	*Sales Growth* (1)	*Transaction Growth* (2)	*Product Rating* (3)	*Service Rating* (4)	*Consignment Rating* (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
N	931,599	931,599	881,387	881,387	881,387
Kleibergen-Paap F-stat.	840			896.4	

(*Continued*)

Table VII—*Continued*

Panel B. Change of Service Ratings

Dependent Var.	Δ*Product Rating* (1)	Δ*Service Rating* (2)	Δ*Consignment Rating* (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
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* (1)	*Transaction Growth* (2)	*Product Rating* (3)	*Service Rating* (4)	*Consignment Rating* (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
N	1,196,887	1,196,887	1,196,887	1,196,887	1,196,887
Kleibergen-Paap *F*-stat.			1,089.0		

(*Continued*)

Table VII—*Continued*

Panel D. Second-Order Polynomial for the Credit Score Variable					
Dependent Var.	*Sales Growth* (1)	*Transaction Growth* (2)	*Product Rating* (3)	*Service Rating* (4)	*Consignment Rating* (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
N	1,196,887	1,196,887	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.			1,105.0		

Panel E. Alternative Bandwidth [465, 495]					
Dependent Var.	Sales Growth (1)	Transaction Growth (2)	Product Rating (3)	Service Rating (4)	Consignment Rating (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
N	862,893	862,893	862,893	862,893	862,893
Kleibergen-Paap F-stat			960.7		

(*Continued*)

Table VII—*Continued*

Panel F. Alternative Bandwidth [470, 490]

Dependent Var.	Sales Growth (1)	Transaction Growth (2)	Product Rating (3)	Service Rating (4)	Consignment Rating (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
N	553,711	553,711	553,711	553,711	553,711
Kleibergen-Paap F-stat.			849.0		

effect on firms. The results could also introduce confounding selection effects, however, since repeated approval depends on good sales performance.

Additional robustness tests (reported in Table VII, Panel B) use the change rather than the level of customer ratings as the dependent variable. We calculate the change in each service quality measure from the month before the credit treatment to the month after, and we denote the differenced variables as $\triangle$*Product Rating*, $\triangle$*Service Rating*, and $\triangle$*Consignment Rating*, respectively. The estimated effect for the *Credit Approval* variable remains statistically significant and economically comparable to the baseline findings. 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 III. In Table VII, Panel 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 nonlinear background effects. Panels E and F reduce the window size from [460, 500] to [465, 495] and [470, 490], respectively. All of 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, Kim, and Tian (2017), we run a simulation 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 one 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*. We then reestimate the first-stage regressions using a local linear model with firm-type and time fixed effects.[40] All other variables are defined 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 for the 1,000 placebo estimates, we find that the average jump in the probability of credit approval is -0.0005 and 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%). Taken together, these results strengthen the validity of our setting and the 2SLS approach.[41]

Finally, we explore whether 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,

[40] 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.

[41] We do not continue with the second-stage regressions based on the predicted access to credit using the falsified cutoffs because they suffer from a weak instrument problem and would lead to very imprecise estimates (Jiang, 2017).

and *Product Rating*, *Service Rating*, *Consignment Rating*, and three additional operational indicators—*Advertisement*, *Product Variety*, and *Customer Conversion Rate*—are measured in the sixth month after the credit approval event. As shown in Table VIII, the performance improvements of credit access remain economically large over the six-month horizon.

IX. Conclusion

In this paper, we examine how access to FinTech credit affects the performance of small e-commerce firms in China. The evidence can inform the policy debate about the growth contribution and welfare benefits of new credit technologies based on new source of extensive customer data (He, Huang, and Zhou (2023)). 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 44% and 31%, 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 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 FinTech lenders.

We further 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 advertising expenditure, an increase in product variety, and a higher visitor-to-purchasing customer conversion rate. Most of these operational changes result in a better customer experience and hence in 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 equalize the growth prospects of small

Table VIII

FinTech Credit Access and Long-term Firm Performance

This table shows the long-term effects of FinTech credit access on firm performance six months following credit approval. The dependent variable is *Sales Growth* and *Transaction Growth*, measured from the month before to six months after a credit allocation event, in columns (1) and (2), respectively, and is *Product Rating*, *Service Rating*, *Consignment Rating*, *Advertising*, *Product Variety*, and *Customer Conversion Rate*, defined in the sixth month following a credit allocation event, in columns (3) to (5), respectively. We use the local linear regression model of 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 the 10%, 5%, and 1% level, respectively.

Dependent Var.	*Sales Growth*	*Transaction Growth*	*Product Rating*	*Service Rating*	*Consignment Rating*	*Advertising* [Ln (1 + Ad Expense)]	*Product Variety* [Ln (1 + Product Types]	*Customer Conversion Rate*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit Approval	0.4868***	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
N	1,196,887	1,196,887	941,232	941,232	941,232	1,196,887	1,196,887	1,196,887
Kleibergen-Paap F-stat.	756.2			600.3			756.2	

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 plausible that the real costs of China's credit market frictions are quantitatively larger in more capital-intensive sectors.

Our findings also 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, with fast development of high-speed internet.[42,43] These developments hold the promise for similar entrepreneurial growth in their respective retail sectors through better credit technologies.

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Appendix

Table AI
Evolution of Firm Credit

Column (1) reports the evolution of annual trading volume on the e-commerce trading platform, Taobao. Columns (2) and (3) report the number of firms eligible for Taobao credit and the number of vendors using at least some of their online credit, respectively. Column (4) reports the total amount of eligible credit lines, and column (5) reports the outstanding balance of credit used. Column (1) is based on cumulative trading volume over four consecutive quarters and columns (2) to (5) are based on snapshots in the corresponding year.

	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)	
	(1)	(2)	(3)	(4)	(5)
2012	824	95,645	11,842	47.2	5.1
2013	1,173	310,946	33,968	116.7	13.8
2014	1597	751,920	152,685	263.0	44.2
2015	1,877	1,103,183	231,512	429.2	75.1
2016	2,202	883,294	310,486	516.9	86.7

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

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

Table AII

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 firm's 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*. We use the local linear regression model for 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 the 10%, 5%, and 1% level, respectively.

Panel A. Summary Statistics

	N	P10	P50	Mean	P90	*SD*
Distribution Cost	1,196,846	0.08	0.60	0.75	1.70	0.61

Panel B. Regressions

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
N	1,196,846	1,196,846	1,196,846	1,196,846	1,196,846
Kleibergen-Paap F-stat.			461.8		

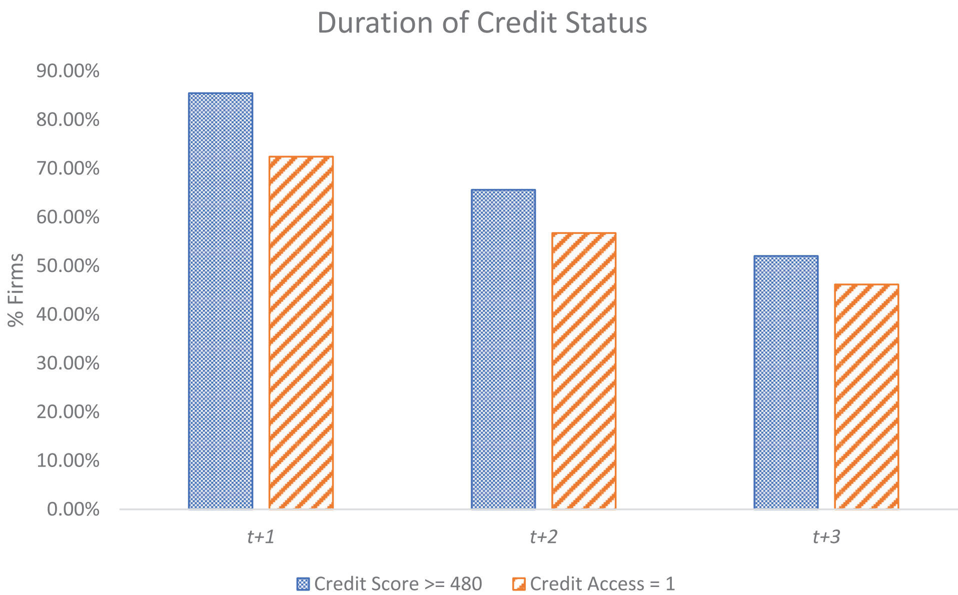

Figure A1. Duration of credit status. This figure plots the average percentage of firms with (i) credit score in the range of [480, 500] in month t that continue to score above 480 in months $t+1$, $t+2$, and $t+3$, respectively, and (ii) credit score in the range of [480, 500] and credit access in month t that maintain the credit access at the end of month $t+1$, $t+2$, and $t+3$, respectively. (Color figure can be viewed at wileyonlinelibrary.com)

Table AIII

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 a proxy for 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 zero to one. 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*. 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 the 10%, 5%, and 1% level, respectively.

Panel A. Summary Statistics

	N	P10	P50	Mean	P90	*SD*
Legal Quality Index	282,010	0.69	0.79	0.79	0.98	0.12

Panel B. Regressions

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
N	282,010	282,010	282,010	282,010	282,010
Kleibergen-Paap F-stat.	312.3				

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.