Finance and Firm Volatility

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May 2019

Abstract

The online trading platform Alibaba provides financial technology (FinTech) credit for millions of micro, small, and medium enterprises (MSMEs). Using a novel dataset of weekly sales and an internal credit score threshold that governs the allocation of credit, we apply a fuzzy Regression Discontinuity Design (RDD) to explore the causal effect of credit access on firm volatility. We find that credit access significantly reduces firm sales volatility and that the effect is strongly countercyclical. We also find that the negative effect on firm volatility is concentrated in firms that are young, that are in regions with lower economic growth and poorer legal environment and contract enforcement, and that are in more competitive industries. We further look at firm exit probability and find that firms with access to FinTech credit are less likely to go bankrupt or exit the business in the future. Overall, our findings contribute to a better understanding of the role of FinTech credit in MSMEs.

Keywords: FinTech Credit; E-Commerce Microcredit; Firm Volatility; Regression Discontinuity Design; Microfinance; Credit Scoring

JEL classification: G21; G32; G33

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1. Introduction

Although a large volume of research shows that access to external financing spurs firm growth (e.g., Beck, Demirgüç-Kunt, & Maksimovic, 2005; Black & Strahan, 2002; Demirgüç-Kunt & Maksimovic, 1998; Rajan & Zingales, 1998), less is known about the impact of credit access on firm volatility.[1] This is surprising given that firm volatility could influence corporate financing and investment (Campbell et al., 2001; Campello et al., 2011) and thus impact economic growth at the national or international level (e.g., Aghion et al., 2010; Ramey & Ramey, 1995; Schwert, 1989a, 1989b, 1990).

Theories offer ambiguous evidence for the direction of credit access's effect on firm volatility (e.g., Aghion et al., 2010; Bacchetta & Caminal, 2000; Holmstrom & Tirole, 1997). On the one hand, theoretical models imply that access to credit reduces volatility because it helps firms to obtain the working capital necessary to finance their operations and investment opportunities during short-run adverse shocks, including economic downturns or natural hazards, that would otherwise trigger inefficient and risk-augmenting fluctuations in output and employment (e.g., Caballero & Krishnamurty, 2001; Larrain, 2006; Morgan, Rime, & Strahan, 2004; Wang, Wen, & Xu, 2018). Related to this, Morgan, Rime and Strahan (2004) find that the increased mobility of bank capital due to interstate banking deregulation dampens state-level fluctuations in economic growth. Furthermore, access to finance helps firms alleviate the predation risks, the risks of losing investment opportunities and market share to rivals caused by an inability to fully finance and invest in these opportunities (Bolton and Scharfstein, 1990; Froot, Scharfstein, & Stein, 1993). As a consequence, access to finance helps reduce the fluctuation of firms' real outputs caused by the predatory behaviors of their rivals. In essence, if the credit provision helps make the firms more resilient to economic cycles, predation risks and natural hazards, it helps dampen the output volatility of firms.

On the other hand, theory also suggests that capital access could actually increase firm

[1] Using industry-level data, Larrain (2006) finds that countries with higher private credit to GDP ratios have lower volatility in industrial output. In addition, Raddatz (2006) uses a similar cross-country, cross-industry approach, finding that the volatility-reducing effect of banking development results partly from the role of the financial system in providing liquidity.

volatility by increasing the typical firm's leverage or leading it to riskier investments, thereby making it more vulnerable to adverse shocks (e.g., Acemoglu, 2005; Bartram, Brown, & Stulz, 2012; Carvalho, 2018; Levchenko et al., 2009). In a recent study, Carvalho (2018) find that fewer financing constraints lead to higher equity volatility, especially among R&D-intensive firms. Additionally, Beck et al. (2006) find no robust relationship between financial intermediation and output volatility, while Acemoglu et al. (2003) find that financial concerns do not affect volatility after controlling for institutions.

We study the effect of FinTech credit on firm volatility in micro, small, and medium-sized enterprises (MSMEs). Most of the extant literature of firm volatility focuses on much larger public firms and looks at stock volatility, yet less has been done on MSMEs (e.g., Bartram et al., 2012; Carvalho, 2018). MSMEs contribute significantly to world economic development[2] but are also faced with a huge finance gap. As the International Finance Corporation (IFC) estimated in 2017, about 40% of MSMEs are financially constrained, with the total finance gap amounting to $5.2 trillion.[3] Therefore, to study the effect of credit access on these firms is of significant value (Berger et al., 1998, 2015; Black & Strahan, 2002; Petersen & Rajan, 2002). Moreover, by exploiting weekly high-frequency real-time transaction data of the MSMEs in our sample, we can look at the real effects of FinTech credit on real outcome measures of volatility.[4] The availability of such high-frequency data to measure the volatility of millions of MSMEs makes itself a contribution to the firm volatility and risk literature.

Using China as a laboratory to study the effect of FinTech credit lending is particularly interesting given that China's informal financing channels have been identified as the most important part of the financial system in supporting the growth of the overall economy, now the second largest in the world (e.g., Allen, Qian, & Gu, 2017; Allen, Qian, & Qian, 2005; Song & Xiong,

[2] According to the United Nations' 2017 estimation, MSMEs account for more than 95% of the world's companies and create about 60% of jobs in private sectors. In China, MSMEs contribute 60% of GDP, 70% of the innovations and 80% of the employment.

[3] See "MSME Finance Gap: Assessment of the Shortfalls and Opportunities in Financing Micro, Small and Medium Enterprises in Emerging Markets", *International Finance Corporation*, 2017.

[4] High-frequency real-time data is crucial for our research to more accurately measure volatility

2018). China is also the largest e-commerce market in the world by value of sales, with an estimated value of US$ 1.1 trillion in 2018[5]. Built on the significant development in the internet and mobile network coverage, FinTech has played a fundamentally important role in facilitating credit allocation to MSMEs by compiling and analyzing their e-commerce transactional data and other digital footprints (Barberis & Arner, 2016). In this paper, we use credit data from Ant Financial, the largest FinTech company in the world serving MSMEs,[6] and Taobao, the largest online retail platform in the world to explore how finance accessibility affects the output volatility of MSMEs.

Compared to traditional banking, FinTech lending has apparent advantages in information acquisition, loan processing, and decision making, by replacing soft information completely with hard information and substituting numerical data and automated decisions for decisions made by human individuals (e.g., Buchak et al., 2017; Liberti & Petersen, 2019). In our setting, Ant Financial has access to a vast amount of data on their borrowers, including real time high-frequency e-commerce transaction data and online financial and behavioral data. The use of technology and big data makes information collection and loan decisions much less costly and much more effective. Along this line, one might expect the role of FinTech to be more significant for firms that are more opaque. Moreover, FinTech lenders are more efficient and effective in loan monitoring and debt enforcement (e.g., Buchak et al., 2017; Fuster et al., 2018). FinTech lenders can monitor the borrowers using real-time data based on multi-dimensional metrics, and the enforcement strategies are based on highly algorithmized models.[7] These unique characteristics enable us to conduct further channel tests by exploring firm-level heterogeneity in information asymmetry and region-level difference in contract enforcement to better understand the role of FinTech credit in overcoming information and debt enforcement problems.

Our paper distinguishes from the previous literature in the following aspects. First, we focus on the real effect of FinTech credit on MSMEs, which is largely understudied in the literature.

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[5] See https://www.thedrum.com/news/2018/08/20/china-e-commerce-market-forecast-reach-18tn-2022.
[6] See "The Fintech100 – Announcing the World's Leading FinTech Innovators for 2017", *KPMG*, November 15, 2017.
[7] We will discuss more about these institutional details in Section 2.1.

Second, we look at the effect of small business lending on real outcome volatility. The real outcome volatility is particularly important as it pertains to firms' operations (e.g., Comin & Mulani, 2006; John, Litov, & Yeung, 2008; Larrain, 2006; Morgan, Rime, & Strahan, 2004; Raddtz, 2006), and is free from misvaluation by the equity market.[8] Specifically, we look at sales growth volatility from high-frequency transaction data. Third, the majority of MSMEs in our sample are very small in scale, have opaque income sources, very limited collateral, no financial statements, or may not even be formally registered. They do not fit into the traditional lending model of banks under stringent capital regulation and are also unable to raise capital from the public market. Moreover, the interest rates from other small-loan platforms are much higher because they do not have the e-commerce transactional data of these firms. In this regard, the FinTech credit from Ant Financial used in our sample is arguably the single source of credit for these MSMEs. Therefore, the sample in our study provides a clean setting to evaluate the effect of credit access on firm volatility without the potential confounding concerns from equity market, bond market, bank loan market, or other financial markets. Fourth, we further examine countercyclical patterns, predation risk, information asymmetry, and partial substitute for institutional quality as underlying channels, through which FinTech credit affects firm volatility. Finally, we also look at the effect on firm's exit probability.

To successfully identify the causal effect of credit access on firm volatility is empirically challenging because credit access is likely endogenous. The first source of endogeneity is reverse causality: firms with more unstable output in general will be less likely to obtain credit from lenders and have lower leverage (e.g., Frank & Goyal, 2009). Recently D'Acunto, Liu, Pflueger, & Weber (2018) study price flexibility and find that firm volatility predicated by price adjustment frequency is negatively associated with the use of bank credit in terms of financial leverage. Furthermore, unobserved firm heterogeneity might be correlated with both credit access and firm volatility, which might further bias the results. To tackle this challenge, we must ensure some randomness in firms' access to credit. To this end, we gather proprietary online banking data on

[8] As we analyze below, the FinTech credit is probably the single source of credit for the firms in our sample.

credit scoring and credit allocation from Ant Financial of Alibaba, the largest FinTech firm in the world serving MSMEs. Ant Financial has developed a proprietary credit scoring system to automate the grant of credit lines based on a cutoff score. This unique feature allows us to use a regression discontinuity design (RDD) to identify the causal effect of access to external finance on firm volatility.

Ant Financial Services Group, a provider of online banking and other financial services, is the world's largest FinTech company after spinning off from its parent company, Chinese Alibaba Group, in 2013. By March 2018, Ant Financial had a valuation of $150 billion.[9] It runs China's first and largest consumer credit scoring system, Zhima Credit and a separate comprehensive credit scoring system for MSMEs, including millions of online merchants on the Alibaba Group's e-commerce platform such as Taobao. The credit score for MSMEs is similar to the FICO score used by many large banks in the U.S. (e.g., Keys et al., 2010). The credit score is generated solely for internal evaluations of credit risk. It is calculated from vast amounts of big data, especially information on the multiple dimensions of a firm's characteristics, reflecting a certain default probability.[10] The score is not disclosed to the firm. Our analysis is built on the RDD approach, exploiting Ant Financial's credit allocation process, which is driven primarily by this credit score. The score is continuous, ranging from 380 to 680. Throughout our sample period, Ant Financial adopted a fuzzy allocation decision rule and set a cutoff score (480) for credit allocation, which was used in tandem with other criteria to reflect firms' aggregate risk profile.[11] The choice of this 480 cutoff was based on a Value-at-Risk (VaR) model, where a cumulative default probability was adopted. As a consequence, whenever firms receive a score higher than 480, they automatically have a significantly higher probability of obtaining access to the credit line than those scoring

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[9] See "China's Ant Financial Raises $10 Billion at $150 Billion Valuation," https://www.reuters.com/article/us-ant-financial-fundraising/chinas-ant-financial-raises-10-billion-at-150-billion-valuation-sources-idUSKCN1IU0EZ.

[10] The top five dimensions distilled from countless online activities include sales related activities (gross merchandise volume and conversion rate), previous loan payment history, sales authenticity/illegal sales, logistical service quality, and customer ratings.

[11] In addition to credit scoring, Ant Financial also imposes a few additional criteria on credit eligibility, including firm age, sales information, previous misconduct record, etc. For instance, if a firm has been in business for less than three months, has had no sales in the past three months, or has been punished for misconduct (e.g., breaching intellectual property rights), then it will not be granted a credit line.

below. Put in another way, firms that score above 480 have greater access to credit from Ant Financial, while those firms that fall below 480 do not have such access.

This unique feature is well suited to the RDD method. We rely on "locally" exogenous variation in credit access based on firms that either succeed or fail to gain access to the credit line by only a small margin of credit scores. This is a powerful and appealing identification strategy because for such close-call cases, having credit access is very close to an independent, random event, and is therefore unlikely to be correlated with firm unobservable characteristics—assuming that the firms do not have precise control over their credit scores (Lee & Lemieux, 2010). This no-precise-manipulation condition is easily met for the following two reasons. First, as the credit score is not revealed to merchants on Taobao, they know neither their credit score nor the specific credit allocation rule. Second, Taobao operates separately from Ant Financial, and the platform would be unable to influence credit allocation decisions. As a result, we can use the locally randomized process to generate causal inferences for the effect of credit access on firm volatility.

Another advantage of the Alibaba data is that the company collects weekly real-time data on trillions of transactions for all firms operating in the Taobao Marketplace, the major retail platform of Alibaba for micro- and small businesses. Furthermore, through its FinTech affiliate, Ant Financial, Alibaba links online merchants' transaction records to credit allocation information and other financial activities using unique IDs. We merge the credit allocation data from Ant Financial to the real-time transaction data along with other firm-level parameters. As credit scores in the system are updated usually on a monthly basis, we conduct our empirical analysis at monthly frequency as well. Consequently, a firm can be treated repeatedly by credit grants, which are readily available for usage upon application, and each grant event represents an independent and exogenous shock to the firm's credit access. After merging, the largest valid sample consists of 8,848,251 firm-month observations from more than 1.9 million unique active merchants on Taobao Marketplace from November 2014 to June 2015.[12] In our main empirical analysis, we focus on firms around the 480 score cutoff to investigate credit access's effect on firm volatility.

[12] As Ant Financial updated the construction of its credit scores and the credit allocation rules after June 2015, the credit scores in our sample are no longer used to grant credit lines.

We also provide diagnostic tests to verify that firms located above or below the cutoff by small bandwidths are truly in line with local randomization.

In our baseline RDD tests, we concentrate on the range of [460, 500], i.e., ±20 from the cutoff (a bandwidth of 20).[13] We obtain the credit score information for each firm in each month and classify the firms into a treated or control group based on the credit allocation information from the end of the current month. We are interested in the firms' sales volatility levels in the three months following a credit allocation event (i.e., *t+1*, *t+2*, and *t+3*, respectively). Treated firms therefore are defined as those that are granted a credit line by the end of the current month and the credit access remains valid throughout the next three months.[14] Control firms are those without credit access in the same month. We then focus on our measures of firm volatility at the end of the next one, two, and three months to attribute differences in firm volatility to differences in credit access. As the credit allocation is largely driven by random variation in credit scores around the 480 cutoff, and given that credit scores predict firms' access to credit, we implement a fuzzy RDD analysis using Two-Stage Least Squares (TSLS) to study the causal effect of credit access on firm volatility (Hahn et al., 2001; Lee & Lemieux, 2010).

We first examine the causal effect of credit access on firm volatility, as captured by two measures of monthly sales growth volatility that exploit weekly real-time transaction data: one based on sales value and the other on sales quantity. We find that firms granted access to credit lines have significantly lower firm volatility. More specifically, firms with credit access have a decrease in sales value growth volatility of 0.0423, 0.0607, and 0.0547, respectively, at *t+1*, *t+2*, and *t+3* compared to firms without credit access. The economic magnitude is also large, accounting for 11%, 16%, and 14% of the sample mean, respectively.

We further conduct two placebo tests. First, we use alternative cutoffs (460 or 500) as the respective cutoffs to assign credit. We conduct the same fuzzy RDD tests and find no significant effect of credit access using these "falsified" cutoffs. Second, we look at a small subsample of firms located in cities with no credit granted in the sample period. These cities are mostly located

[13] We try alternative bandwidths as well, 15 and 10, as detailed in Section 5.5.
[14] We try our analysis without this 3-month constraint, and our results are qualitatively similar.

in remote regions inhabited by ethnic minority groups that are challenging for debt collection due to their remoteness and cultural differences. This subsample provides another ideal setting for a placebo test, as the reasons of no credit granted are orthogonal to firms' sales volatility. As expected, we find no significant effect of credit access using this subsample of firms. We also try alternative bandwidths in RDD and the results further confirm our baseline findings.

We then explore the potential channels through which FinTech lending affects firm volatility along several theoretically motivated dimensions. We examine the first possible channel by studying whether the effect of FinTech credit exhibits any countercyclical patterns in reducing firm volatility. When monetary policies are tightened, firms are subject to more underinvestment risks and short-run adverse liquidity shocks. Therefore, in these occasions, the effect of FinTech credit accessibility is expected to be more profound in reducing inefficient and risk-augmenting fluctuations in outputs. As expected, we indeed find a strong countercyclical effect of FinTech credit. More precisely, we use the monthly growth rates of M2 money supply and Shanghai Interbank Offered Rate (SHIBOR), and find that FinTech credit has significantly larger negative effects on firm volatility when monetary conditions are tightened. The result is consistent with Larrain (2006), who finds that reduction in aggregate volatility is accompanied by increased countercyclical effect of financial development. Furthermore, the countercyclical effect is strengthened by the additional cross-sectional evidence that the negative effect of FinTech credit on volatility is more pronounced in cities and periods with lower GDP growth. Overall, the countercyclical effect is consistent with the role of FinTech in overcoming credit constraints of MSMEs.

Second, we turn to the predation risk and industry competition channel. As pointed out by Froot, Scharfstein, and Stein (1993), a firm's exposure to predation risk largely depends on the interdependence of its investment opportunities with product market competitors. The greater the interdependence, the greater predation risk would be. Therefore, if credit access helps reduce firm volatility, then the effect should be greater in more competitive industries where a firm shares a larger proportion of its growth opportunities with competitors. Our subsample analysis based on product market competition confirms such an expectation.

Next, we look at the legal environment and contract enforcement channel. In the areas with poor legal protection and contract enforcement, banks and other credit providers are less willing to lend to MSMEs as they face more challenges and higher costs in enforcing debt contracts (Djankov et al., 2008; Haselmann et al., 2010). With the new technology in both monitoring and debt enforcement, FinTech lending could remedy such poor legal environment and contract enforcement. First, FinTech lending could monitor the borrowers using real-time and high frequency data. Second, FinTech lender can adopt sanctions and direct enforcement, including cutting off all the online services, withholding the online payments and using them for debt repayment, and may even deduct balance from borrowers' digital wallets. Also FinTech lenders could "track" the borrowers' locations through daily online consumption data, find their related parties, and use other various ways to contact them. We find the negative effect of credit access on firm volatility is driven by the lower legal environment and contract enforcement subsample, which contributes to a better understanding of the role of FinTech in overcoming weaker institutional environment and providing liquidity to MSMEs in those regions.

Furthermore, we study the information asymmetry channel. Compared to traditional banking, the use of technology and big data in FinTech lending makes lender's information collection much less costly and much more effective. In line with this advantage, one might expect the effect of FinTech credit to be stronger in firms with higher level of information asymmetry. To test this conjecture, we focus on firm age since young firms have a much shorter history for traditional lenders to effectively evaluate their credit risk. As expected, we find that the effect of FinTech credit in reducing volatility is more pronounced younger firms. Overall, our channel tests including cyclicality, predation risk, legal environment, and firm age all strengthen our understanding on how FinTech credit affects firm volatility.

Moreover, to better understand the impact of FinTech credit on firm risk, we also look at firm exit probability in the future. We find that FinTech credit access significantly reduces the likelihood a firm's bankruptcy or exit of the business. In addition, we conduct further robustness checks and find that our results are robust when additional firm-level and owner-level controls and city-fixed effects are included and when we use alternative RDD functional forms and higher-order polynomials.

This paper contributes to the following strands of literature. First, it contributes to research on the determinants of firm volatility (Acharya et al., 2011; Boubakri et al., 2013; John, Litov, & Yeung, 2008; Hayes et al., 2012; Kini & Williams, 2012; Low, 2009). We contribute by studying the effect of access to FinTech credit on firm real output volatility in MSMEs as the majority of the literature focus on much larger public firms and stock volatility.[15] Moreover, the availability of high-frequency real-time weekly transaction data for millions of MSMEs helps us to more accurately measure firm volatility. In addition, considering the growth of new credit lines, we evaluate the role of FinTech credit rather than traditional formal financing channels. Since FinTech lenders have advantage in information acquisition and processing, the gains in alleviating information asymmetry is greater for MSMEs.

Second, our paper is related to the literature on informal lending and microcredit (e.g., Banerjee et al., 1994; Madestam, 2014; Rai & Sjöström, 2004). We find that FinTech credit plays a significant role in assisting MSMEs in reducing volatility, and that the effect is strongly countercyclical. We also contribute to the emerging literature on FinTech (e.g., Agarwal, Qian, Yeung, & Zou, 2019; Cheng & Qian, 2018; D'Acunto, Prabhala, & Rossi, 2018; D'Acunto, Rossi, & Weber, 2019; Easley et al., 2018; Sockin & Xiong, 2018).

Third, this study contributes to the literature on finance and the economic growth-volatility nexus initiated by King and Levine (1993) (e.g., Aghion et al., 2005; Bekaert, Harvey, & Lundblad, 2005, 2006; Claessens & Laeven, 2003; He & Tian, 2018; Hsu et al., 2014; Laeven & Levine, 2009; Levine, 1997, 2005; Rajan & Zingales, 1998), and particularly the literature on financing for small businesses (e.g., Berger et al., 1998, 2015; Chen, Hanson, & Stein, 2017; Petersen & Rajan, 2002) and entrepreneurs (e.g., Agarwal, Qian, Yeung, & Zou, 2018; Black & Strahan, 2002; Chen, Miao,

[15] Also, the literature has inconclusive findings. Morgan et al. (2004) found that access to bank capital due to interstate banking deregulation decreases state-level fluctuations in economic growth. Carvalho (2018) found that fewer financing constraints lead to higher equity volatility. In addition, Acemoglu et al. (2003) and Beck et al. (2006) found no robust relationship between financial intermediation and output volatility.

& Wang, 2010; Wang, Wang, & Yang, 2012). In related papers, Hau et al. (2019a, 2019b) study the segmentation of credit market and the take-up decision of FinTech credit and entrepreneurial growth in Chinese small businesses. Whereas research on financial development and economic volatility (Larrain, 2006; Raddatz; 2006) has tended to focus primarily on industry-level cross-sectional analysis, this study contributes by looking at high-frequency firm-level volatility using RDD analysis, thereby providing direct and causal evidence of the effect that access to finance has on firm volatility.

The rest of the paper is organized as follows. Section 2 presents the institutional background and describes the platform Ant Financial. Section 3 describes the data, variable construction, and summary statistics. Section 4 presents our identification strategy and empirical design. Section 5 shows the analysis of the effect of credit access on firm volatility, and Section 6 explores the underlying channels through which FinTech credit affects firm volatility. Section 7 presents additional robustness tests and Section 8 concludes.

2. Institutional Background and the Platform

As the world's largest online retailer and one of the world's largest internet companies,[16] Alibaba enables third-party sellers in China to take their own businesses to the web. Alibaba estimated its China retail marketplaces Taobao and Tmall.com have "contributed to the creation of over 15 million job opportunities with more than 10 million active sellers as of 2015".[17] This enables Alibaba to access the vast big data collected from 300 million registered shoppers and 20 million vendors using Alibaba.

2.1. FinTech Microcredit

Microcredit refers to the extension of very small loans (microloans) without collateral to impoverished borrowers who are typically excluded by the formal financial sector (Morduch,

[16] As of October 2014, Alibaba surpassed Walmart as the world's largest retailer. See "Alibaba is Now the Biggest Retailer in the World," *The Telegraph*, October 28, 2014.
[17] See "Alibaba Affiliate Ant Financial Raises $4.5 Billion in Largest Private Tech Funding Round", *Wall Street Journal*, April 25, 2016; "Alibaba Job Boom: Jack Ma Chats with Trump about How to Create 1 Million US Jobs over 5 Years", *CNBC*, 9 Jan, 2017.

1999). With the development of financial technology, new forms of microfinancing have emerged and developed rapidly, such as e-commerce lending, peer-to-peer (P2P) lending, crowdfunding, and etc.

One clear feature of FinTech e-commerce credit that distinguishes it from traditional banking and P2P financing or crowdfunding is information acquisition. E-commerce credit lenders have access to a vast amount of data on their clients, i.e., e-commerce transaction data and online financial and behavioral data, which include anonymized records of credit card payments, online shopping payments, fund transfers, wealth management, utility payments, house rental information, relocation records, and social relationships. This information helps mitigate the key challenges in traditional banking—adverse selection and moral hazard problems due to information asymmetries (Stiglitz & Weiss, 1981). The use of technology and big data make lender's information collection much less costly and much more effective, compared to traditional forms of lending.

Another important feature of the FinTech e-commerce credit different from traditional lending is information processing and decision making, as it depends on substituting numerical data and automated decisions based on hard information for decisions made by individuals (e.g., Buchak et al., 2017; Liberti & Petersen, 2019). By replacing soft information by hard information, the advantages are apparent in that the loan processing is faster, less expensive, and more effective due to automation (e.g., Fuster et al., 2018; Liberti & Petersen, 2019).

Moreover, FinTech lending is more efficient and effective in both post-loan monitoring and debt enforcement. Traditional bank monitoring relies on public disclosure, information acquisition of firms' financial activities and covenants design, and FinTech lending can utilize real-time data based on multi-dimensional metrics of the borrowers.[18] Lenders can more accurately

[18] For instance, Ant Financial relies on real-time data for post-lending monitoring. It generates a post-lending score based on metrics of Taobao merchants, such as the conversion rate of orders, to assess whether the borrower is likely to have credit deterioration in the following 3-6 months. Depending on the degree of the deterioration, alarms at different levels will be issued and different actions will be triggered automatically according to the pre-defined algorithms. Specifically, for a lower alarm level, the borrowers may be put into watch list; for a medium level, Ant Financial may ask the borrowers to provide more information to support and enhance its credibility, such as bank statements and information on other lending from banks; for a high alarm level and severe cases, the credit

compare submitted financials to databases and thus prevent fraud and default (e.g., Buchak et al., 2017; Fuster et al., 2018). In terms of credit contract enforcement, the traditional banking model relies more on court enforcement. The enforcement procedures/strategies of FinTech firms, however, are based on real-time models and they are highly algorithmized.[19] In the very first place, it is not as easy for borrowers of FinTech credit to default and disappear compared to borrowers of traditional bank credit, because FinTech companies can "track" their locations (based on daily consumption records), identify their related parties, and use other various ways to contact them. This is something that is difficult for traditional banks to do. There are also implicit threats to FinTech borrowers if they fail to repay the debt because the FinTech lender could adopt sanctions and direct enforcement. For example, it could cut off all the services on the platform, use the payments for goods for debt repayment directly, withhold the payments to the related merchants or activities of the borrowers, and may even deduct balance from their digital wallets.[20]

2.2. Ant Financial of Alibaba

As for the 20 million participating vendor businesses operating on the Alibaba platform, nearly 90% are small microenterprises with difficulty accessing finance to fuel their growth. Ant Financial's MYbank, and its predecessor "Alibaba Micro Loan," has for years leveraged a Big Data model to loan offers. MYbank has built its own small business credit scoring system using big data to understand client behaviors and characteristics and offer responsive financial services,

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withdrawn will be frozen immediately and Ant Financial will send members of the contract enforcement team to follow up, and may even seek for legal help. To initiate any of these actions above, it only takes several hours to 2 days from the triggering of an alarm, which is much faster than traditional banks. In addition, all the undrawn credit line will become forfeited automatically.

[19] For example, Ant Financial will classify its overdue debt portfolios into several categories, M1, M2, M3, containing the contracts where borrowers have overdue debt for more than 30 days, 60 days and half year respectively. There will be different enforcement methods applied to each category. That is, Ant's algorithm will optimize the solution given the category and the amount due on a daily basis. Moreover, the algorithm will update the strategies when triggered by different responses from the borrowers.

[20] In the case of Ant Financial, borrowers who default will also risk being not able to use the China's largest e-commerce platform Taobao and the China's largest mobile and online payment platform Alipay, receiving lower score in Zhima Credit, the China's first and largest consumer credit scoring system, and having reputation tarnished in social network in addition to court enforcement.

overturning traditional banking models and leveraging the group's cloud computing services to keep response time to customers short and operational costs low. Based on this credit scoring system, Ant Financial developed a "3-1-0" model of online lending—that is, a service standard characterized by a 3-minute application process, 1-second loan granting, and zero manual intervention.[21]

As of August 2016, Ant Financial had provided a total of over RMB 700 billion (about $102 billion)[22] in loans to over four million small and micro-sized enterprises and entrepreneurs over the previous five years,[23] helping tackle capital shortages and allowing the businesses survive and grow. The average loan is about 20,000 RMB (about $3,000), and the average rate of non-performing loans is below 3%. Without these loans, small and micro-sized businesses would be left out in the cold and thus credit-starved by China's banking system, which oftentimes favors bigger firms and state-owned enterprises.

Built on the vast scale of big data gleaned from Alibaba's various platforms, Ant Financial has developed an automated credit allocation system. The system is characterized by a proprietary credit scoring model that exploits multiple dimensions of firm characteristics to reflect default probability from its trillions of online activities, including sales related activities, previous loan payment history, sales authenticity/illegal sales, logistical service quality, and customer ratings. The credit scoring is continuous, with scores ranging from 380 to 680, and is updated monthly. The fuzzy rule that Ant Financial adopts in allocating credit, under which firms with scores higher than 480 are more likely to get credit, allows us to use fuzzy RDD to study the causal effect of credit access.

3. Data, Sample, and Variable Construction

In this section, we describe the data, variable construction, and summary statistics for our analysis.

[21] See Ant Financial's website: https://www.antfin.com/.

[22] We use the exchange rate on 22 Aug, 2018 for conversion: 1RMB/USD=0.15.

[23] This is about five times of the total volume provided by the Grameen Bank in 39 years.

3.1. Sample Construction

Our major data come from two sources. The proprietary credit line-level data come from Ant Financial, the financial platform of Alibaba. The information includes discretionary credit scores, access to credit lines, actual usage of credit, etc. The real-time transaction records, along with basic firm-level information about the merchants (e.g., industry, location, firm age, and information about the firm owner), come from Taobao Marketplace, Alibaba's e-commerce platform. The two parts are merged at the firm level using unique merchant IDs.

Our sample collection began by examining all vendors on Alibaba from November, 2014 to June, 2015, after which Ant Financial updated its credit score model and credit allocation rules. Requiring information in measures of firm volatility and other major variables, our full sample included 8,848,251 firm-month observations, associated with 1,898,180 unique firms. We narrowed the sample by focusing on active merchants with a bandwidth of 20 from the credit score cutoff of 480 (i.e., [460, 500] sample) and group them into treated and control groups based on Ant Financial's credit allocation decisions. Treated firms are defined as those that were granted a credit line by the end of the current month and whose credit access remained valid throughout the following three months. Control firms are defined as those without credit access in the same month. As for this [460, 500] sample, we have 561,313 firm-month observations, associated with 274,690 unique firms.

3.2. Measuring Firm Volatility

We capture our main dependent variable of firm volatility using two measures of monthly sales growth volatility (*SalesGrVol*) drawn from weekly real-time transaction data: one based on sales value (*Sales value growth vol*), the other on sales quantity (*Sales quantity growth vol*). Specifically, *Sales value growth vol* is the monthly standard deviation of the weekly growth rate for the total transaction amount in RMB, calculated for the next one, two, and three months for each firm in the sample, and *Sales quantity growth vol* is the monthly standard deviation of weekly growth rate of the total transaction quantity calculated for the next one, two, and three months for each firm in the sample. The summary statistics of our major variables are presented in Table 1. As shown in Panel A of Table 1, *Sales value growth vol* (*Sales value growth vol*) has an average value of 0.44 (0.40) with large variations, as indicated by a standard deviation of 0.25 (0.26) in the full sample.

[Table 1 about here]

3.3. Independent Variables

The independent variables in our analysis can be categorized into three groups. The first group relates to a firm's credit status. The key independent variable is *Credit access* (*D*), which is based on actual credit access. This is equal to 1 if a firm in the current month is granted a credit line from the end of month *t* to the end of month *t+3*. We denote *Credit access* as *D* in abbreviation. As shown in Panel B of Table 1, *Credit access* has a mean value of 0.716, indicating that 71.6% of the firm-month observations had credit access in the [460, 500] sample. Credit score (*Credit score*) is defined as the score generated by Ant Financial's credit-scoring model by exploiting big data for firm *i* in month *t*. In the [460, 500] sample, we find that *Credit score* has a mean value of 486.257 with a median of 479.073. We further define an indicator variable based on the credit score, *T [Credit score≥480]*, which is equal to 1 if *Credit score* is greater than 480, and 0 otherwise. We also capture the amount of the credit line granted for the firm by *Credit amount*. As shown in Table 1, the average credit amount is 20,536 RMB (about 3,000 USD) for the [460, 500] sample.

The second group of independent variables include a battery of control variables to measure firm-level characteristics. Specifically, *Sales value* is the total transaction amount in RMB completed by a firm *i* in month *t*. *Firm age* refers to the firm's age, as measured by the total number of months the firm was present on the Taobao Marketplace in the interim since the firm's date of registration on the site. *Owner gender* is an indicator variable that equals 1 if the firm owner is male and 0 if female. *Owner married* is an indicator variable that equals 1 if the firm owner is married and 0 otherwise. *Owner income* is the firm owner's estimated monthly income earned from other sources. *Owner property* is an indicator variable that equals 1 if the firm owner owns real estate assets and 0 otherwise. We also include several variables to measure the owner's education. *Owner Associate*, *Owner undergraduate*, and *Owner postgraduate* are indicators that equal 1 if the highest degree the owner obtains is an Associate's, Bachelor's, or Master's degree, respectively, and 0 otherwise. As shown in Panel B of Table 1, an average firm in our sample had a monthly sales value of 39,504 RMB (about 5,775 USD) and was 26 months old. The average firm size was in line with the scale of credit lines, confirming that Ant Financial mainly serves MSMEs. About 54.8% of firm owners were male and 63.6% were married.

The last group of independent variables includes the firms' regional-, industry-, and economy-level characteristics, which are used to analyze the potential channels in Section 6. For example, we use HHI at the industry level to measure market competition. *NDisaster* is an indicator variable set to 1 if a firm is located in a city that experienced a severe natural disaster in the most recent two months, and 0 otherwise. Appendix A provides a detailed description of our variable definitions.

4. Methodologies and Empirical Design

In this section, we introduce the identification strategy, describe the empirical design, and conduct diagnostic tests.

4.1. RDD Specification

Our main empirical design is based on RDD which is structured around the discontinuity of Ant Financial's credit allocation decisions. As discussed above, Ant Financial is more likely to grant credit lines to firms when their credit scores are higher than 480, which creates a "locally" exogenous variation in credit access generated by firms that succeed or fail to gain access to credit by a small margin in the score distribution. In this regard, variation in credit access can be regarded "as good as random" under the assumption that the credit score cannot be precisely manipulated around the threshold (Imbens & Lemieux, 2008; Lee & Lemieux, 2010). This unique feature allows us to make causal inferences about the effect of credit access on firm volatility with RDD. We provide further diagnostic tests in Section 4.2.

We present the probability of credit access against credit scores in Figure 1. As shown in Figure 1, a firm with a credit score above 480 has a significantly higher probability of receiving a line of credit from Ant Financial. Specifically, the probability jumps by about 30% at the cutoff of 480, which creates a clear discontinuity. However, the probability rates also indicate that passing the threshold does not perfectly determine credit allocation decisions. Therefore, we cannot simply compare outcome variables on each side of the cutoff to estimate the treatment effect. Instead of a sharp RDD, we implement an RDD strategy using the difference in the expected outcome variables and the change in the likelihood of credit access around the cutoff to recover the treatment effect (e.g., Imbens & Lemieux, 2008; Lee & Lemieux, 2010).

[Figure 1 about here]

Specifically, we use a Two-Stage Least Squares (TSLS) model under a standard instrumental variable (IV) framework (Hahn et al., 2001) to estimate credit access's treatment effect. In the first step, we estimate the probability of credit access using the following model specification:

$$D_{i,t} = \alpha + \pi T_{i,t} + \sum_{k=1}^{K} \rho^k (s_{it} - s^*)^k + T_{i,t} \sum_{k=1}^{K} \sigma^k (s_{it} - s^*)^k + \varphi_j + \theta_t + \mu_{it}, \qquad (1)$$

where *i* denotes a shop, *t* denotes the month, s_{it} denotes the credit score that shop *i* received at the end of month t, and $s*$ is the cutoff credit score (i.e., 480). *D* refers to *Credit access*, which is a dummy variable that equals 1 if a firm has credit access from the end of the current month to the end of the next month, and 0 otherwise. $T[Credit\ score \geq 480]$ is a dummy variable that equals 1 if a firm's credit score in the current month is greater than 480, and 0 otherwise. We include polynomial functions of $(s_{it} - s^*)$ up to an order of *K*. ρ^k is the coefficient of the k^{th}-order standardized credit score $(s_{it} - s^*)$ on the left side of the cutoff (when *T*=0), and $\rho^k + \sigma^k$ is for the right side (when *T*=1).[24] We also included industry-fixed effects, φ_j, and time-fixed effects, θ_t, to control for industry characteristics and contemporaneous confounding events.

We use the estimates in equation (1) to predict the probability of credit access and denote it with $\widehat{D}$. Then in the second step, we regress our measures of firm volatility on $\widehat{D}$ following equation (2), given below:

$$SalesGrVol_{i,t+n} = \alpha + \beta \widehat{D}_{it} + \sum_{k=1}^{K} \gamma^k (s_{it} - s^*)^k + T_{it} \sum_{k=1}^{K} \delta^k (s_{it} - s^*)^k + \varphi_j + \theta_t +$$

[24] The polynomials capture the underlying relationship between relevant firm characteristics and credit scores, and help control for the influence of firms that are located away from the cutoff on the credit allocation decisions and consequently firm volatility.

$$\mu_{it}, \qquad (2)$$

where the dependent variable is $SalesGrVol$, captured by two measures of monthly sales growth volatility exploiting weekly real-time transaction data. Specifically, *Sales value growth vol* is the monthly standard deviation of weekly growth rate for the total transaction amount in RMB, calculated for the next one, two, and three months for each firm in the sample, and *Sales quantity growth vol* is the monthly standard deviation of the weekly growth rate of the total transaction quantity calculated for the next one, two, and three months for each firm in the sample. Other variables are the same as defined in the first stage. Our major interest is the estimate of β, the coefficient of $\widehat{D}$, which offers an estimate of the local average treatment effect of credit access on our firm volatility measures.

We face a tradeoff between precision and bias in choosing bandwidth and polynomial orders. A larger bandwidth with higher order polynomials provides more precise estimations, as it uses a larger pool of observations. However, it also introduces biases by using firm-month observations farther away from the discontinuity. Meanwhile, a local linear regression with a narrow bandwidth reduces the bias but might be limited in the number of observations used to obtain precise results. In our main specification, we use a local linear regression (*K*=1) over a small range of credit scores from 460 to 500 (i.e., a bandwidth of 20). We test for robustness using alternative bandwidths in Section 5.5, higher order polynomials (*K*=2 and *K*=3), and alternative model specifications in Section 7.2.

4.2. Diagnostic Tests for Setting Validity

The RDD relies on "locally" exogenous variations in credit access generated by credit scores above or below 480 by a small margin of points. A key identifying assumption of the RDD is that agents (both firms and Ant Financial) cannot precisely manipulate the forcing variable (i.e., the credit scores) near the cutoff (Lee & Lemieux, 2010). If this assumption is satisfied, then the variation in access to credit lines is as good as that from a randomized experiment (e.g., Bradley et al., 2017; Chemmanur & Tian, 2018; Imbens & Lemieux, 2008). As discussed above, Ant Financial does not disclose the firms' credit scores or the specific algorithms governing the credit allocation decisions. Moreover, Ant Financial runs separately from Taobao Marketplace; as such, Taobao cannot influence allocation decisions.

Although it seems theoretically clear that the assumption is satisfied, we further perform two sets of diagnostic tests to provide empirical evidence. First, we study the density of firm distribution around the cutoff 480. If there is systematic sorting of firms within close proximity of the threshold, then this sorting would be observed by a discontinuity in the credit score distribution at the 480 threshold. Specifically, we follow McCrary (2008) and provide a formal test of discontinuity in the density. We draw a density of the sample distribution of credit scores in equally-spaced credit score bins, as presented in Figure 2. The horizontal axis represents the firms' credit scores over the full credit score range, from 380 to 680. The circles depict density estimates. The solid line refers to the fitted density function of the forcing variable (the number of firms) with a 95% confidence interval around the fitted line. The figure shows that the density appears generally smooth and the estimated curve gives no indication of a discontinuity near the 480 threshold. The discontinuity estimate is 0.0059 with a standard error of 0.0045. Therefore, we cannot reject the null hypothesis that the difference in density at the cutoff point is zero. Overall, this suggests that our validating assumption—that there is no precise manipulation of credit scores at the threshold—is not violated.

[Figure 2 about here]

Another important assumption of the RDD is that there should not be discontinuity in other covariates correlated with firm volatility at the cutoff point. In other words, firms that have credit access should not be systematically different ex ante from firms that do not have credit access. We perform this diagnostic test by comparing the covariates of firms that fall in the narrowest band of credit scores used in our analysis (i.e., [470, 490] around the threshold). Specifically, we plot the pre-treatment measures of firm characteristics and firm volatility, as presented in Figure 3. Panel (1) focuses on *Sales value* one month prior to the treatment event and Panel (2) on *Firm age*. In both figures, we do not find any jumps in firm characteristics before the exogenous change in credit access. Panels (3) and (4) present the plot for our measures of firm volatility (*Sales value growth vol* and *Sales quantity growth vol*) at *t-1*. We find no jumps in these two measures either.

[Figure 3 about here]

Overall, the diagnostic tests presented above suggest that there does not appear to be a precise manipulation of credit scores within close proximity over the 480 threshold. Furthermore, there is no discontinuity in other covariates at the cutoff point as well.

5. Baseline RDD Results

In this section, we present the baseline RDD results. We start with a graphical analysis to visually check relationships around the cutoff and move to formal fuzzy RDD regressions for the baseline results. We then provide two sets of placebo tests using alternative cutoff points and examining cities where no credit was granted. We further conduct a robustness test by exploring alternative bandwidths.

5.1. Graphical RDD Analysis

We first present a set of discontinuity plots in Figure 4 as an intuitive way to illustrate the causal effect of credit access on firm volatility. Given the fuzziness in the credit allocation decisions, this approach is not precise; however, it does provide a preliminary approximation of credit access's treatment effect. We concentrate on the narrowest band used in our analysis (i.e., from 470 to 490). The left-hand figures (i.e., Panels (1), (3), and (5)) present plots for *Sales value growth vol* and the right-hand plots (i.e., Panels (2), (4), and (6)) present plots for *Sales quantity growth vol*. We study our measures of firm volatility at *t+1*, *t+2*, and *t+3* subsequent to a credit allocation decision at both sides of the cutoff. We divide the spectrum of credit scores into equally-spaced bins (with a bin width of 1). For firms with a credit score lower than the cutoff, the average firm volatility measures are denoted by blue dots, and the average value of firm volatility measures for firms with a score above the threshold are denoted by red dots. The solid line represents the fitted linear estimate with a 95% confidence interval around the fitted value.

[Figure 4 about here]

The figures show a strong discontinuity in both *Sales value growth vol* and *Sales quantity growth vol* at the threshold in each of the three months after the credit allocation decision. Specifically, within close proximity of the threshold, our measures of firm volatility drop significantly once the credit scores move from the bin below 480 to the one above. This observation points to a causal and negative effect of FinTech credit on firm volatility.

5.2. *Fuzzy RDD Tests*

We now present our analysis using the fuzzy RDD. We follow the two-equation system in Section 4.1 to perform the analysis. We focus on a bandwidth of 20 (i.e., the [460, 500] sample) and present our results in Table 2. Panel A reports the first-stage regression. In the first stage, we regress the credit access dummy *D* on an indicator variable *T*, which is set to 1 when the credit score is greater than 480 and 0 otherwise, a linear term for the standardized credit scores (i.e., $s_{it}-s*$), and an interaction item between *T* and the standardized credit scores, together with industry- and time-fixed effects. In this way, we provide an estimate of the change in the likelihood of credit access when the credit score moves above 480. As shown in Panel A, passing the threshold of 480 results in a 23 percentage points increase in the probability of obtaining credit access. We use the first-stage result to predict the probability of credit access for each individual firm and denote this as $\widehat{D}$. This predicted credit access can be viewed as instrumented *Credit access* and is the key variable of interest in the second stage.

[Table 2 about here]

Panel B of Table 2 displays the second-stage regression result, where the dependent variables are our measures of firm volatility: *Sales value growth vol* and *Sales quantity growth vol*. We follow equation (2) with *K*=1 (i.e., local linear regression). We perform the second stage regression for each firm volatility measure at *t+1*, *t+2*, and *t+3*, respectively, to identify the causal effect of credit access on firm volatility. From Panel B we find that credit access significantly reduces firm volatility for both measures at *t+1*, *t+2*, and *t+3*. For example, in column (1), we see that access to credit leads to a 0.0423 reduction in *Sales value growth vol*. In terms of economic magnitude, the treatment effect is 9.5% of the mean value in the full sample and 11% of the mean value in the local regression sample (i.e., [460, 500]). At *t+2* and *t+3*, the credit access results in a decrease of 0.0607 and 0.0547 in *Sales value growth vol*, which translate into a treatment effect of 15.8% and 14.2% of the mean value in the local sample, respectively. Columns (4) to (6) report the results for *Sales quantity growth vol*. These are similar and the economic magnitudes are larger. For example, in column (4), credit access leads to a reduction of 0.0607 in *Sales quantity growth*. The treatment effect is 17.8% of the mean value in the local regression sample. Overall, these baseline results suggest that credit access has a negative causal effect on firm volatility.

5.3. Placebo Tests: Alternative Cutoffs

We perform a placebo test using falsified cutoff points to assign credit. If the reduction in firm volatility can indeed be attributed to credit access (as induced by locally random variations in credit scores around the threshold), then we should not find the same results using alternative thresholds. Therefore, we choose 460 and 500 as falsified cutoff points for our analysis. We redefine *T* and the standardized credit scores using the new cutoffs. Everything else is the same, as outlined in Section 5.2. We perform the regressions using the TSLS model and focus on a local region of credit scores with a bandwidth of 20. We report the results in Table 3.

[Table 3 about here]

Panel A of Table 3 shows the first-stage regression results. We find that the coefficient estimate for *T* is not significantly different from 0 for both the placebo cutoffs of 460 and 500, indicating that the probability of a firm receiving a credit line does not change significantly at the new thresholds. Moving onto the second-stage regression, using the predicted *Credit access* as the major independent variable, we find an insignificant effect on our measures of firm volatility. We focus on *t+1* subsequent to the credit allocation decision in this analysis, and the untabulated results for *t+2* and *t+3* are qualitatively similar.

5.4. Placebo Tests: Cities with No Credit Granted

We conduct another placebo test by looking to the firms located in cities with no credit granted during the sample period. These cities are mostly located in remote regions, inhabited by ethnic minority groups, where debt collection is challenging because of the lower density of shops, the cities' geographical remoteness, and the population's cultural differences.[25] This

[25] We consulted with experts from Ant Financial in credit allocation decision rules and were informed about these possible reasons for having no credit granted in these cities. These cities include Rikaze (Xizang), Gannanzangzuzizhizhou (Gansu), Linxiahuizuzizhizhou (Gansu), Xilinguole (Neimenggu), Alashan (Neimenggu), Yinchuan (Ningxia), Longnan (Gansu), Pingliang (Gansu), Boertalamengguzizhizhou (Xinjiang), Linzhi (Xizang), Yushuzangzuzizhizhou (Qinghai), Zhongwei (Ningxia), Ali (Xizang), Dingxi (Gansu), Wuzhong (Ningxia), Yilihasakezizhizhou (Xinjiang), Baiyin (Gansu), Sanya (Hainan), Wulumuqi (Xinjiang), BayinGuolemengguzizhizhou (Xinjiang), Huhehaote (Neimenggu), Haikou (Hainan), Tulufan (Xinjiang), Tianshui (Gansu), Xinganmeng (Neimenggu), Aletai (Xinjiang), Xining (Qinghai), Lanzhou (Gansu), Bayannaoer (Neimenggu), Kelamayi (Xinjiang), and Jiuquan

subsample provides another ideal setting for a placebo test, as the reasons why firms there did not receive credit lines are orthogonal to firms' sales volatility. Because of the identical value of *Credit access* (i.e., 0) in the first stage and the sharp decrease in the number of observations (i.e., a total of 1,340 firm-time observations for the [470, 490] range), we perform the discontinuity plots instead of running TSLS regressions. Presumably, we should observe no change in firm volatility when the credit score moves from below 480 to above for these firms. We present the results in Figure 5. As expected, we find no discontinuity in any of our measures of firm volatility at *t+1*, *t+2*, and *t+3* around the threshold using this subsample of firms.

[Figure 5 about here]

Overall, the placebo tests using falsified cutoffs and cities with no credit granted strengthen the validity of our RDD setting and provide additional support for a causal interpretation of our baseline results.

5.5. Robustness Test: Alternative Bandwidths

Given the tradeoff between precision and bias in our estimates when choosing the bandwidths for RDD, we use two alternative bandwidths to re-estimate our analysis and check the robustness of our results. The first alternative bandwidth is 15 credit score points around the cutoff to have a local range from 465 to 495, and the second is 10 points around the cutoff to create a local region of 470 to 490. The results are reported in Table 4. All other specifications are identical to our baseline regression.

[Table 4 about here]

As shown in Panel A, firms with a score above the threshold have a higher probability of accessing credit lines. We use the predicted *Credit access* as the major independent variable of interest in the second stage and find that credit access significantly reduces firm volatility, as indicated in Panel B. We focus on *t+1* subsequent to the credit allocation decision in this analysis, and the results for *t+2* and *t+3* are qualitatively similar. The results confirm that credit access has a negative causal effect on firm volatility and that this effect is not sensitive to the selection of bandwidths.

(Gansu).

6. Further Explorations of Firm Volatility: Potential Channels

In this section, we further explore the effect of credit access on firm volatility to analyze the underlying channels through which credit access could affect firm volatility. As Rajan and Zingales (1998) point out, to determine "the 'smoking gun' in the debate about causality" requires focusing on the details of theoretical mechanisms and documenting how they work. Specifically, we focus here on several theoretically motivated dimensions to better understand the channels through which access to FinTech credit affects firm volatility: countercyclical patterns in terms of both monetary policies and business cycles, predation risk, legal environment and contract enforcement, and information asymmetry. We further look at the firm exit probability, and study how FinTech credit could affect firms' bankruptcy and exit choices.

6.1. Monetary Policies Channel: Countercyclical Effects

We first study whether the effect of FinTech credit exhibits any countercyclical patters in reducing firm volatility. In other words, we want to know whether the effect of FinTech credit access is more pronounced when the monetary condition is tightened or relaxed. Theoretically, a tightened monetary condition indicates that firms are subject to more underinvestment risks and short-run adverse liquidity shocks and, under such conditions, FinTech credit should matter more to the firms in reducing inefficient and risk-augmenting volatility in outputs. We measure the monetary condition (*Monetary*) by using 1) monthly M2 growth rate (*M2_growth*); 2) monthly SHIBOR growth rate (*SHIBOR_growth*). Lower *M2_growth* or higher *SHIBOR_growth* indicates tighter monetary conditions. Specifically, we augment our baseline model by adding the interaction of instrumented *D* with our measures of monetary condition (*Monetary*) in the second-stage regression, which is specified as follows:

$$SalesGrVol_{i,t+n} = \alpha + \beta_1 \widehat{D}_{it} + \beta_2 \widehat{D}_{it} \times Monetary_t + \sum_{k=1}^{K} \gamma^k (s_{it} - s^*)^k + T_{it} \sum_{k=1}^{K} \delta^k (s_{it} - s^*)^k + \varphi_j + \theta_t + \mu_{it}, \quad (3)$$

As we are interested in the causal effect of credit access, we stick to the fuzzy RDD and instrument Credit access in the first stage. In the second stage, we interact *Monetary* with the instrumented credit access dummy ($\widehat{D}$). We do not need to add the single term of *Monetary*, as this is absorbed in time-fixed effects. We are interested in β_2, the coefficient of the interaction term between *Monetary* and $\widehat{D}$. A positive β_2 when using *M2_growth* and a negative β_2 when using *SHIBOR_growth* would indicate that the effect of FinTech credit is countercyclical. As in the baseline analysis, we use a local linear regression model over the local bandwidth of 20. We also control for industry- and time-fixed effects. Table 5 presents the regression results.

[Table 5 about here]

The first-stage regression result is the same as the baseline regression (Panel A of Table 2). Panel A of Table 5 reports the second-stage regression results for when *M2_growth* is used to measure monetary condition, and Panel B reports the results for when we use *SHIBOR_growth* to measure monetary condition. We find that the predicted credit access ($\widehat{D}$) maintains a significantly negative effect on sales volatilities. More interestingly perhaps, we find that the estimate of β_2 is significantly positive in Panel A and significantly negative in Panel B, implying that the effect of credit access on firm volatility is more pronounced when the monetary condition is tightened. Overall, the results indicate that the effect of FinTech credit is countercyclical.

6.2. Business Cycle Channel: Cross-sectional Local GDP Growth

We next look at local economic growth to measure business cycle. In Section 6.1, we examine the cyclicality effect by looking at time-series variations in monetary policies. City- and time-level measures of economic growth would strengthen our previous results by adding another cross-sectional dimension to our understanding of cyclicality. Intuitively, firms in cities with low economic growth or in periods of economic downturns are facing more short-run liquidity shocks and credit constraints from traditional banking, and therefore we expect the effect of FinTech credit to be stronger in reducing risk-augmenting volatility.[26] Specifically, we use the quarterly change in GDP in a city as the measure of local GDP growth. The high GDP growth subsample

[26] On the other hand, negative income shocks could also result in reduced consummation demand from consumers (e.g., Agarwal & Qian, 2014; Jappelli & Pistaferri, 2010). Credit access could help the firms to expand products category or put more commercials which help diversify the revenue sources.

consists of firms operating in a city where GDP growth is in the top tercile of the sample, while the low GDP growth subsample consists of firms operating in a city where GDP growth is in the bottom tercile of the sample. We use the TSLS regression system in equations (1)-(2) to implement the design, with the local linear regression model over the credit scores from 460 to 500 in both stages. We present the subsample analysis results in Table 6.

[Table 6 about here]

In the first stage (shown in Panel A), we regress the credit access dummy *D* over an indicator variable *T*, which is set to 1 when credit score is greater than 480 and 0 otherwise, in addition to an interaction of *T* with the standardized credit scores. As shown in Panel A, in both subsamples, passing the credit score threshold leads to a similar increase in the likelihood that the firm obtains credit access. Panels B, C, and D report the second-stage results. The dependent variable is *Sales value growth vol* in columns (1) and (2), and *Sales quantity growth vol* in columns (3) and (4). Industry- and time-fixed effects are included. Consistent with the findings in Section 6.1, the significant and negative effect of credit access on firm volatility is driven by the low local GDP growth subsample, strengthening our countercyclical results and again pointing to the role of FinTech in overcoming credit constraints of MSMEs.[27]

6.3. Predation Risk Channel

In this subsection, we investigate the impact of predation risk and industry competition in influencing the effect of credit access on firm volatility. A firm's exposure to predation risk is largely based on the interdependence of its investment opportunities with product market peers (Froot et al., 1993). If credit access helps reduce firm volatility, then the effect should be greater in more competitive industries: given that these firms are exposed to higher competitive and predation risks, improved access to credit could motivate firms to invest in diversifying their products, improving service quality, or adopting more aggressive pricing strategies to gain a higher market share. In other words, we expect to observe a stronger effect for credit access in more competitive industries where a firm shares a larger proportion of its growth opportunities

[27] We test the equality of the coefficient estimates in the two subsamples and find that they are significantly different.

with competitors.

We use the Herfindahl-Hirschman index (*HHI*) at the industry level to measure market competition. Specifically, for each month before a credit allocation event, we construct the HHI of each industry based on the market share of the firms. We then categorize the firms into the most (least) competitive group if their industry HHI is in the bottom (top) tercile of the sample. We perform TSLS regressions for each subsample following the same two-equation system used in the baseline analysis. The results are reported in Table 7. Consistent with our expectation, we find that the effect of credit access is more pronounced in the subsample with higher levels of industry competition. We test the equality of the coefficient estimates in the two subsamples and find that they are significantly different.

[Table 7 about here]

6.4. Legal Environment and Contract Enforcement Channel

We also consider different levels of legal environment and contract enforcement in shaping the effect of FinTech credit on firm volatility. There is a large variation of legal environment across different provinces in China (e.g., Agarwal, Qian, Seru, & Zhang, 2018; Allen, Qian, & Qian, 2005; Fan & Wang, 2003; Qian, Strahan, & Yang, 2015), and Qian & Strahan (2007) document that legal and institutional environment could shape financial contract.

In the areas with poor legal protection and contract enforcement, banks and other credit providers are less willing to lend to MSMEs as they face more challenges in debt collection (e.g., Djankov et al., 2008). FinTech lenders could remedy such poor legal environment and contract enforcement with the new technology in both monitoring and debt enforcement. As discussed in Section 2.1., different from traditional bank post-loan monitoring that relies on public disclosure, information acquisition of firms' financial activities and covenants design (e.g., Goldstein & Yang, 2017, 2018; Wang & Xia, 2014), FinTech lending can rely on real-time data based on multi-dimensional metrics of the borrowers, and lenders can more accurately compare submitted financials to databases and thus prevent fraud and default (e.g., Buchak et al., 2017; Fuster et al., 2018). Rather than the traditional banking model that relies more on court enforcement, the enforcement of FinTech firms, however, is based on highly algorithmized real-time models. Firstly, there are also implicit threats to FinTech borrowers if they fail to repay the debt because the FinTech firm could adopt sanctions and direct enforcement. Secondly, FinTech companies can "track" their locations based on daily consumptions, find their related parties, and use other various ways to contact them. Therefore, we expect that the effect of FinTech credit on firm volatility would be stronger in regions with poorer legal environment and contract enforcement.

We use a widely-used measure of legal environment and contract enforcement in China: a subcategory index in market development index (MDI).[28] MDI was developed by Fan & Wang (2003) and updated to 2014. This index has been widely used in economics and finance research on China, including that by Gwartney et al. (2005), Jian & Wong (2010), and Li et al. (2006). We use the value in 2014 at the province level to measure legal environment and contract enforcement. We perform subsample analysis by dividing the [460, 500] sample into high and low legal environment and contract enforcement subsamples. The high legal environment and contract enforcement subsample consists of firms operating in a specific province in which the measure is in the top tercile of the sample, while the low legal environment and contract enforcement subsample consists of firms operating in provinces for which the measure is in the bottom tercile of the sample. We use the TSLS regression system in equations (1)-(2) to implement the analysis. Table 8 shows the results.

[Table 8 about here]

As shown in Panel A, in both subsamples, passing the credit score threshold leads to a similar increase in the likelihood that the firm obtains credit access. In the second stage (Panels B, C, and D), we regress our measures of firm volatility over instrumented *D* and an interaction of *T* with the standardized credit scores. We control for industry- and time-fixed effects in both stages of the regressions. We find that across all of the models in Panels B, C, and D, the effect of FinTech credit concentrates in the subsample with lower legal environment and contract enforcement for both of our measures of firm volatility at *t+1*, *t+2*, and *t+3* respectively. We test the equality of the coefficient estimates in the two subsamples and find that they are significantly different. To sum, we find the negative effect of credit access on firm volatility is driven by the lower legal environment and contract enforcement subsample, which contributes to a better understanding

[28] We have tried using the aggregate MDI index to do the same analysis, and the results are qualitatively similar.

of the role of FinTech in overcoming weaker legal environment and contract enforcement and less support from financial markets received by MSMEs.

6.5. Information Asymmetry Channel

As discussed earlier, FinTech lending has clear advantage in information acquisition and processing over traditional forms of banking and relies on hard information with the use of technology and big data. Along this line, one might expect the effect of FinTech credit to be stronger in firms with higher level of information asymmetry.

To test this hypothesis, we look at firm age. Younger firms have a much shorter history for traditional lenders to effectively evaluate its credit risk. First, they are more likely to be denied credit from traditional lenders. Second, Ant Financial can access a vast amount data of transactions and financial activities of these young firms. Therefore, the gains to FinTech in alleviating information asymmetry between lender and borrower is greater for these firms. Specifically, we divide the sample into young and old subsamples and redo the analysis. The young subsample consists of firms whose age is in the bottom tercile of the sample, while the old subsample consists of firms whose age is in the top tercile of the sample. We use a local linear regression model over the local bandwidth of 20 and we control for industry- and time-fixed effects. We show our results in Table 9.

[Table 9 about here]

Panel B presents the second-stage results. We find that the instrumented credit access maintains a significantly negative effect on sales volatility for young firms, as indicated by a negative and significant estimate of β in columns (2) and (4). It is nevertheless insignificant in columns (1) and (3) for old firms. We test the equality of the coefficients between the subsamples and find that they are statistically different. The results indicate that the negative effect of FinTech credit on firm volatility is concentrated in younger firms, consistent with our expectation that FinTech credit access helps reduce firm risk by alleviating information asymmetry between lenders and borrowers.

6.6. FinTech Credit and Firm Exit Probability

E-commerce competition is intense, and MSMEs that cannot survive with large risk-augmenting fluctuations in output could go bankrupt or exit the business. Indeed as shown in our sample, 4.6% of firms on average exit business in a particular month. The figure goes up to about 10% if we look at a 3-month horizon. Therefore, firm exit probability is a natural and extreme measure of firm risk. In this section, we examine whether FinTech credit affects firms' exit choices.

To test this, we augment the second-stage equation (2) and construct the following model specification:

$$Exit_{i,t+n} = \alpha + \beta \widehat{D}_{it} + \sum_{k=1}^{K} \gamma^k (s_{it} - s^*)^k + T_{it} \sum_{k=1}^{K} \delta^k (s_{it} - s^*)^k + \varphi_j + \theta_t + \mu_{it}, \quad (4)$$

$Exit$ is a dummy variable, which is equal to 1 if a firm goes bankrupt or exits the business in a given month, and 0 otherwise. As in our baseline results, we use a local linear regression model over the local bandwidth of 20 and we control for industry- and time-fixed effects.[29] We show our results in Table 10.

[Table 10 about here]

Panel A of Table 10 shows the first-stage regression result. Similar to our baseline results, passing the credit score threshold leads to a similar increase in the likelihood that the firm obtains credit access. The second-stage regression results are presented in Panel B. We find that FinTech credit access significantly reduces firms' probability of bankruptcy or exit of the business. Specifically, the likelihood of bankruptcy or exit is reduced by 10% in the next month, 12% in the next two months, and 15% in the next three months. To sum, the results imply that FinTech credit not only significantly reduces firm volatility but also reduces firm's bankruptcy and exit probability in the future.

7. Additional Robustness Tests

In this section, we perform additional robustness tests by adding additional firm-level and owner-level controls, city-fixed effects, and using alternative RDD specifications.

[29] Compared to Table 2, the number observations increases as we could regain the firm-month observations after they exit the business.

7.1. Additional Firm-level and Owner-level Controls and City Fixed Effects

We add a battery of firm covariates into the regressions to check the robustness of our previous findings. In a valid RDD setting, it is not necessary to include control variables, but doing so could improve estimation precision (Lee & Lemieux, 2010). We include firm size, firm age, and owner characteristics into the regressions. Owner variables include *Owner gender*, *Owner married*, *Owner income*, *Owner property*, *Owner Associated*, *Owner undergraduate*, and *Owner postgraduate*. *Owner gender* is an indicator variable that equals 1 if the firm owner is male and 0 if female. *Owner married* is an indicator variable that equals 1 if the firm owner is married and 0 otherwise. *Owner income* is the estimated monthly income of the firm owner that is earned from other sources. *Owner property* refers to an indicator variable that equals 1 if the firm owner owns real estate assets and 0 otherwise. We also include several variables to measure the owner's education. *Owner Associate*, *Owner undergraduate*, and *Owner postgraduate* are indicators that equal 1 if the highest degree the owner obtains is an Associate's, Bachelor's, or Master's degree, respectively, and 0 otherwise. The results are presented in Table 11.

[Table 11 about here]

Panel A of Table 11 reports the first-stage regression, where the sample is restricted to observations for which we have all of the available information for our additional controls. A firm with a credit score just above 480 is 22% more likely to get a credit line than a firm below the cut-off, and the size of the jump in the treatment probability is similar to the baseline results. Panel B reports the second-stage regression results with additional covariates. We find a negative and significant effect for instrumented credit access on our measures of firm volatility, and the magnitudes are similar to the baseline results. In Panel C, we further add city-fixed effects, and the estimated results are not significantly different from our baseline results as well. Taken together, our results are robust to adding more firm and owner covariates and city-fixed effects.

7.2. Alternative RDD Specifications

Finally, we use alternative RDD specifications to investigate the effect of FinTech credit on firm volatility. Throughout the analyses above, we allow for different functional forms of the polynomial terms on both sides of the cutoff. We now adopt the same functional form of the polynomial terms in the standardized credit score on both sides of the cutoff point. Specifically, we update equations (1) and (2) to be as follows:

$$D_{i,t} = \alpha + \pi T_{i,t} + \sum_{k=1}^{K} \rho^k (s_{it} - s^*)^k + \varphi_j + \theta_t + \mu_{it}, \quad (5)$$

$$SalesGrVol_{i,t+n} = \alpha + \beta \widehat{D}_{it} + \sum_{k=1}^{K} \gamma^k (s_{it} - s^*)^k + \varphi_j + \theta_t + \mu_{it}, \quad (6)$$

We set K=1 by implementing a local linear regression. The results are presented in Panel A of Table 12. We find that the estimated treatment effect of credit access on firm volatility is similar to the baseline results.

[Table 12 about here]

We further use a higher order of polynomials in the standardized credit score to check the robustness of our results. In Panel B, we set K=2 in the two-equation system (1) and (2). In Panel C, we set K=3. We do not find significantly different results; in fact, the significance increases in Panel B and Panel C when we use higher order polynomials.

Taken together, these findings indicate that our results are not sensitive to alternative RDD specifications, higher orders of polynomials, or including additional firm and owner covariates and city-fixed effects. Overall, we confirm that FinTech credit reduces firm volatility.

8. Concluding Remarks

The online trading platform Alibaba provides automated FinTech credit for millions of MSMEs through its financial subsidiary, Ant Financial. By gauging a novel database of weekly real-time sales data, we measure firm volatility at a higher frequency. Various threshold effects governing the allocation of credit allow us to apply RDD and explore the causal effect of credit access on firm volatility. We focus on the real effect of FinTech credit on MSMEs, which is largely understudied in the literature. We use locally exogenous allocation of credit to identify the causal effect of credit access on firm volatility. Moreover, the FinTech credit our sample is arguably the single source of credit for these MSMEs, and therefore, our study provides a clean setting to evaluate the effect of credit access on firm volatility without the potential confounding concerns from equity market, bond market, bank loan market, or other financial markets.

Overall, our results show that credit access significantly reduces firm volatility. We further explore the potential underlying channels through which FinTech lending affects firm volatility along several theoretically motivated dimensions. We find that the negative effect of FinTech credit on firm volatility is strongly countercyclical. The results also indicate that the negative effect on firm volatility is concentrated in firms that are young, that are in regions with lower economic growth and poorer legal environment and contract enforcement, and that are in more competitive industries. We also find that FinTech credit significantly reduces firms' bankruptcy and exit probability in the future. Overall, our findings contribute to a better understanding of the role of FinTech credit in reducing the risk of the MSMEs through countercyclical effect, predation risk, contract enforcement, and information asymmetry.

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Figure 1. Discontinuity Plot on the Probability of Credit Access

This figure displays the discontinuity plot on the probability of credit access against credit scores. The vertical axis is the probability of credit access. The horizontal axis is the credit score in the local range of [460, 520]. Each dot on the figure represents the average probability that a credit line is granted to a firm located in the corresponding range of credit score with a bandwidth of one. The probability is estimated by dividing the total number of firms with credit access over the total number of eligible firms in the same bin. A quadratic line is fit to the scattered dots on each side the cutoff score (i.e., 480), surrounded by a 95% confidence interval in light grey lines.

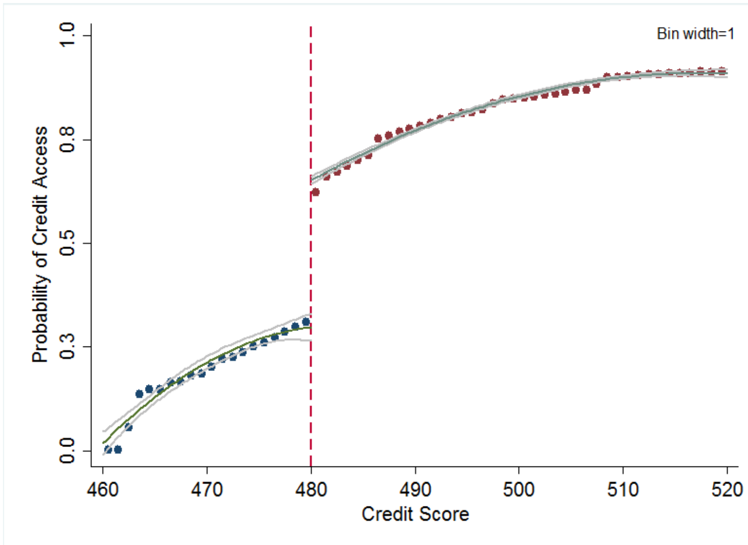


Figure 2. Density of Firms: McCrary (2008) Plot

This figure plots a density of sample firms along the credit score spectrum, following the procedure in McCrary (2008). The horizontal axis is the credit score in the full spectrum of [380, 680]. The circles depict the density estimate. The solid line refers to the fitted density function of the forcing variable (the number of firms) with a 95% confidence interval around the fitted line.

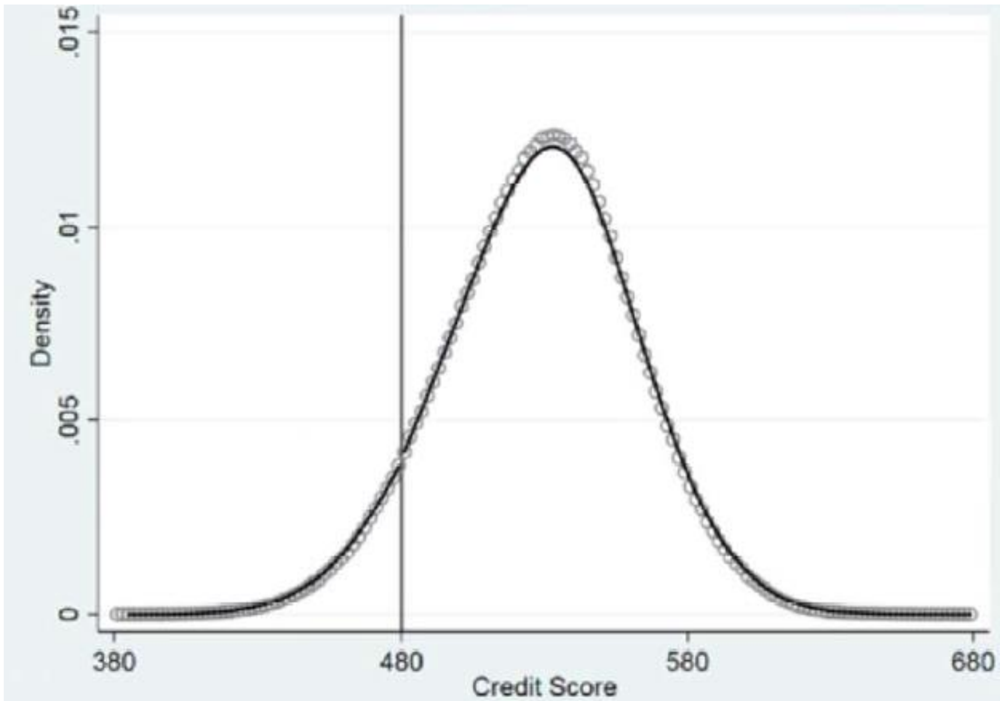
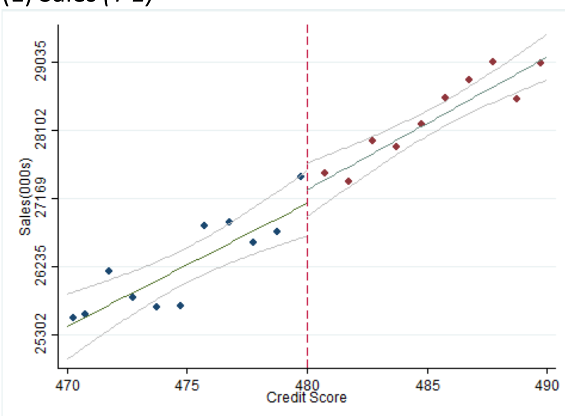


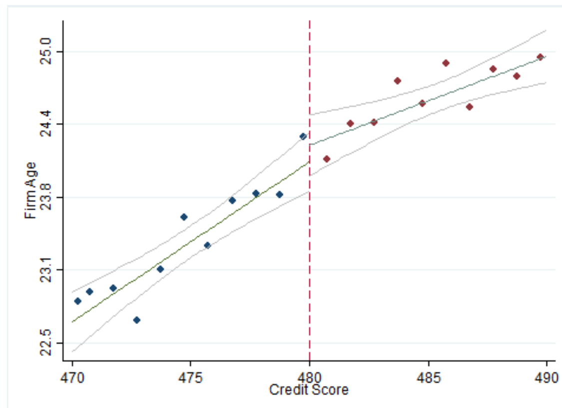
Figure 3. Discontinuity Plot on Pre-existing Firm Characteristics

This figure presents the discontinuity plots of a firm's characteristics prior to the credit allocation events against its credit scores. Panel (1) plots the average *Sales* in month *t-1* against the credit score in month *t*. Panel (2) plots the average *Firm Age* in month *t-1* against the credit score in month *t*. Panels (3) and (4) plot the average *Sales value growth vol*, and *Sales quantity growth vol*, respectively, in month *t-1* against the credit score in month *t*. The vertical axis is the value of the respective firm's characteristics; the horizontal axis is the credit score in the local range of [470, 490]. Each dot on the figure represents the average value of the respective firm characteristics for firms located in the corresponding range of credit score with a bandwidth of one. A linear line is fitted to the scattered dots on each side the cutoff score (i.e., 480), surrounded by a 95% confidence interval in light grey lines.

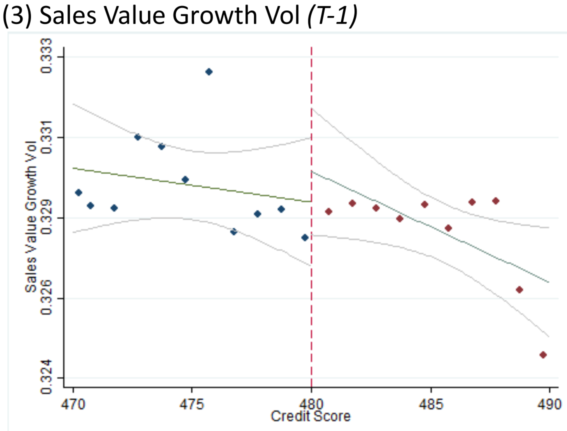
(1) Sales *(T-1)*



(2) Firm Age *(T-1)*



(3) Sales Value Growth Vol *(T-1)*



(4) Sales Quantity Growth Vol *(T-1)*

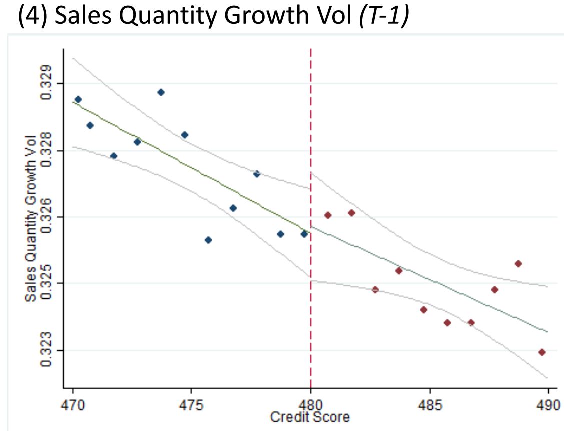
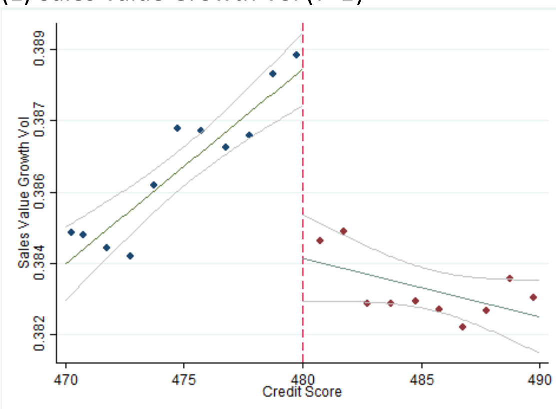


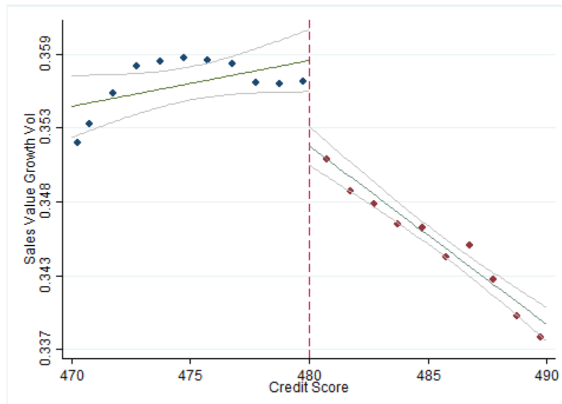
Figure 4. Discontinuity Plot on Firm Volatility

This figure presents the discontinuity plots of a firm's volatility measures subsequent to the credit allocation events against its credit scores. Panels (1) and (2) plot the average *Sales value growth vol* and *Sales quantity growth vol*, respectively, in month *t+1* against the credit score in month *t*. Panels (3) and (4), and Panels (5) and (6) plot the average of these variables in months *t+2* and *t+3* against the credit score in month *t*. The vertical axis is the value of the respective service quality measure; the horizontal axis is the credit score in the local range of [470, 490]. Each dot on the figure represents the average value of the respective service quality measure for firms located in the corresponding range of credit scores with a bandwidth of one. A linear line is fitted to the scattered dots on each side the cutoff score (i.e., 480), surrounded by a 95% confidence interval in light grey lines.

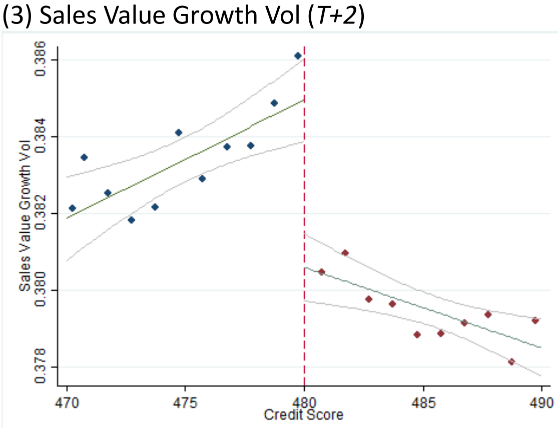
(1) Sales Value Growth Vol (*T+1*)



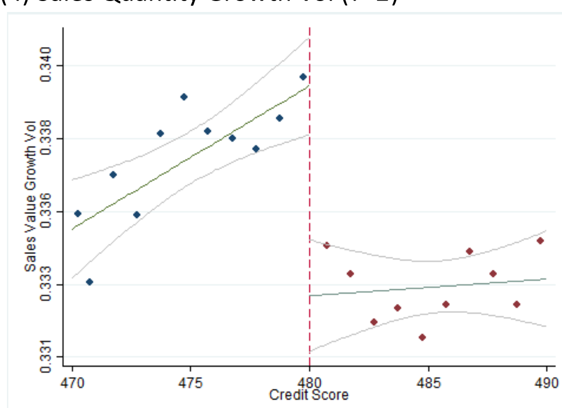
(2) Sales Quantity Growth Vol (*T+1*)



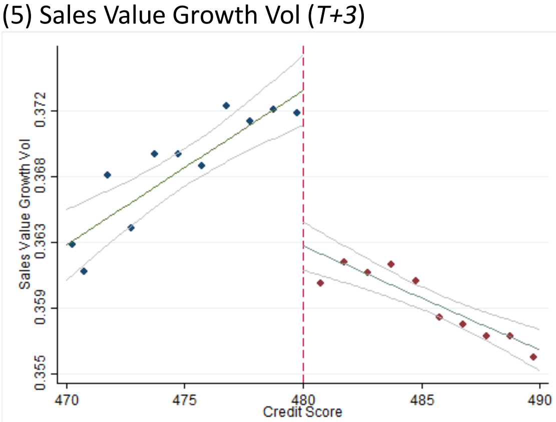
(3) Sales Value Growth Vol (*T+2*)



(4) Sales Quantity Growth Vol (*T+2*)



(5) Sales Value Growth Vol (*T+3*)



(6) Sales Quantity Growth Vol (*T+3*)

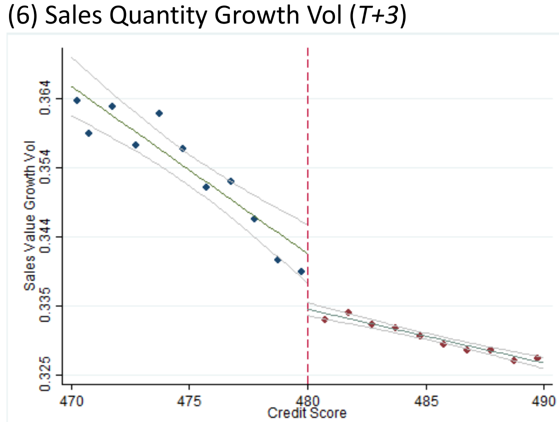
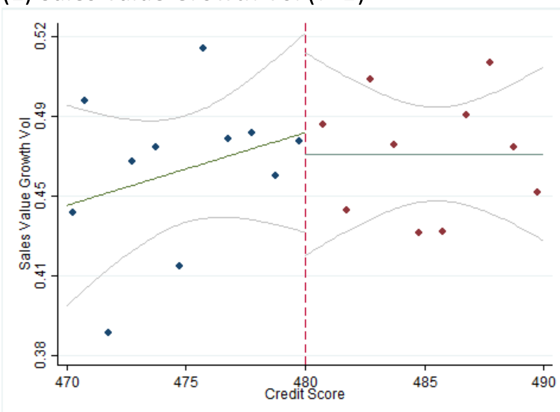


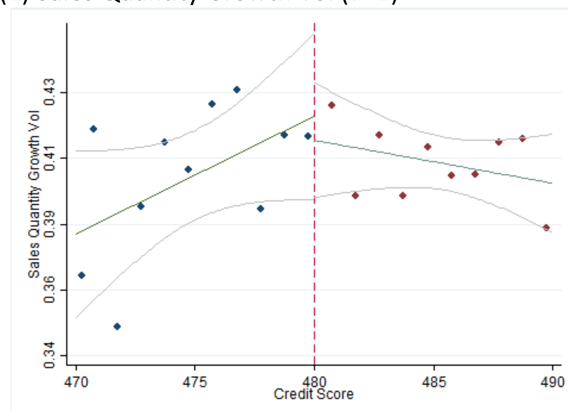
Figure 5. Placebo Tests: Discontinuity Plot on Firm Volatility in Cities with No Credit Granted

This figure presents the discontinuity plots of a firm's volatility measures subsequent to the credit allocation events against its credit scores in cities with no credit granted during the sample period. The detailed list of cities can be found on p. 21. The sample includes 18,810 firm-time observations for the full sample, and 1,340 firm-time observations for the [470, 490] range. Panels (1) and (2) plot the average *Sales value growth vol* and *Sales quantity growth vol*, respectively, in month *t+1* against the credit score in month *t*. Panels (3) and (4), and Panels (5) and (6) plot the average of these variables in months *t+2* and *t+3* against the credit score in month *t*.

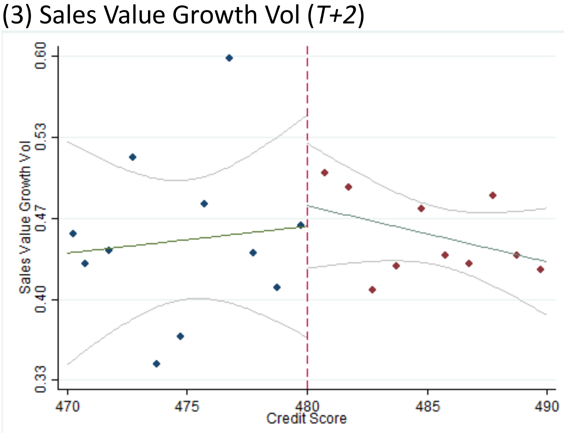
(1) Sales Value Growth Vol (*T+1*)



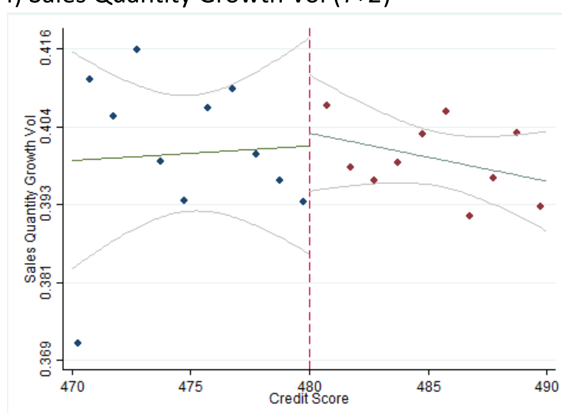
(2) Sales Quantity Growth Vol (*T+1*)



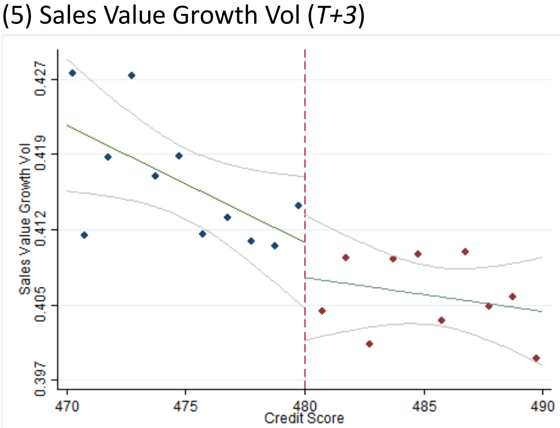
(3) Sales Value Growth Vol (*T+2*)



(4) Sales Quantity Growth Vol (*T+2*)



(5) Sales Value Growth Vol (*T+3*)



(6) Sales Quantity Growth Vol (*T+3*)

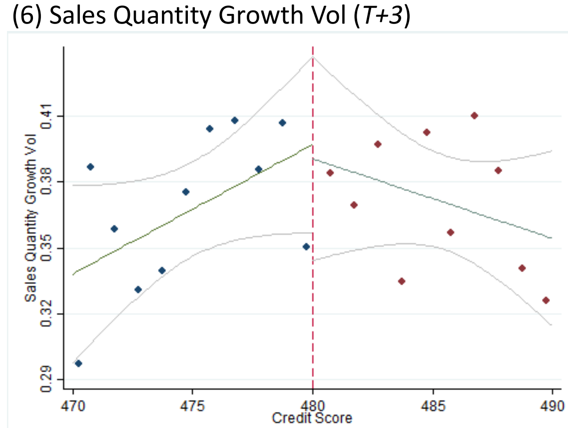


Table 1. Summary Statistics

This table provides summary statistics for the key variables in our analysis. Panel A is based on the full sample, as defined in Section 3.1. Panel B is based on the local sample with credit scores within the [460,500] range. *Credit Score* is the credit score generated by Ant Financial's credit scoring model for a firm in a month. *Credit Access* is an indicator variable that equals 1 if a firm has been granted with a credit line in a month, and 0 otherwise. *Credit Amount* is the maximum line of credit granted for a firm in a month. *Sales value growth vol* is the monthly standard deviation of weekly growth rate of total transaction amount in RMB, which is calculated for the subsequent month for each firm in the sample. *Sales quantity growth vol* is the monthly standard deviation of the weekly growth rate of total transaction quantity, which is calculated for the subsequent month for each firm in the sample. *Sales* is the monthly sales of a firm in RMB. *Firm Age* is the number of months since the firm's registration on the Taobao Marketplace platform. Detailed definition of each variable is provided in Appendix A.

Panel A. Full Sample						
	Mean	Std. Dev.	Q1	Median	Q3	N
Credit score	525.628	36.153	501.001	525.866	550.423	8,848,251
Credit access	0.803	0.398	1	1	1	8,848,251
Credit amount	33544.035	102348.495	10000	11000	13000	8,848,251
Sales value growth vol	0.444	0.250	0.265	0.398	0.561	8,848,251
Sales quantity growth vol	0.404	0.261	0.229	0.343	0.499	8,848,251
Sales value	48962.376	203829.640	4400	13500	38900	8,848,251
Firm age	38.744	26.669	17	32	56	8,848,251
Owner gender	0.526	0.499	0	1	1	8,848,251
Owner married	0.655	0.476	0	1	1	8,848,251
Owner owns property	0.038	0.191	0	0	0	8,848,251
Owner income	6394.643	1681.109	5238.695	6195.177	7421.106	8,848,251
Owner Associate	0.051	0.219	0	0	0	8,848,251
Owner undergraduate	0.044	0.206	0	0	0	8,848,251
Owner postgraduate	0.049	0.215	0	0	0	8,848,251
Panel B. [460, 500] Sample						
	Mean	Std. Dev.	Q1	Median	Q3	N
Credit score	486.257	10.709	479.073	488.956	495.206	561,313
Credit access	0.716	0.451	1	1	1	561,313
Credit amount	20536.199	67227.175	10000	10000	15000	561,313
Sales value growth vol	0.384	0.181	0.259	0.360	0.475	561,313
Sales quantity growth vol	0.341	0.173	0.228	0.311	0.411	561,313
Sales value	39504.480	116840.982	5700	14500	36300	561,313
Firm age	25.635	17.643	13	21	34	561,313
Owner gender	0.548	0.498	0	1	1	561,313
Owner married	0.636	0.481	0	1	1	561,313
Owner owns property	0.029	0.168	0	0	0	561,313
Owner income	5966.835	1430.819	5000.370	5810.597	6865.209	561,313
Owner Associate	0.059	0.236	0	0	0	561,313
Owner undergraduate	0.041	0.198	0	0	0	561,313
Owner postgraduate	0.040	0.195	0	0	0	561,313
Firm exit (t+1)	0.046	0.210	0	0	0	793,420
Firm exit (t+2)	0.067	0.249	0	0	0	793,420
Firm exit (t+3)	0.093	0.290	0	0	0	793,420

Table 2. Access to Credit and Firm Volatility: Fuzzy RDD

This table shows the Fuzzy RD estimates of credit access on firm volatility. We use the TSLS regression system in equations (1)-(2) to implement the design. In the first stage (Panel A), we regress the credit access dummy *D* over an indicator variable *T*, which is set to 1 when credit score is greater than 480, and 0 otherwise, and an interaction of *T* with the standardized credit scores. In the second stage (Panel B), we regress the dependent variable over instrumented *D* and an interaction of *T* with the standardized credit scores. We use the local linear regression model over the credit scores from 460 to 500 in both stages. The dependent variable is *Sales value growth vol* in columns (1) to (3), which is the monthly standard deviation of weekly growth rate of total transaction amount in RMB, calculated for the next one, two, and three months for each firm in the sample, and *Sales quantity growth vol* in columns (4) to (6), which is the monthly standard deviation of weekly growth rate of total transaction quantity, which is calculated for the next one, two, and three months for each firm in the sample. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. First Stage

	Dependent Variable
	D [Credit Access]
	(1)
T [Credit score≥480]	0.2274***
	(104.7387)
Industry FE	Yes
Time FE	Yes
Adj. R^2	0.3594
N	561,313

Panel B. Second Stage

	Dependent Variable					
	Sales Value Growth Vol			Sales Quantity Growth Vol		
	T+1	*T+2*	*T+3*	*T+1*	*T+2*	*T+3*
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{D}$ [Predicted credit access]	-0.0423***	-0.0607***	-0.0547***	-0.0607***	-0.0609***	-0.0571***
	(-9.2865)	(-13.0115)	(-11.9719)	(-14.0764)	(-13.8682)	(-13.1494)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0943	0.0849	0.0884	0.1098	0.1049	0.1056
N	561,313	561,313	561,313	561,313	561,313	561,313

Table 3. Placebo Tests: Alternative Cutoffs to Assign Credit

This table shows the results of placebo tests, where 460 and 500 are used as the respective cutoffs to assign credit. We use the TSLS regression system in equations (1)-(2) to implement the design. In the first stage (Panel A), we regress the credit access dummy *D* over an indicator variable *T*, which is set to 1 when credit score is greater than 480, and 0 otherwise, and an interaction of *T* with the standardized credit scores. In the second stage (Panel B), we regress the dependent variable over instrumented *D* and an interaction of *T* with the standardized credit scores. We use the local linear regression model over the credit scores from 460 to 500 in both stages. The dependent variable is *Sales value growth vol* in columns (1) and (3), which is the monthly standard deviation of weekly growth rate of the total transaction amount in RMB, calculated for the subsequent month for each firm in the sample, and *Sales quantity growth vol* in columns (2) and (4), which is the monthly standard deviation of weekly growth rate of total transaction quantity, calculated for the subsequent month for each firm in the sample. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. First Stage

	Dependent Variable	
	D [Credit Access]	
	(1)	(2)
T [Credit score≥460 or 500]	0.0321	-0.0134
	(1.0156)	(-1.3927)
Placebo cutoff	460	500
Score range	[440,480]	[480,520]
Industry FE	Yes	Yes
Time FE	Yes	Yes
Adj. R^2	0.2393	0.1352
N	222,659	1,298,741

Panel B. Second Stage

	Dependent Variable			
	Sales Value Growth Vol	Sales Quantity Growth Vol	Sales Value Growth Vol	Sales Quantity Growth Vol
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	-0.0479	-0.0647	-0.0701	-0.0677
	(-1.0752)	(-1.5585)	(-1.4387)	(-1.4390)
Placebo cutoff	460		500	
Score range	[440,480]		[480,520]	
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0860	0.0985	0.0990	0.1164
N	222,659	222,659	1,298,741	1,298,741

Table 4. Alternative Bandwidths

This table shows the results of RDD tests, where alternative bandwidths are used for the fuzzy RDD estimates. We use the TSLS regression system in equations (1)-(2) to implement the design. Column (1) of Panel A and columns (1) and (2) of Panel B report to the first and second stage of regressions over a local range of credit scores from 465 to 495 (i.e., a bandwidth of 15). Column (2) of Panel A and columns (3) and (4) of Panel B report to the first and second stage of regressions over a local range of credit scores from 470 to 490 (i.e., a bandwidth of 10). In Panel B, the dependent variable is *Sales value growth vol* in columns (1) and (3), which is the monthly standard deviation of weekly growth rate of the total transaction amount in RMB, calculated for the subsequent month for each firm in the sample, and *Sales quantity growth vol* in columns (2) and (4), which is the monthly standard deviation of weekly growth rate of total transaction quantity, calculated for the subsequent month for each firm in the sample. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. First Stage

	Dependent Variable	
	D [Credit Access]	
	(1)	(2)
T [Credit score≥480]	0.1948***	0.1467***
	(71.9635)	(41.3123)
Score range	[465,495]	[470,490]
Industry FE	Yes	Yes
Time FE	Yes	Yes
Adj. R^2	0.2954	0.2296
N	387,263	238,995

Panel B. Second Stage

	Dependent Variable			
	Sales Value Growth Vol	Sales Quantity Growth Vol	Sales Value Growth Vol	Sales Quantity Growth Vol
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	-0.0621***	-0.0567***	-0.062***	-0.0662***
	(-10.1303)	(-9.8358)	(-6.2137)	(-7.0714)
Score range	[465,495]		[470,490]	
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj. R^2	0.0934	0.1088	0.0938	0.1078
N	387,263	387,263	238,995	238,995

Table 5. Access to Credit and Firm Volatility: Countercyclical Effect

This table shows the countercyclical effect of FinTech credit on firm volatility. We use *M2_growth* and *SHIBOR_growth* to measure the degree of monetary condition. Lower *M2_growth* and higher *SHIBOR_growth* indicate tighter monetary conditions. We use the TSLS regression system in equations (1)-(2) to implement the design. The first stage is the same as Panel A of Table 2. In the second stage (Panels A and B), we regress the dependent variable over instrumented *D*, an interaction of instrumented *D* with our measures of monetary tightness, and an interaction of *T* with the standardized credit scores. We use the local linear regression model over the credit scores from 460 to 500 in both stages. The dependent variable is *Sales value growth vol* in columns (1) to (3), which is the monthly standard deviation of weekly growth rate of the total transaction amount in RMB, calculated for the next one, two, and three months for each firm in the sample, and *Sales quantity growth vol* in columns (4) to (6), which is the monthly standard deviation of weekly growth rate of the total transaction quantity, calculated for the next one, two, and three months for each firm in the sample. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. Second Stage (M2_Growth)

	Dependent Variable					
	Sales Value Growth Vol			Sales Quantity Growth Vol		
	T+1	*T+2*	*T+3*	*T+1*	*T+2*	*T+3*
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{D}$ [Predicted credit access]	-0.0645***	-0.0746***	-0.0609***	-0.0603***	-0.0572***	-0.0595***
	(-15.0423)	(-16.9886)	(-14.1474)	(-14.8755)	(-13.8277)	(-14.5593)
$\widehat{D}$ × M2_growth	0.0069***	0.0093***	0.0080***	0.0078***	0.0091***	0.0080***
	(4.4465)	(5.8342)	(5.1129)	(5.3217)	(6.0937)	(5.4243)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0932	0.0849	0.0884	0.1104	0.1037	0.1046
N	561,313	561,313	561,313	561,313	561,313	561,313

Panel B. Second Stage (SHIBOR_Growth)

	Dependent Variable					
	Sales Value Growth Vol			Sales Quantity Growth Vol		
	T+1	*T+2*	*T+3*	*T+1*	*T+2*	*T+3*
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{D}$ [Predicted credit access]	-0.0427***	-0.0477***	-0.0495***	-0.0272***	-0.0384***	-0.0477***
	(-7.0774)	(-7.7132)	(-8.1791)	(-4.7665)	(-6.6013)	(-8.2949)
$\widehat{D}$ × SHIBOR_growth	-0.0038***	-0.0030***	-0.0025**	-0.0037***	-0.0055***	-0.0055***
	(-4.0294)	(-3.1165)	(-2.6287)	(-4.1746)	(-6.0353)	(-6.0800)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0931	0.0850	0.0886	0.1078	0.1044	0.1050
N	561,313	561,313	561,313	561,313	561,313	561,313

Table 6. Access to Credit and Firm Volatility: Subsample Analysis by Local GDP Growth

This table shows the differential effect of credit access on firm volatility in subsamples of cities with varying levels of local GDP growth. We use the quarterly change in GDP in a city as the measure of local GDP growth. Only firms with city locations are included in the analysis. The high GDP growth subsample consists of firms operating in a city where GDP growth is in the top tercile of the sample, while the low GDP growth subsample consists of firms operating in a city where GDP growth is in the bottom tercile of the sample. We use the TSLS regression system in equations (1)-(2) to implement the design. In the first stage (Panel A), we regress the credit access dummy *D* over an indicator variable *T*, which is set to 1 when credit score is greater than 480, and 0 otherwise, and an interaction of *T* with the standardized credit scores. In the second stage (Panels B, C, and D), we regress the dependent variable over instrumented *D* and an interaction of *T* with the standardized credit scores. We use the local linear regression model over the credit scores from 460 to 500 in both stages. The dependent variable is *Sales value growth vol* in columns (1) and (2), which is the monthly standard deviation of weekly growth rate of the total transaction amount in RMB, calculated for the subsequent month for each firm in the sample, and *Sales quantity growth vol* in columns (3) and (4), which is the monthly standard deviation of weekly growth rate of the total transaction quantity, calculated for the subsequent month for each firm in the sample. Panels C and D reports the subsample results for *Sales value growth vol* and *Sales quantity growth vol* for the next two and three months respectively. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. We test the difference of the coefficients between the high and low groups based on Wald test and the P-values are reported. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. First Stage		
	Dependent Variable	
	D [Credit Access]	
	GDP Growth	
	High	*Low*
	(1)	(2)
T [Credit score≥480]	0.2429***	0.2242***
	(30.021)	(32.5574)
Industry FE	Yes	Yes
Time FE	Yes	Yes
Adj. R^2	0.2981	0.2960
N	36,945	50,874

Panel B. Second Stage (T+1)				
	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	GDP Growth		GDP Growth	
	High	*Low*	*High*	*Low*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	-0.0146	-0.0697***	0.0206	-0.0805***
	(-0.8438)	(-4.4562)	(1.2270)	(-5.4199)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0551**		0.1011***	
(P-value)	(0.028)		(0.000)	
Adj. R^2	0.0811	0.1054	0.1081	0.1312
N	36,945	50,874	36,945	50,874

Panel C. Second Stage (T+2)

	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	GDP Growth		GDP Growth	
	High	*Low*	*High*	*Low*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	0.0102	-0.0861***	-0.0019	-0.0718***
	(0.5772)	(-5.3734)	(-0.1104)	(-4.7226)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0963***		0.0699***	
(P-value)	(0.000)		(0.006)	
Adj. R^2	0.0772	0.1004	0.1037	0.1272
N	36,945	50,874	36,945	50,874

Panel D. Second Stage (T+3)

	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	GDP Growth		GDP Growth	
	High	*Low*	*High*	*Low*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	0.0030	-0.0830***	0.0055	-0.0859***
	(0.1761)	(-5.2917)	(0.3310)	(-5.7367)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0860***		0.0914***	
(P-value)	(0.001)		(0.001)	
Adj. R^2	0.0799	0.1075	0.1086	0.1275
N	36,945	50,874	36,945	50,874

Table 7. Access to Credit and Firm Volatility: Subsample Analysis by Industry Competition

This table shows the differential effect of credit access on firm volatility in subsamples of industries with varying degrees of industry competition (HHI). Higher HHI indicates less competition in the industry. We use the sales in the month before the treatment events to calculate the industry HHI. The high HHI subsample consists of firms operating in a specific industry where HHI is in the top tercile of the sample, while the low HHI subsample consists of firms operating in a specific industry where HHI is in the bottom tercile of the sample. We use the TSLS regression system in equations (1)-(2) to implement the design. In the first stage (Panel A), we regress the credit access dummy *D* over an indicator variable *T*, which is set to 1 when credit score is greater than 480, and 0 otherwise, and an interaction of *T* with the standardized credit scores. In the second stage (Panels B, C, and D), we regress the dependent variable over instrumented *D* and an interaction of *T* with the standardized credit scores. We use the local linear regression model over the credit scores from 460 to 500 in both stages. The dependent variable is *Sales value growth vol* in columns (1) and (2), which is the monthly standard deviation of weekly growth rate of total transaction amount in RMB, calculated for the subsequent month for each firm in the sample, and *Sales quantity growth vol* in columns (3) and (4), the monthly standard deviation of weekly growth rate of the total transaction quantity, which is calculated for the subsequent month for each firm in the sample. Panels C and D reports the subsample results for *Sales value growth vol* and *Sales quantity growth vol* for the next two and three months respectively. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. We test the difference of the coefficients between the high and low groups based on Wald test and the P-values are reported. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. First Stage

	Dependent Variable	
	D [Credit Access]	
	Industry HHI	
	High	*Low*
	(1)	(2)
T [Credit score≥480]	0.2252***	0.2131***
	(56.7754)	(59.3606)
Industry FE	Yes	Yes
Time FE	Yes	Yes
Adj. R^2	0.3579	0.3686
N	185,730	196,964

Panel B. Second Stage (T+1)

	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	Industry HHI		Industry HHI	
	High	*Low*	*High*	*Low*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	-0.0006	-0.0436***	0.0122	-0.0334***
	(-0.0655)	(-9.5939)	(1.2740)	(-8.6409)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0430***		0.0456***	
(P-value)	(0.000)		(0.000)	
Adj. R^2	0.0302	0.0152	0.0414	0.0329
N	185,730	196,964	185,730	196,964

Panel C. Second Stage (T+2)				
	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	Industry HHI		Industry HHI	
	High	*Low*	*High*	*Low*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	-0.0050	-0.0373***	0.0073	-0.0157***
	(-0.5009)	(-8.6729)	(0.7528)	(-4.0373)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0323***		0.0230**	
(P-value)	(0.008)		(0.040)	
Adj. R^2	0.0274	0.0147	0.0389	0.0229
N	185,730	196,964	185,730	196,964

Panel D. Second Stage (T+3)				
	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	Industry HHI		Industry HHI	
	High	*Low*	*High*	*Low*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	-0.0014	-0.0223***	0.0138	-0.0110***
	(-0.1411)	(-5.2438)	(1.4277)	(-2.7251)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0209*		0.0248**	
(P-value)	(0.067)		(0.028)	
Adj. R^2	0.0286	0.0238	0.0397	0.0273
N	185,730	196,964	185,730	196,964

Table 8. Access to Credit and Firm Volatility: Subsample Analysis by Legal Environment and Contract Enforcement

This table shows the differential effect of credit access on firm volatility in subsamples of regions with varying levels of legal environment and contract enforcement. The measure of legal environment and contract enforcement comes from a subcategory of market development index (MDI). The MDI was developed by Fan & Wang (2003) and updated to 2014, which has been widely used to measure institutional environment in economics and finance research on China. The high legal environment and contract enforcement subsample consists of firms operating in a province where the measure is in the top tercile of the sample, while the low legal environment and contract enforcement subsample consists of firms operating in a province where the measure is in the bottom tercile of the sample. We use the TSLS regression system in equations (1)-(2) to implement the design. In the first stage (Panel A), we regress the credit access dummy *D* over an indicator variable *T*, which is set to 1 when credit score is greater than 480, and 0 otherwise, and an interaction of *T* with the standardized credit scores. In the second stage (Panels B, C, and D), we regress the dependent variable over instrumented *D* and an interaction of *T* with the standardized credit scores. We use the local linear regression model over the credit scores from 460 to 500 in both stages. The dependent variable is *Sales value growth vol* in columns (1) and (2), which is the monthly standard deviation of weekly growth rate of total transaction amount in RMB, calculated for the subsequent month for each firm in the sample, and *Sales quantity growth vol* in columns (3) and (4), which is the monthly standard deviation of weekly growth rate of total transaction quantity, which is calculated for the subsequent month for each firm in the sample. Panels C and D report the subsample results for *Sales value growth vol* and *Sales quantity growth vol* for the next two and three months respectively. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. We test the difference of the coefficients between the high and low groups based on Wald test and the P-values are reported. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. First Stage

	Dependent Variable	
	D [Credit Access]	
	Legal Environment and Contract Enforcement	
	High	*Low*
	(1)	(2)
T [Credit score≥480]	0.1825***	0.175***
	(27.5099)	(23.5505)
Industry FE	Yes	Yes
Time FE	Yes	Yes
Adj. R^2	0.3337	0.3066
N	61,802	50,146

Panel B. Second Stage (T+1)

	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	Legal Environment and Contract Enforcement		Legal Environment and Contract Enforcement	
	High	*Low*	*High*	*Low*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	-0.0163	-0.0786***	-0.0033	-0.0886***
	(-0.9191)	(-3.5598)	(-0.1973)	(-4.1959)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Difference	0.0623**		0.0853***	
(P-value)	(0.040)		(0.005)	
Adj. R^2	0.1142	0.1022	0.1222	0.1297
N	61,802	50,146	61,802	50,146

Panel C. Second Stage (T+2)

	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	Legal Environment and Contract Enforcement		Legal Environment and Contract Enforcement	
	High	*Low*	*High*	*Low*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	-0.0124	-0.0627***	-0.0133	-0.0652***
	(-0.6943)	(-2.7839)	(-0.7774)	(-3.0414)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0503*		0.0519*	
(P-value)	(0.096)		(0.073)	
Adj. R^2	0.1040	0.0933	0.1164	0.1226
N	61,802	50,146	61,802	50,146

Panel D. Second Stage (T+3)

	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	Legal Environment and Contract Enforcement		Legal Environment and Contract Enforcement	
	High	*Low*	*High*	*Low*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	0.0021	-0.0670***	-0.0009	-0.0750***
	(0.1217)	(-3.0097)	(-0.0529)	(-3.5537)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0692**		0.0741***	
(P-value)	(0.024)		(0.013)	
Adj. R^2	0.1048	0.0954	0.1171	0.1235
N	61,802	50,146	61,802	50,146

Table 9. Access to Credit and Firm Volatility: Subsample Analysis by Firm Age

This table shows the differential effect of credit access on firm volatility in subsamples based on firm age. The young subsample consists of firms whose age is in the bottom tercile of the sample, while the old subsample consists of firms whose age is in the top tercile of the sample. We use the TSLS regression system in equations (1)-(2) to implement the design. In the first stage (Panel A), we regress the credit access dummy *D* over an indicator variable *T*, which is set to 1 when credit score is greater than 480, and 0 otherwise, and an interaction of *T* with the standardized credit scores. In the second stage (Panels B, C, and D), we regress the dependent variable over instrumented *D* and an interaction of *T* with the standardized credit scores. We use the local linear regression model over the credit scores from 460 to 500 in both stages. The dependent variable is *Sales value growth vol* in columns (1) and (2), which is the monthly standard deviation of weekly growth rate of total transaction amount in RMB, calculated for the subsequent month for each firm in the sample, and *Sales quantity growth vol* in columns (3) and (4), which is the monthly standard deviation of weekly growth rate of total transaction quantity, which is calculated for the subsequent month for each firm in the sample. Panels C and D report the subsample results for *Sales value growth vol* and *Sales quantity growth vol* for the next two and three months respectively. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. We test the difference of the coefficients between the old and young groups based on Wald test and the P-values are reported. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. First Stage

	Dependent Variable	
	D [Credit Access]	
	Firm Age	
	Old	*Young*
	(1)	(2)
T [Credit score≥480]	0.1609***	0.285***
	(40.3492)	(79.0489)
Industry FE	Yes	Yes
Time FE	Yes	Yes
Adj. R^2	0.2806	0.4184
N	181,811	195,695

Panel B. Second Stage (T+1)

	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	Firm Age		Firm Age	
	Old	*Young*	*Old*	*Young*
	(1)	(2)	(3)	(4)
$\widehat{D}$ [Predicted credit access]	-0.0061	-0.0401***	-0.0080	-0.0407***
	(-0.9461)	(-6.9153)	(-1.3208)	(-7.3745)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0340***		0.0327***	
(P-value)	(0.001)		(0.001)	
Adj. R^2	0.0938	0.0822	0.0915	0.1060
N	181,811	195,695	181,811	195,695

Panel C. Second Stage (T+2)

	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	Firm Age		Firm Age	
	Old	*Young*	*Old*	*Young*
	(1)	(2)	(3)	(4)
$\widehat{\mathrm{D}}$ [Predicted credit access]	0.0061	-0.0416***	-0.0077	-0.0309***
	(0.9340)	(-6.9857)	(-1.2451)	(-5.4747)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0477***		0.0232**	
(P-value)	(0.000)		(0.012)	
Adj. R^2	0.0664	0.0736	0.0895	0.0994
N	181,811	195,695	181,811	195,695

Panel D. Second Stage (T+3)

	Dependent Variable			
	Sales Value Growth Vol		Sales Quantity Growth Vol	
	Firm Age		Firm Age	
	Old	*Young*	*Old*	*Young*
	(1)	(2)	(3)	(4)
$\widehat{\mathrm{D}}$ [Predicted credit access]	-0.0061	-0.0477***	0.0068	-0.0353***
	(-0.9468)	(-10.1306)	(1.1409)	(-7.8415)
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Difference	0.0416***		0.0421***	
(P-value)	(0.000)		(0.000)	
Adj. R^2	0.0740	0.0776	0.0857	0.1013
N	181,811	195,695	181,811	195,695

Table 10. Access to Credit and Firm Exit

This table shows the Fuzzy RD estimates of credit access on firm exit probability. We use the TSLS regression system in equations (1)-(2) to implement the design. In the first stage (Panel A), we regress the credit access dummy *D* over an indicator variable *T*, which is set to 1 when credit score is greater than 480, and 0 otherwise, and an interaction of *T* with the standardized credit scores. In the second stage (Panel B), we regress the dependent variable over instrumented *D* and an interaction of *T* with the standardized credit scores. We use the local linear regression model over the credit scores from 460 to 500 in both stages. The dependent variable is *Firm exit*, the probability of exit of the business for the next one, two, and three months for each firm in the sample. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. First Stage	
	Dependent Variable
	D [Credit Access]
	(1)
T [Credit score≥480]	0.2551***
	(133.5651)
Industry FE	Yes
Time FE	Yes
Adj. R^2	0.3646
N	793,420

Panel B. Second Stage			
	Dependent Variable		
	Firm Exit		
	T+1	*T+2*	*T+3*
	(1)	(2)	(3)
$\widehat{D}$ [Predicted credit access]	-0.1013***	-0.1228***	-0.1496***
	(30.4724)	(26.3103)	(27.6191)
Industry FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj. R^2	0.0176	0.0248	0.0341
N	793,420	793,420	793,420

Table 11. Robustness Tests: with Additional Firm-level Controls

This table shows the results of robustness tests, where we add additional firm covariates to control for firm-level heterogeneities. We use the TSLS regression system in equations (1)-(2) to implement the design. In the first stage (Panel A), we regress the credit access dummy *D* over an indicator variable *T*, which is set to 1 when credit score is greater than 480, and 0 otherwise, and an interaction of *T* with the standardized credit scores. In the second stage (Panels B and C), we regress the dependent variable over instrumented *D*, an interaction of *T* with the standardized credit scores, and a series of firm-level variables, including the natural logarithm of monthly sales value (*Sales value*), the natural logarithm of firm age (*Firm age*), the gender of the firm owner (*Owner gender*), whether the firm owner is married or not (*Owner married*), whether the owner owns real estate asset or not (*Owner owns property*), the natural logarithm of other monthly income (*Owner income*), and measures of owner education (*Owner Associate*, *Owner undergraduate*, and *Owner graduate*). We use the local linear regression model over the credit scores from 460 to 500 in both stages. In Panel C, we further include city-fixed effect. In Panels B and C, the dependent variable is *Sales value growth vol* in columns (1) and (3), which is the monthly standard deviation of the weekly growth rate of total transaction amount in RMB, calculated for the subsequent month for each firm in the sample, and *Sales quantity growth vol* in columns (2) and (4), which is the monthly standard deviation of weekly growth rate of total transaction quantity, which is calculated for the subsequent month for each firm in the sample. Industry- and time-fixed effects are included. T-statistics are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% respectively.

Panel A. First Stage

	Dependent Variable
	D [Credit Access]
	(1)
T [Credit score≥480]	0.2244***
	(100.9154)
Industry FE	Yes
Time FE	Yes
Adj. R^2	0.3629
N	529,537

Panel B. Second Stage (with More Controls)

	Dependent Variable					
	Sales Value Growth Vol			Sales Quantity Growth Vol		
	T+1	*T+2*	*T+3*	*T+1*	*T+2*	*T+3*
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{D}$ [Predicted credit access]	-0.0450***	-0.0497***	-0.0459***	-0.0460***	-0.0501***	-0.0530***
	(-9.9555)	(-10.5931)	(-9.8405)	(-10.5041)	(-11.1192)	(-11.8097)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.1721	0.1410	0.1219	0.1497	0.1319	0.1185
N	529,537	529,537	529,537	529,537	529,537	529,537

Panel C. Second Stage (with More Controls and City Fixed Effect)

	Dependent Variable					
	Sales Value Growth Vol			Sales Quantity Growth Vol		
	T+1	*T+2*	*T+3*	*T+1*	*T+2*	*T+3*
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{D}$ [Predicted credit access]	-0.0389***	-0.0507***	-0.0448***	-0.0424***	-0.0475***	-0.0496***
	(-8.7215)	(-10.9823)	(-9.7549)	(-9.8329)	(-10.7307)	(-11.2178)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.1724	0.1440	0.1226	0.1506	0.1326	0.1163
N	529,537	529,537	529,537	529,537	529,537	529,537

Table 12. Robustness Tests: Alternative RDD Specifications

This table shows the results of robustness tests, using alternative RDD model specifications. We use the TSLS regression system in equations (5)-(6) and uses the same functional form of the linear term in the standardized credit score on both sides of the cutoff point to implement the design. Panel B uses second-order polynomials, while Panel C uses third-order polynomials. The dependent variable is *Sales value growth vol* in columns (1) to (3), which is the monthly standard deviation of the weekly growth rate of total transaction amount in RMB, calculated for the next one, two, and three months for each firm in the sample, and *Sales quantity growth vol* in columns (4) to (6), the monthly standard deviation of weekly growth rate of total transaction quantity, calculated for the next one, two, and three months for each firm in the sample. Industry- and time-fixed effects are included. T-statistics are reported in the parentheses. *, **, and *** denotes for statistical significance at 10%, 5%, and 1% respectively.

Panel A. Same functional forms

	Dependent Variable					
	Sales Value Growth Vol			Sales Quantity Growth Vol		
	T+1	*T+2*	*T+3*	*T+1*	*T+2*	*T+3*
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{D}$ [Predicted credit access]	-0.0421***	-0.0420***	-0.0311***	-0.0387***	-0.0566***	-0.0476***
	(-11.9700)	(-11.6696)	(-8.8217)	(-11.6474)	(-16.6751)	(-14.1783)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0941	0.0856	0.0895	0.1112	0.1051	0.1057
N	561,313	561,313	561,313	561,313	561,313	561,313

Panel B. Second-order polynomials (k=2)

	Dependent Variable					
	Sales Value Growth Vol			Sales Quantity Growth Vol		
	T+1	*T+2*	*T+3*	*T+1*	*T+2*	*T+3*
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{D}$ [Predicted credit access]	-0.0528***	-0.0445***	-0.0458***	-0.0428***	-0.0538***	-0.0439***
	(-13.6321)	(-11.8294)	(-12.4440)	(-12.3474)	(-15.1912)	-12.5544
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.091	0.0856	0.0892	0.1113	0.1054	0.1060
N	561,313	561,313	561,313	561,313	561,313	561,313

Panel C. Third-order polynomials (k=3)

	Dependent Variable					
	Sales Value Growth Vol			Sales Quantity Growth Vol		
	T+1	*T+2*	*T+3*	*T+1*	*T+2*	*T+3*
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{D}$ [Predicted credit access]	-0.0278***	-0.0282***	-0.0272***	-0.0254***	-0.0212***	-0.0290***
	(-21.3373)	(-21.2324)	(-20.8534)	(-20.7335)	(-16.9290)	(-23.4073)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.0755	0.0641	0.0664	0.0978	0.0814	0.0812
N	561,313	561,313	561,313	561,313	561,313	561,313

Appendix A Variable Definition

This appendix provides the definition of all of the variables used in the paper.

Variable names	Variable definitions
Credit score	The Ant Financial credit score for a firm in a month.
Credit access	An indicator variable that equals 1 if a firm is granted a credit line by Ant Financial from the end of the current month *t* to the end of month *t+3*, and 0 if it is not granted a credit line from the end of current month to the end of next month.
Credit amount	The maximum line of credit granted for a firm in month.
Sales value growth vol	The monthly standard deviation of the weekly growth rate of total transaction amount in RMB, calculated for the subsequent month for each firm in the sample.
Sales quantity growth vol	The monthly standard deviation of the weekly growth rate of total transaction quantity, calculated for the subsequent month for each firm in the sample.
Sales value	The total transaction amount in RMB completed by a firm in a month.
Firm age	The age of a firm, measured by the total number of months present on Taobao Marketplace since the official registration date.
NDisaster	An indicator variable that equals 1 for a firm if it is located in a city that has been shocked by a major natural disaster in the recent two months, and 0 otherwise.
M2_growth	Monthly growth rate of M2 money supply. Lower *M2_growth* indicates tighter monetary conditions.
SHIBOR_growth	Monthly growth rate of Shanghai Interbank Offered Rate (SHIBOR). Higher *SHIBOR_growth* indicate tighter monetary conditions.
GDP growth	The quarterly change in GDP in a city to measure local GDP growth.
Industry HHI	For each month before a credit allocation event, we construct the Herfindahl-Hirschman index (HHI) of each industry based on the market share of the firms in terms of sales. Higher HHI indicates less competition in the industry.
Legal Environment and Contract Enforcement	The measure of legal environment and contract enforcement comes from a subcategory of market development index (MDI). The MDI was developed by Fan & Wang (2003) and updated to 2014, which has been widely used to measure institutional environment in economics and finance research on China.
Owner gender	An indicator variable that equals 1 if the firm owner is male and zero if female.
Owner married	An indicator variable that equals 1 if the firm owner is married and 0 otherwise.
Owner income	The estimated monthly income of the firm owner earned from other sources.
Owner owns property	An indicator variable that equals 1 if the firm owner owns real estate assets and 0 otherwise.
Owner Associate	An indicator variable that equals 1 if the firm owner has an Associate's degree and 0 otherwise.
Owner undergraduate	An indicator variable that equals 1 if the firm owner has a Bachelor's degree and 0 otherwise.
Owner postgraduate	An indicator variable that equals 1 if the firm owner has a postgraduate degree and 0 otherwise.