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Finance and Firm Volatility: Evidence from Small Business Lending in China

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Abstract. The online trading platform Alibaba provides financial technology (FinTech) credit for millions of micro, small, and medium-sized enterprises (MSMEs). Using a novel data set of daily 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 stronger for firms with fewer alternative sources of financing. 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. Additional channel tests reveal that firms with FinTech credit invest more in advertising and product/sector diversification, particularly during business downturns, which serves as effective mechanisms through which credit access reduces firm volatility. Overall, our findings contribute to a better understanding of the role of FinTech credit in MSMEs.

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Keywords: FinTech credit • e-commerce microcredit • firm volatility • regression discontinuity design • microfinance • credit scoring

1. Introduction

We study the effect of financial technology (FinTech) credit on firm volatility in micro, small, and medium-sized enterprises (MSMEs). Most of the extant literature on 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[1] but also face a huge finance gap. As the International Finance Corporation estimated in 2017, about 40% of MSMEs are financially constrained, with the total finance gap amounting to US$5.2 trillion.[2] Therefore, studying the effect of credit access on these firms is of significant value (Berger et al. 1998, Black and Strahan 2002, Petersen and Rajan 2002, Berger et al. 2015). Moreover, by exploiting daily 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.[3] The availability of such granular 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 (e.g., Allen et al. 2005, 2017; Song and Xiong 2018). China is also the largest e-commerce market in the world by value of sales, with an estimated value of $1.1 trillion in 2018. Built on the significant development in the Internet and mobile network coverage, FinTech has played a fundamental role in facilitating credit allocation to MSMEs by compiling and analyzing their e-commerce transactional data (Barberis and Arner 2016). In this paper, we use credit data from Ant Financial, the largest FinTech company in the world serving MSMEs,[4] and Taobao, the largest online retail platform in the world, to explore how finance accessibility affects the output volatility of MSMEs.

Compared with traditional bank financing, 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 individuals (e.g., Buchak et al. 2018, Liberti and 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. Therefore, a natural research question is whether FinTech credit is a positive force in helping firms better smooth firms' operation and reduce volatility, which is what we focus on in this paper.

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. 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., Morgan et al. 2004, Comin and Mulani 2006, Larrain 2006, John et al. 2008), and is free from misvaluation by the equity market. Specifically, we look at sales growth volatility from high-frequency daily 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. Finally, we further examine the underlying channels, through which FinTech credit affects firm volatility.

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., D'Acunto et al. 2018). 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 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. 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 United States (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.[5] 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.[6] The choice of this 480 cutoff was based on a value-at-risk (VaR) model, where a cumulative default probability was adopted. Consequently, 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 below. Put another way, firms that score above 480 have greater access to credit from Ant Financial, whereas 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 and 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 are that the company collects daily 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.[7] In our main empirical analysis, we focus on firms around the 480 score cutoff to investigate credit access's effect on firm volatility. 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], that is, ±20 from the cutoff (a bandwidth of 20).[8] 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.[9] 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 and 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 daily 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 0.0382, 0.0412, and 0.0391, respectively, at $t + 1$, $t + 2$, and $t + 3$ compared with firms without credit access. The economic magnitude is also large, accounting for 16%, 17%, and 16% of the sample mean, respectively.

We further conduct two placebo tests and a battery of robustness checks. First, we use alternative cutoffs (460 or 500). 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 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 likely orthogonal to firms' sales volatility. As expected, we find no significant effect of credit access using this subsample of firms. We also try three alternative bandwidths in RDD and the results further confirm our baseline findings. 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.

We then perform further explorations of firm volatility along one theoretically motivated dimension: firms' alternative financing sources. We find that the effect of FinTech credit in reducing volatility is more pronounced for younger firms since young firms have a much shorter history for traditional lenders to effectively evaluate their credit risk and consequently less alternative financing choices.

Moreover, we also look at firm exit probability. We find that FinTech credit access significantly reduces the likelihood of a firm's bankruptcy or exit of the business. To better understand how FinTech credit affects firm volatility, we further conduct mechanism tests by looking into how firms utilize the credit. We find that firms having credit access invest more in advertising and product/sector diversification, particularly during business downturns, which serves as the effective mechanisms through which credit access reduces firm volatility.

This paper contributes to the following strands of literature. First, it relates to research on the determinants of firm volatility (e.g., John et al. 2008, Acharya et al. 2011, Hayes et al. 2012). We contribute by studying the effect of access to FinTech credit on firm real output volatility in MSMEs as the majority of the literature focuses on much larger public firms and stock volatility.[10] Moreover, the availability of high-frequency real-time daily transaction data for millions of MSMEs helps us to more accurately measure firm volatility. In addition, 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 are greater for MSMEs.

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

Third, this study contributes to the literature on finance and the economic growth volatility nexus initiated by King and Levine (1993), and particularly the literature on financing for small businesses (e.g., Berger et al. 1998, Petersen and Rajan 2002, Berger et al. 2015, Chen et al. 2017) and entrepreneurs (e.g., Black and Strahan 2002, Chen et al. 2010, Wang et al. 2012, Agarwal et al. 2019). In related papers, Hau et al. (2019, 2020) study the segmentation of credit market and the take-up decision of FinTech credit and entrepreneurship growth in Chinese small businesses. Hau et al. (2020) find that FinTech credit increases sales growth. We differ widely from Hau et al. (2019, 2020), as we are looking at a different research question as well as relying on data at significantly higher frequency (daily versus monthly) and all of our results are based on RDD estimation by exploiting locally exogenous variations in credit access.[11] We also check the effect on sales growth in our sample, and find that FinTech credit significantly increases sales growth, consistent with Hau et al. (2020). We further explore the firms' aggregate sales growth rate in the narrow bandwidth around the cutoff, and find that on average firms within [480, 485] grow the sales by 2% (significant at 1%) one month later, whereas the sales for the firms within [475, 480] stay the same (whose estimate is 0.2%, insignificant at 10%). This might imply that the FinTech credit from Ant Financial effectively grows a market.

The rest of the paper is organized as follows. Section 2 presents the institutional background and describes the Ant Financial platform. 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 concludes.

2. Institutional Background and the Platform

As the world's largest online retailer and one of the world's largest Internet companies,[12] Alibaba enables third-party sellers in China to take their own businesses to the web. This enables Alibaba to access the vast big data collected from 300 million registered shoppers and 20 million vendors using Alibaba.

2.1. FinTech E-commerce Credit

One clear feature of FinTech e-commerce credit that distinguishes it from traditional banking, peer-to-peer (P2P) financing, or crowdfunding is information acquisition. E-commerce credit lenders have access to a vast amount of data on their clients, that is, 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, and social relationships. This information helps mitigate the key challenges in traditional banking—adverse selection and moral hazard problems due to information asymmetries (Stiglitz and Weiss 1981).

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. 2018, Liberti and Petersen 2018). By replacing soft information with 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. 2019, Liberti and Petersen 2019).

Moreover, FinTech e-commerce lending is more efficient and effective in both postloan monitoring and debt enforcement. It can utilize real-time high-frequency data based on multidimensional metrics of the borrowers. The enforcement procedures/strategies of FinTech firms are based on real-time models and they are highly algorithmized. 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 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.

2.2. Ant Financial of Alibaba

Of the 20 million participating vendor businesses operating on the Alibaba platform, nearly 90% are small and 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. 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 three-minute application process, one-second loan granting, and zero manual intervention.[13]

As of August 2016, Ant Financial had provided a total of more than 700 billion Renminbi (RMB) (about $102 billion)[14] in loans to over four million small and microsized enterprises and entrepreneurs over the previous five years,[15] helping tackle capital shortages and allowing the businesses to survive and grow. The average loan is about 20,000 RMB (about $3,000), and the average rate of nonperforming loans is below 3%. The loans are relatively short term, from six to 12 months in maturity.

3. Data, Sample, and Variable Construction

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

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, and so on. 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 an unbalanced panel of 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 grouped 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 daily real-time transaction data: one based on sales value (*Sales value growth vol*), the other on sales quantity (*Sales quantity growth vol*). Specifically, *Sales quantity growth vol* is the monthly standard deviation of the daily 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 daily growth rate of the total transaction quantity calculated for the next one, two, and three months for each firm in the sample.[16] 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 quantity growth vol*) has an average value of 0.22 (0.19) with large variations, as indicated by a standard deviation of 0.20 (0.17) in the full sample.

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 $t + 3$. As shown in panel B of Table 1, 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 with a median of 479.

Table 1. Summary Statistics

Panel A: Full Sample						
Variable	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	33,544.035	102,348.495	10,000	11,000	13,000	8,848,251
Sales value growth vol	0.222	0.203	0.076	0.176	0.315	8,848,251
Sales quantity growth vol	0.187	0.173	0.063	0.147	0.263	8,848,251

Table 1. (Continued)

Panel B: Local Sample: Credit Score Range of [460, 500]

Variable	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	20,536.199	67,227.175	10,000	10,000	15,000	561,313
Sales value growth vol	0.242	0.203	0.095	0.191	0.390	561,313
Sales quantity growth vol	0.225	0.198	0.085	0.171	0.365	561,313
Sales value	39,504.480	116,840.982	5,700	14,500	36,300	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	5,966.835	1,430.819	5,000.370	5,810.597	6,865.209	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
Industry-adjusted advertising growth rate	−0.040	0.227	−0.304	0	0.012	561,313
Direct advertising output/sales value	0.129	0.424	0	0	0.154	561,313
New product	0.410	0.124	0	0.404	0.487	561,313
New industry	0.200	0.400	0	0	0	561,313
Industry sales growth	0.054	0.432	−0.280	−0.042	0.348	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

Note: A detailed definition of each variable is provided in the appendix.

We further define an indicator variable based on the credit score, T [*Credit score* $\geq$ 480], which is equal to 1 if *Credit score* is greater than 480, and 0 otherwise. As shown in Table 1, the average credit amount is 20,536 RMB (about $3,000) 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. The variable *Firm age* refers to the firm's age, as measured by the total number of months the firm was present on Taobao Marketplace in the interim since the firm's date of registration on the site. We further take the natural logarithm of *Sales value* and *Firm age* when we include them as control variables. The indicator variables *Owner gender* equals 1 if the firm owner is male and 0 if female, and *Owner married* equals 1 if the firm owner is married and 0 otherwise. We also include several variables to measure the owner's education: *Owner associate*, *Owner undergraduate*, and *Owner postgraduate*. 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) 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 firm- and economy-level characteristics for heterogeneity tests in Section 5.9 and firm-level measures to analyze the potential channels in Section 6. For example, *Industry-adjusted advertising growth rate* is the growth rate of the total amount of advertising expense that the seller invests to list their products as recommended products on Taobao Marketplace for the subsequent month for each firm in the sample, adjusted by its industry average value. The appendix provides detailed descriptions of our variables.

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 earlier, 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 and Lemieux 2008, Lee and 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 and Lemieux 2008, Lee and Lemieux 2010).

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). The dummy variable D, which refers to *Credit access*, 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. The dummy variable $T[Credit\,score \geq 480]$ 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. We use ρ^k as the coefficient of the kth-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 $T = 1$).[17] We also included industry fixed effects, φ_j, and time fixed effects, θ_t, to control for industry characteristics and contemporaneous confounding events.

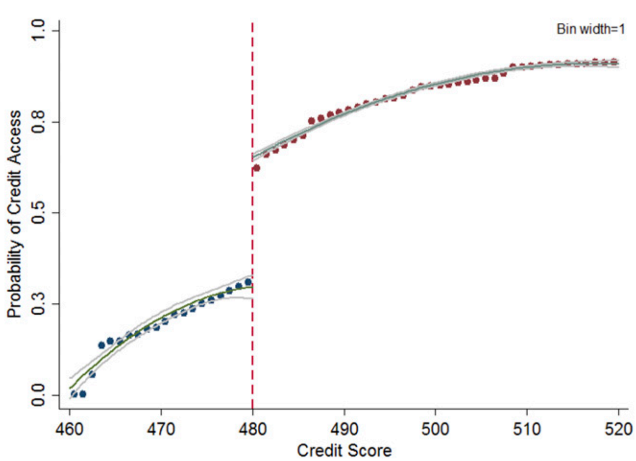
We use the estimates in Equation (1) to predict the probability of credit access and denote it with $\hat{D}$. Then in the second step, we regress our measures of firm volatility on $\hat{D}$ following Equation (2):

$$SalesGrVol_{i,t+n} = \alpha + \beta \hat{D}_{it} + \sum_{k=1}^{K} \gamma^k (s_{it} - s^*)^k + T_{it} \sum_{k=1}^{K} \delta^k (s_{it} - s^*)^k + \varphi_j + \theta_t + \mu_{it}, \qquad (2)$$

where the dependent variable is *SalesGrVol*, captured by two measures of monthly sales growth volatility by exploiting daily transaction data: *Sales value growth vol* and *Sales quantity growth vol*. Other variables are the same as defined in the first stage. Our major interest is the estimate of β, the coefficient of $\hat{D}$, 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 (15, 10, and 5) in Section 5.5, higher-order polynomials (K = 2 and K = 3), and alternative model specifications in Section 5.7.

Figure 1. (Color online) Discontinuity Plot on the Probability of Credit Access



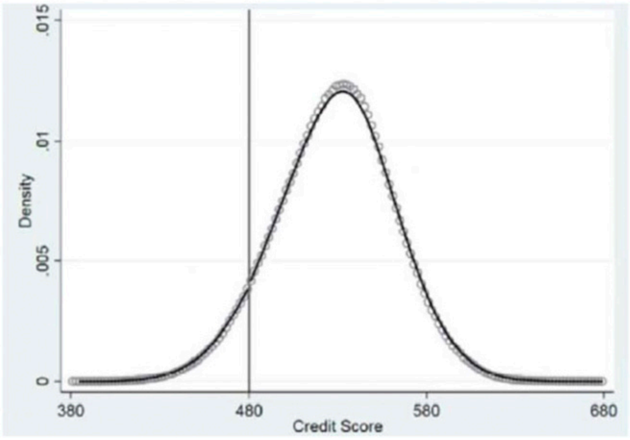
Notes. Each dot on the figure represents the average probability that a credit line is granted to a firm located in the corresponding range of credit score with a bandwidth of one. The probability is estimated by dividing the total number of firms with credit access over the total number of eligible 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.

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 and 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., Imbens and Lemieux 2008, Bradley et al. 2017, Chemmanur and Tian 2018). As discussed earlier, Ant Financial does not disclose the firms' credit scores or the specific algorithms governing 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. (Color online) Density of Firms: McCrary (2008) Plot



Another important assumption of the RDD is that there should be no 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 diagnostic tests by comparing the covariates of firms that fall in the baseline band of credit scores used in our analysis (i.e., [460, 500] around the threshold). Specifically, we plot the pretreatment measures of firm characteristics and firm volatility, as presented in Figure 3. Panel (a) focuses on *Sales value* one month prior to the treatment event, and panel (b) on *Firm age*. In both panels, we do not find any jumps in firm characteristics before the change in credit access. Panels (c) and (d) 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.

Overall, the diagnostic tests presented previously 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.

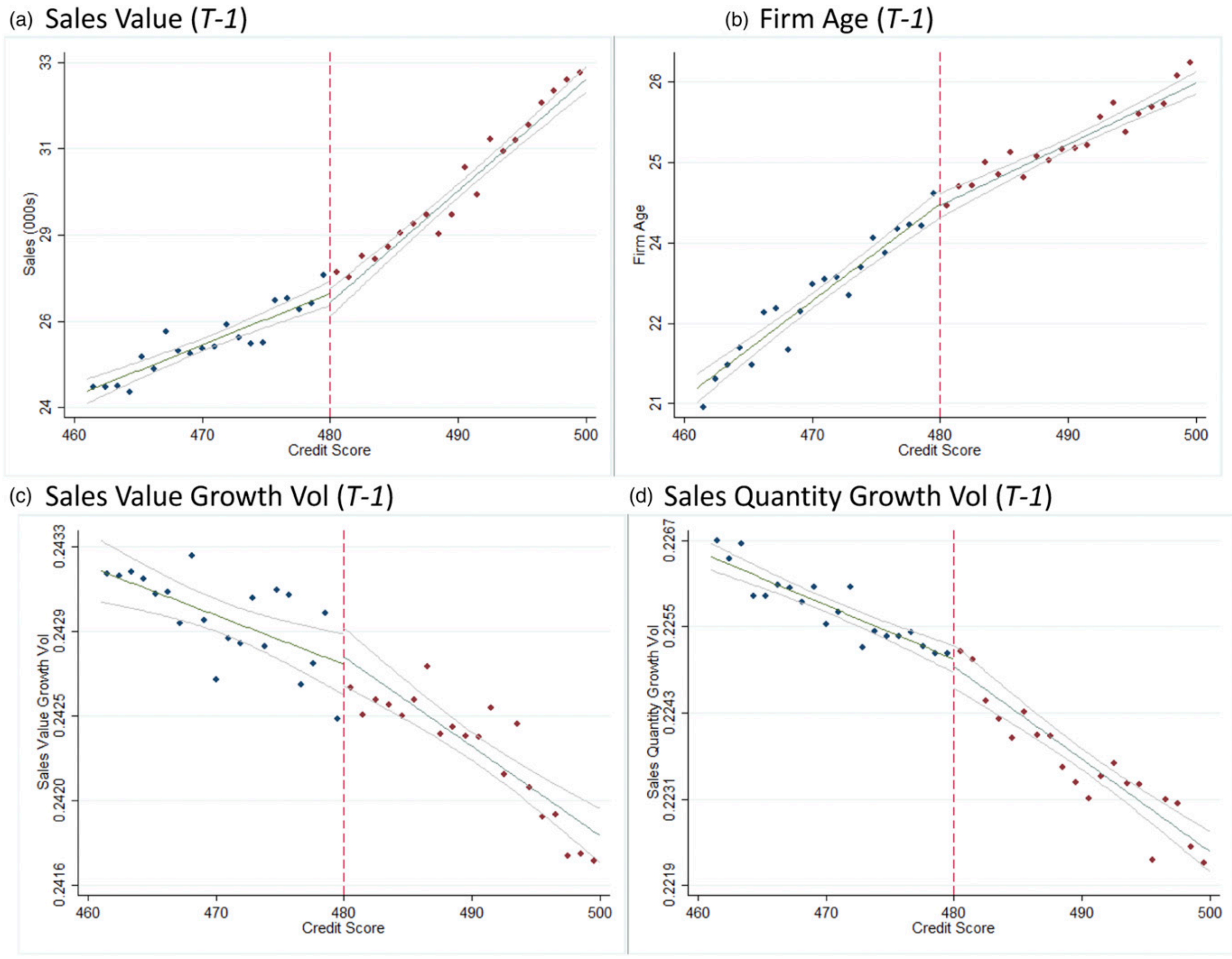
5. RDD Results

In this section, we present the baseline RDD results, a battery of robustness checks, and further explorations of firm volatility. 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 conduct robustness tests by exploring alternative bandwidths, adding additional firm-level and owner-level controls, city fixed effects, and using alternative RDD specifications. We provide further explorations of firm volatility by several heterogeneity tests. In addition, we further look at the firm exit probability, and study how FinTech credit could affect firms' bankruptcy and exit choices.

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 baseline bandwidth used in our analysis (i.e., from 460 to 500). The left-hand plots (i.e., panels (a), (c), and (e)) present plots for *Sales value growth vol* and the right-hand plots (i.e., panels (b), (d), and (f)) present plots for *Sales quantity growth vol*. We study our measures of firm volatility at $t + 1$, $t + 2$, and

Figure 3. (Color online) Discontinuity Plot on Pre-existing Firm Characteristics



Notes. 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.

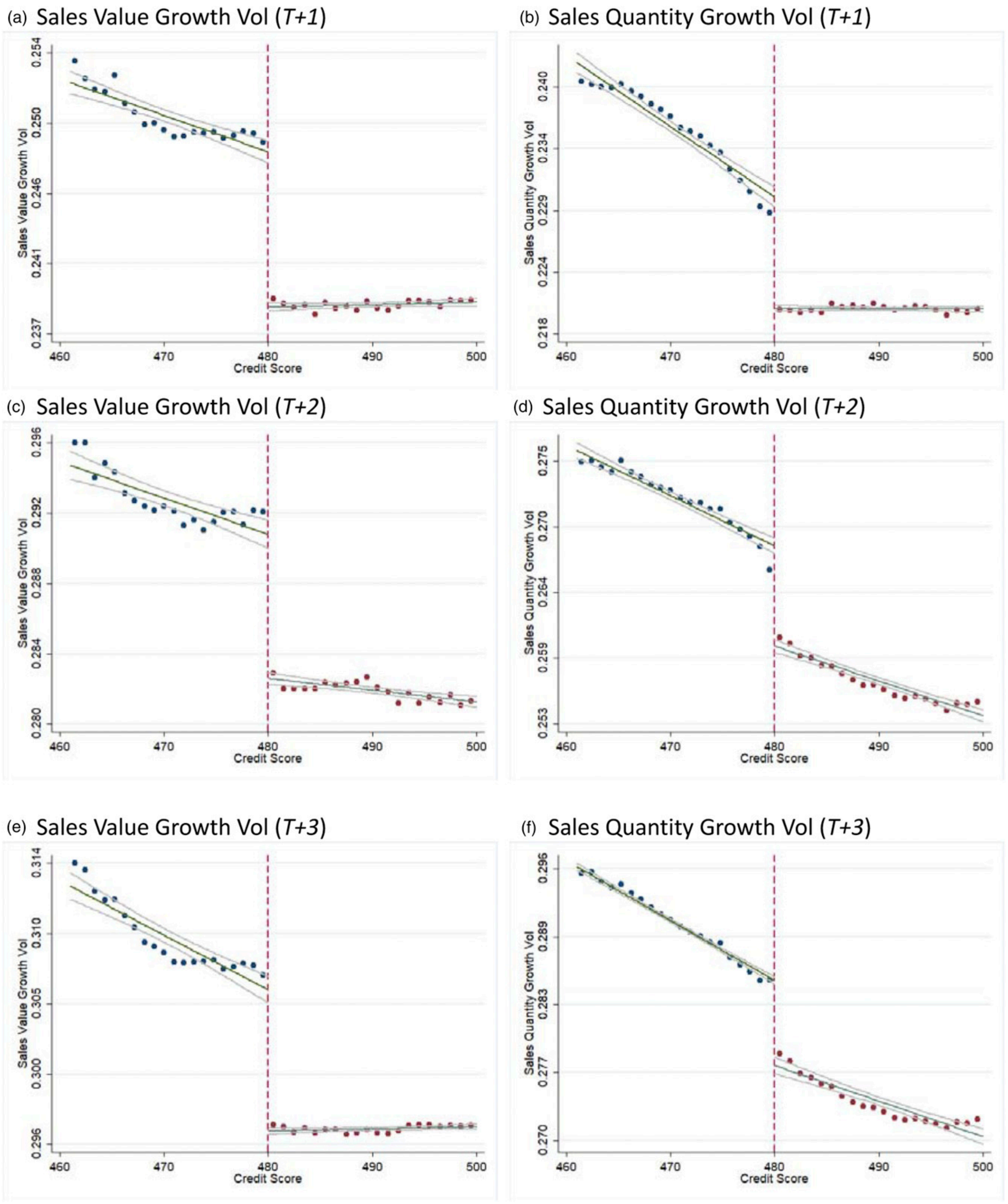
$t+3$ subsequent to a credit allocation decision at both sides of the cutoff. We divide the spectrum of credit scores into equally spaced bins (with a bin width of one). For firms with a credit score lower than the cutoff, the average firm volatility measures are denoted by the dots on the left of 480, and the average value of firm volatility measures for firms with a score above the threshold are denoted by the dots on the right of 480. The solid line represents the fitted linear estimate with a 95% confidence interval around the fitted value.

The plots 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. Baseline 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

Figure 4. (Color online) Discontinuity Plot on Firm Volatility



Notes. Each dot on the figure represents the average value of the respective volatility 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.

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

Panel A. First Stage

	Dependent variable
	D [Credit access]
	(1)
T [Credit score ≥480]	0.2274***
	(104.7387)
Industry fixed effects	Yes
Time fixed effects	Yes
Adjusted 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)
$\hat{D}$ [Predicted credit access]	−0.0382***	−0.0412***	−0.0391***	−0.0485***	−0.0428***	−0.0348***
	(−11.2082)	(−12.7195)	(−12.6505)	(−10.0561)	(−13.5527)	(−11.3221)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0306	0.0317	0.0297	0.0319	0.0399	0.0404
N	561,313	561,313	561,313	561,313	561,313	561,313

Note: T-statistics robust to adjustment for heteroscedasticity and clustering at the firm level are reported in parentheses.
***$p < 0.01$.

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 $\hat{D}$. This predicted credit access can be viewed as instrumented *Credit access* and is the key variable of interest in the second stage.

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 0.0382 reduction in *Sales value growth vol*. In terms of economic magnitude, the treatment effect is 17.2% of the mean value in the full sample and 15.7% 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 0.0412 and 0.0391 in *Sales value growth vol*, which translates into a treatment effect of 17% and 16% 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 0.0485 in *Sales quantity growth*. The treatment effect is 21.5% 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 panels A and B of Table 3.

Panel A of Table 3 shows the first-stage regression results. We find that the coefficient estimate for T is not significantly different from zero 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, 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.[18] This 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

Table 3. Robustness Tests: Placebo Cutoffs to Assign Credit and Alternative Bandwidths

Panel A: First Stage (Placebo Cutoffs)

	Dependent variable	
	D [Credit access]	
	(1)	(2)
T [Credit score ≥ 460 or 500]	0.03141	–0.0128
	(0.0038)	(–1.3214)
Placebo cutoff	460	500
Score range	[440, 480]	[480, 520]
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adjusted R^2	0.1585	0.1351
N	222,659	1,298,741

Panel B: Second Stage (Placebo Cutoffs)

	Dependent variable			
	Sales value growth vol	*Sales quantity growth vol*	*Sales value growth vol*	*Sales quantity growth vol*
	(1)	(2)	(3)	(4)
$\hat{D}$ [Predicted credit access]	–0.0042	0.0011	0.0144	–0.0016
	(–0.7490)	(0.1946)	(0.3764)	(–0.1577)
Placebo cutoff	460		500	
Score range	[440, 480]		[480, 520]	
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.0311	0.0296	0.0347	0.0345
N	222,659	222,659	1,298,741	1,298,741

Panel C: First Stage (Alternative Bandwidths)

	Dependent variable		
	D [Credit access]		
	(1)	(2)	(3)
T [Credit score ≥480]	0.1951***	0.1472***	0.1097***
	(72.1122)	(41.4731)	(20.7227)
Score range	[465, 495]	[470, 490]	[475, 485]
Industry fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Adjusted R^2	0.2958	0.2297	0.1492
N	387,263	238,995	110,394

Table 3. (Continued)

Panel D. Second Stage (Alternative Bandwidths)

	Dependent variable					
	Sales value growth vol	*Sales quantity growth vol*	*Sales value growth vol*	*Sales quantity growth vol*	*Sales value growth vol*	*Sales quantity growth vol*
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{D}$ [Predicted credit access]	−0.0475***	−0.0550***	−0.0446***	−0.0305***	−0.0552***	−0.0424***
	(−7.4193)	(−8.8633)	(−10.3780)	(−7.3344)	(−4.0973)	(−4.3015)
Score range	[465, 495]		[470, 490]		[475, 485]	
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0298	0.0314	0.0297	0.0310	0.0300	0.0359
N	387,263	387,263	238,995	238,995	110,394	110,394

Notes. 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 460 or 500, 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. T-statistics robust to adjustment for heteroscedasticity and clustering at the firm level are reported in parentheses.

***$p < 0.01$.

in the number of observations (i.e., a total of 1,340 firm-time observations for the [460, 500] 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.

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 three alternative bandwidths to reestimate 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, the second is 10 points around the cutoff to create a local region of 470 to 490, and the third is five points around the cutoff to create a local range from 475 to 485. The results are reported in panels C and D of Table 3. All other specifications are identical to our baseline regression.

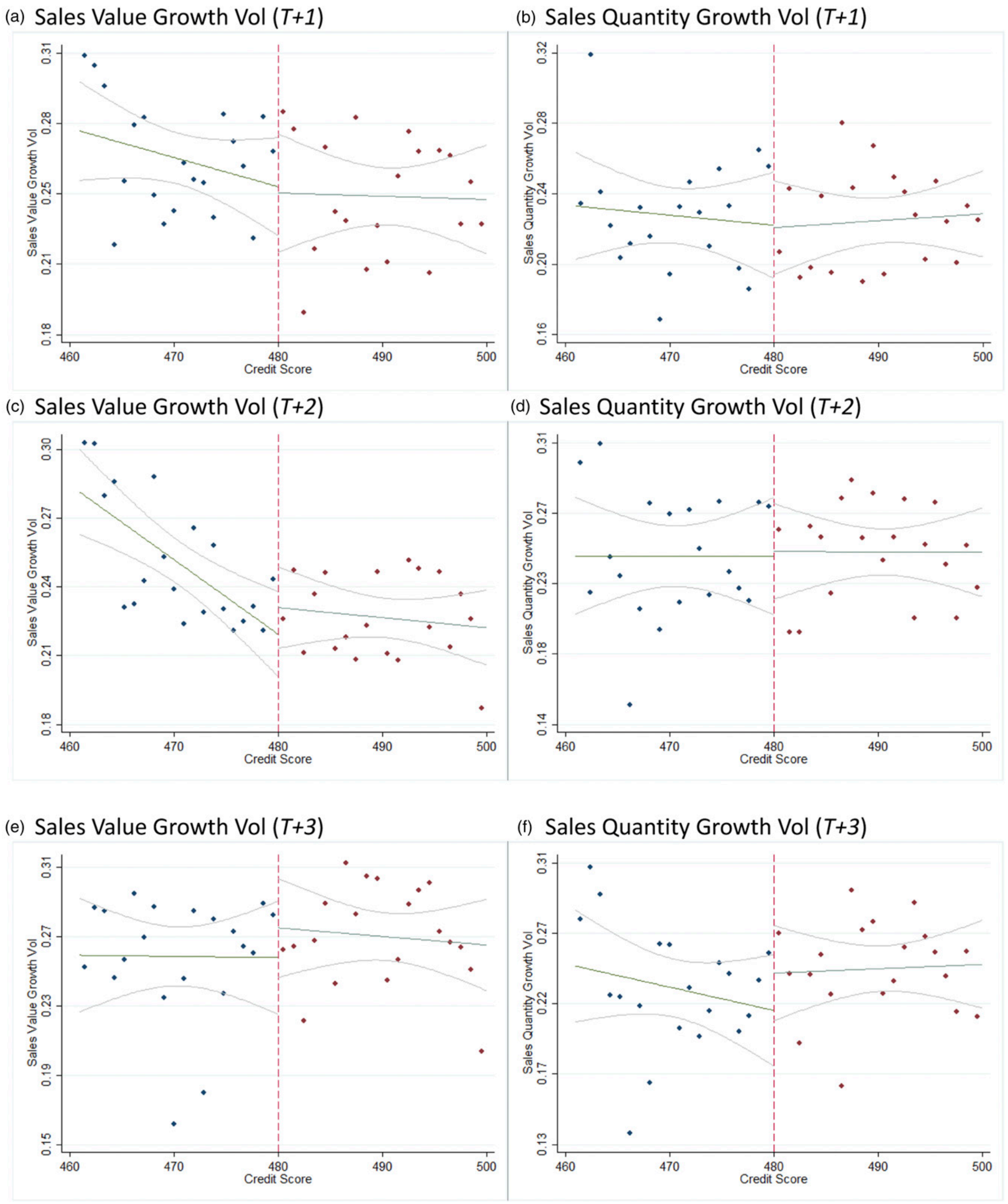
As shown in panel C, firms with a score above the threshold have a higher probability of accessing credit lines. We use the predicted *Credit access* as the major independent variable of interest in the second stage and find that credit access significantly reduces firm volatility, as indicated in panel D.[19] The results confirm that credit access has a negative causal effect on firm volatility and that the effect is not sensitive to the selection of bandwidths.

5.6. 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 and Lemieux 2010). We include sales value, firm age, and owner characteristics into the regressions. We further take natural logarithm of *Sales value* and *Firm age* when we include them as control variables. Owner variables include *Owner gender*, *Owner married*, *Owner income*, *Owner property*, *Owner associated*, *Owner undergraduate*, and *Owner postgraduate*. We also include several variables to measure the owner's education: *Owner associate*, *Owner undergraduate*, and *Owner postgraduate*. The results are presented in Table 4.

Panel A of Table 4 reports the first-stage regression. The number of observations is slightly reduced due to the 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 cutoff, 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.[20] Taken together, our results are robust to adding more firm and owner covariates and city fixed effects.

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



Notes. The sample includes 18,810 firm-time observations for the full sample, and 1,340 firm-time observations for the [460, 500] range.

5.7. Alternative RDD Specifications

We use alternative RDD specifications to investigate the effect of FinTech credit on firm volatility. Throughout the previous analyses, 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.

Table 4. Robustness Tests: Additional Firm-level Controls, Alternative RDD Specifications, and Alternative Measures of Credit Access

Panel A: First Stage

	Dependent variable
	D [Credit access]
	(1)
T [Credit score ≥480]	0.2244***
	(100.9154)
Controls	Yes
Industry fixed effects	Yes
Time fixed effects	Yes
Adjusted R^2	0.3629
N	529,537

Panel B: Second Stage (with More Controls)

	Dependent variable	
	Sales value growth vol	*Sales quantity growth vol*
	(1)	(2)
$\hat{D}$ [Predicted credit access]	−0.0400***	−0.0450***
	(−11.8819)	(−9.4606)
Controls	Yes	Yes
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adjusted R^2	0.0350	0.0375
N	529,537	529,537

Panel C: Second Stage (with More Controls and City Fixed Effects)

	Dependent variable	
	Sales value growth vol	*Sales quantity growth vol*
	(1)	(2)
$\hat{D}$ [Predicted credit access]	−0.0435***	−0.0449***
	(−12.9289)	(−9.4920)
Controls	Yes	Yes
City fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adjusted R^2	0.0356	0.0377
N	529,537	529,537

Panel D. Different Functional Forms

	Dependent variable	
	Sales value growth vol	*Sales quantity growth vol*
	(1)	(2)
$\hat{D}$ [Predicted credit access]	−0.0444***	−0.0385***
	(−8.9525)	(−7.9852)
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adjusted R^2	0.0306	0.0318
N	561,313	561,313

Table 4. (Continued)

Panel E. Second-Order Polynomials (k = 2)

	Dependent variable	
	Sales value growth vol	*Sales quantity growth vol*
	(1)	(2)
$\hat{D}$ [Predicted credit access]	−0.0381***	−0.0316***
	(−7.6831)	(−6.4851)
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adjusted R^2	0.0303	0.0314
N	561,313	561,313

Panel F. Third-Order Polynomials (k = 3)

	Dependent variable	
	Sales value growth vol	*Sales quantity growth vol*
	(1)	(2)
$\hat{D}$ [Predicted credit access]	−0.0440***	−0.0421***
	(−8.8749)	(−8.7313)
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adjusted R^2	0.0306	0.0319
N	561,313	561,313

Panel G. Second Stage (First-Time Credit Access)

	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)
$\hat{D}$ [Predicted credit access]	−0.0526***	−0.0643***	−0.0644***	−0.0540***	−0.0513***	−0.0585***
	(−4.8497)	(−6.7992)	(−6.9093)	(−5.3976)	(−5.3787)	(−6.3087)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0274	0.0371	0.0316	0.0257	0.0306	0.0379
N	146,350	146,350	146,350	146,350	146,350	146,350

Panel H. Second Stage (Credit Usage)

	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)
$\hat{U}$[Predicted credit usage]	−0.0777***	−0.0791***	−0.0692***	−0.0788***	−0.0781***	−0.0767***
	(−4.1417)	(−4.4749)	(−4.0459)	(−4.3110)	(−4.3871)	(−3.7886)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0305	0.0329	0.0423	0.0315	0.0391	0.0404
N	561,313	561,313	561,313	561,313	561,313	561,313

Notes. In panels A, B, C, E, F, G, and H, we use the TSLS regression system in Equations (1) and (2) to implement the design. We use the TSLS regression system in Equations (3) and (4) to implement the design in panel D. T-statistics robust to adjustment for heteroscedasticity and clustering at the firm level are reported in parentheses.

***p < 0.01.

Specifically, we update Equations (1) and (2) to be as follows:

$$D_{i,t} = \alpha + \pi T_{i,t} + \sum_{k=1}^{K} \rho^k (s_{it} - s^*)^k + \varphi_j + \theta_t + \mu_{it}, \quad (3)$$

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

We set $K = 1$ by implementing a local linear regression. The results are presented in panel D of Table 4. We find that the estimated treatment effect of credit access on firm volatility is similar to the baseline results.

We further use a higher order of polynomials in the standardized credit score to check the robustness of our results. In panel E, we set $K = 2$ in the two-equation system (1) and (2). In panel F, we set K=3. We do not find significantly different results.

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.

5.8. Alternative Measures of Credit Access

As additional robustness tests, we further use alternative measures of FinTech credit access. First, we trace the credit history of the firms and define treated firms as only those receiving credit grants for the first time in our sample. In our RDD setting, we rely on locally exogenous variation in credit access based on firms that either succeed or fail to access credit by only a small margin of credit scores. For such close-call cases, having credit access is very close to an independent, random event. Consequently, a firm can be treated repeatedly by credit grants, and each grant event represents an independent and exogenous shock to the firm's credit access. Therefore, it is less of a concern whether the treated firms access credit for the first time or not. However, looking at this subset of firms could help strengthen our results, as presumably we would expect stronger results for the months immediately following credit availability. We present the results in panel G of Table 4. As shown in panel G, we have about one quarter of the original observations and the effect of credit access is indeed more pronounced than in the baseline results.

Second, we look at a subset of firms that actually utilize the credit that they gain from Ant Financial. Specifically, we replace access dummy D by credit usage dummy U, an indicator variable that equals 1 if a firm actually uses the credit line by Ant Financial from the end of the current month to the end of next month, and 0 otherwise. The results are shown in panel H of Table 4 and we find stronger effect than our baseline RDD estimation.

5.9. Further Explorations of Firm Volatility: Heterogeneity Tests by Alternative Financing Sources

In this section, we further explore the effect of FinTech credit on firm volatility by heterogeneity tests. Specifically, we focus here on a theoretically motivated dimension to better understand the mechanism through which access to FinTech credit affects firm volatility: alternative financing sources of the firm. Intuitively, we should expect firms when having fewer alternative financing choices from traditional banks to benefit more from FinTech credit, and the effect of credit access to Ant Financial should be more pronounced for these firms. To test this conjecture, we look at firm age.

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, younger firms have a much shorter history for traditional lenders to effectively evaluate its credit risk, and hence they are more likely to be denied credit from traditional lenders and have less alternative financing sources (e.g., Hadlock and Pierce 2010). Therefore, the gains to FinTech in alleviating financial constraint should be greater for these firms. To test this hypothesis, we divide the sample into young and old subsamples and redo the analysis. We show our second-stage results in Table 5.

In the untabulated first-stage regression, we find that in both subsamples, passing the credit score threshold leads to a similar increase in the likelihood that the firm obtains credit access. In Table 5, 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.[21] 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 financial constraint problems.

5.10. FinTech Credit and Firm Exit Probability

In this section, we further look at the firm exit probability, and study how FinTech credit could affect firms' bankruptcy and exit choices. 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

Table 5. Further Explorations of Firm Volatility: Heterogeneity Tests

	Dependent variable			
	Sales value growth vol		*Sales quantity growth vol*	
	Firm age		*Firm age*	
	Old	*Young*	*Old*	*Young*
	(1)	(2)	(3)	(4)
$\hat{D}$ [Predicted credit access]	−0.0027	−0.0390***	−0.0019	−0.0430***
	(−0.3798)	(−7.5362)	(−0.2696)	(−8.5809)
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Difference	0.0363***		0.0411***	
(p-value)	(0.0000)		(0.0000)	
Adjusted R^2	0.0278	0.0256	0.0315	0.0278
N	181,811	195,695	181,811	195,695

Notes. We use the TSLS regression system in Equations (1) and (2) to implement the design. We report the second-stage results for subsample analyses by firm age. We divide into subsamples based on top vs. bottom terciles. T-statistics robust to adjustment for heteroscedasticity and clustering at the firm level 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.

***$p < 0.01$.

about 10% if we look at a three-month horizon. Therefore, firm exit probability is a natural and extreme measure of firm risk.

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

$$Exit_{i,t+n} = \alpha + \beta\hat{D}_{it} + \sum_{k=1}^{K}\gamma^k(s_{it} - s^*)^k + T_{it}\sum_{k=1}^{K}\delta^k(s_{it} - s^*)^k + \varphi_j + \theta_t + \mu_{it}, \quad (5)$$

where *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.[22] We show our results in Table 6.

Panel A of Table 6 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.

6. Tests of Potential Channels

So far, we have found that FinTech credit significantly reduces sales volatility, and the effect is more pronounced when firms have fewer alternative sources of financing. In this section, we further explore the underlying mechanism through which credit access affects firm volatility. As Rajan and Zingales (1998) point out, to determine "the 'smoking gun' in the debate about causality" (p. 560) requires focusing on the details of theoretical mechanisms and documenting how they work. We focus on how firms utilize the credit obtained from Ant Financial. Specifically, we hypothesize that credit access could help the firms to put more commercials or expand product categories, which help diversify the revenue sources. To this purpose, we collect detailed data about each firm's advertising activities and product categories.

First, we look at advertising. A large volume of literature has documented that advertising can increase consumers' tendency to purchase the promoted product, create intangible assets, and reduce the firm risk (e.g., Byzalov and Shachar 2004, Grullon et al. 2004, McAlister et al. 2007, Bharadwaj et al. 2011), while another line of research finds that firm's financing and capital structure could affect firms' advertising expenditure (e.g., Grullon et al. 2006, Fee et al. 2009). In the same spirit, firms having credit access could invest more in advertising compared with industry peers and the steady purchase from consumers could result in lower sales growth volatility. In our setting, the sellers could invest to list their products as recommended products on Taobao Marketplace.

Table 6. FinTech Credit and Firm Exit

Panel A. First Stage

	Dependent variable
	D [Credit access]
	(1)
T [Credit score ≥480]	0.2551***
	(133.5651)
Industry fixed effects	Yes
Time fixed effects	Yes
Adjusted R^2	0.3646
N	793,420

Panel B: Second Stage

	Dependent variable		
	Firm exit		
	$T+1$	$T+2$	$T+3$
	(1)	(2)	(3)
$\hat{D}$ [Predicted credit access]	−0.1013***	−0.1228***	−0.1496***
	(30.4724)	(26.3103)	(27.6191)
Industry fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Adj. R^2	0.0176	0.0248	0.0341
N	793,420	793,420	793,420

Notes. We use the TSLS regression system in Equations (1) and (5) 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. T-statistics robust to adjustment for heteroscedasticity and clustering at the firm level are reported in parentheses.

***$p < 0.01$.

We gauge this data and first measure advertising by the growth rate of the total amount of advertising expenditure invested by the seller in the next month, and further adjust by its industry average value since the investment is more relevant to the seller's peers in one industry (*Industry-adjusted advertising growth rate*).

It is worth noting that the platform has traced customers' purchase habits, in particular, when customers click advertised products and buy them. This data characterizes the unique advantages of e-commerce platforms, which are generally not available to researchers of traditional marketing techniques. To further examine the effectiveness of advertising, we look at the direct output due to advertisement measured by the total revenue when customers click advertised products and buy them. We standardize this direct output due to advertisement by total sales value to get *Direct advertising output/sales value*.

To test our hypothesis, we augment the second-stage Equation (2) and replace the dependent variable by our measures of advertising. The results are presented in panel A of Table 7. The first stage of the estimation is the same as the baseline results in Section 5.2, and we omit them here for brevity. As shown in panel A of Table 7, we find that access to FinTech credit significantly increases advertising, both in advertising expenditure and its effectiveness.

Second, we turn to product and sector diversification. Extant literature has found that credit access and financial strength influence firms' competition strategy in the product market (e.g., Chevalier 1995, Chevalier and Scharfstein 1995, Phillips 1995, Fresard 2010). Presumably, firms with credit access could expand the scope of the products that they sell, and the consequent more diversified revenue sources could reduce sales volatility. To test this, we measure diversification by the probability of the firms to sell a new product (*New product*) or enter a new industry (*New industry*) in the subsequent month. We show the results in panel B of Table 7. As expected, we find that firms having FinTech credit access are more likely to sell a new product or enter a new industry. The results are not only statistically but also economically significant. For instance, credit access increases the firm's probability to sell a new product in the consequent month by 13.5%, which is about one third of the sample mean.

Various studies indicate that business cycle has a significant effect on advertising (e.g., Srinivasan et al. 2011, Dekimpe and Deleersnyder 2018) and diversification (e.g., Chevalier and Scharfstein 1996, Dimitrov and Tice 2006) and also their impact on firms (e.g., Tellis and Tellis 2009, Kuppuswamy and Villalonga 2016). As a final attempt to strengthen our story, we further test whether business cycle affects the effect of FinTech credit on advertising and diversification. We hypothesize that the advantage of having access to FinTech credit during business downturns matters more as sellers could compete more aggressively by investing in commercials or expanding products. We measure business cycle by industry sales growth, calculated as the growth rate of the total sales value in a month in an industry (*Business cycle*). To test this, we instrument D and an interaction between D and *Business cycle* by T and an interaction between T and business cycle variables. Specifically, in the first stage, we regress the credit access dummy D and an interaction between D and *Business cycle* over an indicator variable T, an interaction between T and *Business cycle*, *Business cycle* itself, and an interaction of T with the standardized credit scores. In the second stage, we regress the dependent variable over instrumented D, the predicted value of the interaction between T and *Business cycle*, *Business cycle* itself, and an interaction of T with the standardized credit scores. We present our results in Table 8.

Table 7. Channel Tests: Advertising and Product/Sector Diversification

Panel A: Second Stage (Advertising)

	Dependent variable	
	Industry-adjusted advertising growth rate	*Direct advertising output/sales value*
	(1)	(2)
$\hat{D}$ [Predicted credit access]	0.0388***	0.2093*
	(6.8866)	(1.9120)
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adjusted R^2	0.2577	0.0256
N	561,313	561,313

Panel B: Second Stage (Product/Sector Diversification)

	Dependent variable	
	New product	*New industry*
	(1)	(2)
$\hat{D}$ [Predicted credit access]	0.1352***	0.0681***
	(3.8211)	(6.9795)
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Adjusted R^2	0.0577	0.2550
N	561,313	561,313

Notes. We use the TSLS regression system in Equations (1) and (2) to implement the design. In the first stage, 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, 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. T-statistics robust to adjustment for heteroscedasticity and clustering at the firm level are reported in parentheses.
$^{*}p < 0.10$; $^{***}p < 0.01$.

As shown in Table 8, the estimate of the predicted value of the interaction of T and *Business cycle* is negative and significant through all the four models, indicating that the effect of FinTech credit on advertising and diversification is indeed stronger during downturns. In a nutshell, we find that FinTech

Table 8. Advertising and Product Diversification: Business Cycle

	Dependent variable			
	Industry-adjusted advertising growth rate	*Direct advertising output/sales value*	*New products*	*New industry*
	(1)	(2)	(3)	(4)
$\hat{D}$ [Predicted credit access]	0.0821***	0.3062***	0.1364***	0.1052***
	(6.4531)	(4.8653)	(7.2922)	(6.3351)
Predicted [Credit access × Business cycle]	−0.2512***	−0.6615***	−0.4142***	−0.2306***
	(−3.8525)	(−10.5654)	(−5.9176)	(−9.3641)
Business cycle	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.2071	0.1862	0.1332	0.1925
N	561,313	561,313	561,313	561,313

Notes. We use the TSLS regression system in Equations (1) and (2) to implement the design. We use the local linear regression model over the credit scores from 460 to 500 in both stages. T-statistics robust to adjustment for heteroscedasticity and clustering at the firm level are reported in parentheses.
$^{***}p < 0.01$.

credit increases firm's investment in advertising and product/sector diversification, which serves as the mechanisms for the decreased firm volatility.

7. 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 daily 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 in 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 FinTech credit access significantly reduces firm volatility, and the effect is more pronounced for firms with fewer alternative financing sources. We also find that FinTech credit significantly reduces firms' bankruptcy and exit probability. Further analysis reveals that credit access increases advertising and product/sector diversification, which serves as the mechanisms for the reduced firm volatility. Overall, our findings contribute to a better understanding of the role of FinTech credit in reducing the risk of the MSMEs.

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Appendix. Variable Definitions

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

Variable name	Variable definition
Credit score	The Ant Financial credit score of a firm in a month.
Credit access (D)	An indicator variable that equals 1 if a firm is granted a credit line by Ant Financial from the end of the current month to the end of next month, 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 a month.
Sales value growth vol	The monthly standard deviation of daily growth rate of total transaction amount in RMB, which is calculated for the next one, two, and three months for each firm in the sample.
Sales quantity growth vol	The monthly standard deviation of daily growth rate of total transaction quantity, which is calculated for the next one, two, and three months for each firm in the sample.
Sales value	The total transaction amount in RMB completed by a firm in a month. We further take a natural logarithm when we include it as a control variable.

Appendix. (Continued)

Variable name	Variable definition
Firm age	The age of a firm, measured by the total number of months present on Taobao Marketplace since the official registration date. We further take a natural logarithm when we include it as a control variable.
Firm exit	The probability of exit of the business in a particular month for each firm in the sample.
Industry-adjusted advertising growth rate	The growth rate of the total amount of advertising expense that the seller invests to list their products as recommended products on Taobao Marketplace, adjusted by its industry average value for the subsequent month for each firm in the sample.
Direct advertising output/sales value	The ratio of advertisement direct output (the total revenue when the customers click advertised products and buy them) to total sales value.
New product	A dummy variable whose value is one when the firm sells a new product on Taobao Marketplace in the subsequent month for each firm in the sample, and zero otherwise.
New industry	a dummy variable whose value is 1 when the firm enters a new industry in the subsequent month for each firm in the sample, and 0 otherwise.
Business cycle	Proxied by industry sales growth, measured as the growth rate of total sales value in a month in an industry.
Owner gender	An indicator variable that equals 1 if the firm owner is male and 0 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 that is earned from other sources.
Owner owns property	An indicator variable that equals 1 if the firm owner owns real estate asset 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's degree and 0 otherwise.

Endnotes

[1] 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 the gross domestic product, 70% of the innovations, and 80% of the employment.

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

[3] High-frequency real-time data are crucial for our research to measure volatility more accurately and granularly.

[4] See "The Fintech100 – Announcing the World's Leading FinTech Innovators for 2017," *KPMG*, November 15, 2017.

[5] 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.

[6] In addition to credit scoring, Ant Financial also imposes a few additional criteria on credit eligibility, including firm age, sales information, and previous misconduct record. 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.

[7] 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.

[8] We try alternative bandwidths as well, 15, 10, and five, as detailed in Section 5.5.

[9] We try our analysis without this three-month constraint, and our results are qualitatively similar.

[10] 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.

[11] Whereas research on financial development and economic volatility (Larrain 2006, Raddatz 2006) has tended to focus primarily on industry-level cross-sectional analysis, our 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.

[12] As of October 2014, Alibaba surpassed Walmart as the world's largest retailer. See Rushton (2014).

[13] The process works this way: Ant Financial analyzes customer data and gives a pre-approved credit line to the customer up-front. Customers can choose to ignore or accept the offer. If the customer accepts the offer, the customer can apply for a loan amount (up to the pre-approved line) and complete the identification verification process. Once completed, the loan will be automatically approved and granted. See Ant Financial's website at https://www.antfin.com/.

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

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

[16] We also try using weekly data to calculate monthly firm volatility measures, and our results throughout the paper are robust to these alternative measures of volatility. The results are not tabulated but available upon request.

[17] 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.

[18] 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.

[19] 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.

[20] The first-stage results are quite similar to panel A, and we do not tabulate for brevity.

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

[22] Compared with Table 2, the number of observations increases as we could regain the firm-month observations after they exit the business (coded as one for *Exit*).

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