

Article

Financial Technology, Big Data Enterprise Financing Constraints and Big Data Industry Development: Empirical Analysis Based on Mediating Effect and Threshold Effect

Mu Zhang^{1,*}, Cheng Cao^{1,2} and Zhiyuan Lv^{1,2}

¹ School of Big Data Application and Economics, Guizhou University of Finance and Economics, Guiyang (550025), Guizhou, China

² Guizhou Institution for Technology Innovation & Entrepreneurship Investment, Guizhou University of Finance and Economics, Guiyang (550025), Guizhou, China

* Correspondence: zhangmu01@163.com; Tel.: +86-0851-88510575

Received: June 6, 2021; Accepted: November 26, 2021; Published: January 25, 2022

Abstract: Based on theoretical analysis, we select the relevant data of 30 provinces (autonomous regions and municipalities) in China from 2013 to 2019, and empirically test the impact of financial technology on the development of big data industry and its mechanism using dynamic panel data model, mediating effect test method and threshold effect model. The benchmark regression results show that the regression coefficient of financial technology to big data industry is significantly positive at the significance level of 10%, indicating that the financial technology can directly promote the development of big data industry. The regression coefficient of the dynamic lag term of big data industry is negative, but not significant, indicating that the dynamic lag effect of big data industry is not obvious. The mediating effect test results show that the financial technology can indirectly promote the development of big data industry by alleviating the big data enterprise financing constraints. The big data enterprise financing constraints have a partial mediating effect, and the mediating effect account for 27.63% of the total effect. In addition, the threshold effect test results show that the direct effect of financial technology on big data industry is significantly enhanced when the development level of financial technology is higher than 5.8790, that is, there is a positive threshold effect of financial technology directly promoting the development of big data industry. However, the indirect effect of financial technology on big data industry is relatively weak when the development level of financial technology is higher than 5.4328, that is, financial technology indirectly promotes the development of big data industry by alleviating the big data enterprise financing constraints, which has a negative threshold effect.

Keywords: Financial Technology; Big Data Enterprise; Financing Constraints; Big Data Industry; Mediating Effect; Threshold Effect

1. Introduction

Big data industry refers to related economic activities focusing on data production, collection, storage, processing, analysis, and services, including data resource construction, big data software and hardware product development, sales and leasing activities, and related information technology services. Seizing the opportunity to promote the development of the big data industry is of great significance to improving government governance capabilities, optimizing people's livelihood public

services, promoting economic transformation and innovative development ("Big Data Industry Development Plan (2016-2020)" (Ministry of Industry and Information Technology (2016)) No. 412)). The State Council put forward the policy opinion of "encouraging financial institutions to strengthen and improve financial services and increase support for big data companies" in the "Action Program for Promoting the Development of Big Data" (Guo Fa [2015] No. 50). In the context of big data, encouraging and guiding financial institutions to apply big data technology to improve financial service level and risk prevention and control capabilities has become an important way to accelerate the integrated development of finance and big data industries.

The definition that financial technology is a technology-driven financial innovation, as proposed by the Financial Stability Board (FSB) in 2016, becomes a global consensus. Financial technology aims to use modern science and technology to transform or innovate traditional financial products, financial business processes, and financial industry business models, to fully empower financial development to improve quality and increase efficiency [1-2]. According to the research of FSB, the development of modern emerging cutting-edge technologies such as big data, artificial intelligence, cloud computing, and blockchain has brought a significant impact on the traditional financial market and traditional financial service industry, forcing financial institutions to accelerate the development of financial technology [3]. According to the axiom of action and reaction, the big data industry acts on financial technology, it is countered by financial technology at the same time. On the one hand, the development of financial technology has stimulated the demand for big data technology products and technical services in the financial industry, thereby directly promoting the development of the big data industry; on the other hand, the development of financial technology can also broaden financing channels, reduce financing costs and increase financing efficiency, which can alleviate the financing constraints faced by big data companies [4], thereby indirectly promoting the development of the big data industry. Therefore, in-depth exploration of the impact of financial technology on the development of the big data industry and its mechanism is of great significance for accelerating the integrated development of the financial and big data industries and cultivating new momentum for high-quality economic and social development.

At present, researches resulting on financial technology promoting the development of the big data industry are relatively rare, and the relevant researches mainly focus on the discussion of the relationship between financial technology and industrial structure upgrading [5-6]. On that account, we select relevant data from 30 provinces (autonomous regions and municipalities) in China from 2013 to 2019, and use dynamic panel data models, intermediary effect test methods, and threshold effect models to empirically test the impact of financial technology on the development of the big data industry and its mechanism. The remainder of this article is organized as follows: In section 2, we provide theoretical analysis and research hypotheses. Section 3 refers to empirical model setting, variable selection, research samples and data sources. In Section 4, we take benchmark regression, intermediate effect test, threshold effect test and robustness inspection. Finally, conclusion and policy recommendations are given in Section 5.

2. Theoretical Analysis and Research Hypotheses

Financial technology is the result of the in-depth application of modern emerging frontier technologies in the financial industry, and is an inevitable product of a new round of information technology progress [7]. Chishti and Barberis [8] believe that financial technology refers to start-up

or small and medium-sized technology companies that continuously provide innovative applications and financial product development in the financial industry according to the needs of the financial industry. Arner et al. [9] think that financial technology is a new combination of financial services and information technology, and a financial solution supported by modern information technology. Based on the definition of financial technology in current researches, it can be considered that financial technology is the financial innovation that modern information technology is applied to improve financial products, improve the quality of financial services, strengthen the governance of financial institutions, thus improving the efficiency of financial markets [10]. It can be seen from the connotation of financial technology that the development of financial technology can stimulate the demand for big data technology products and technical services in the financial industry, thereby directly promoting the development of the big data industry. As a result, hypothesis H1 is proposed.

Hypothesis H1: Financial technology can directly promote the development of the big data industry.

From a macro perspective, financial technology can promote economic growth. Financial technology can also bring about changes in traditional financing methods and payment methods from a micro perspective [11]. On the one hand, compared with traditional sources of capital, financial technology, a new and alternative financing method, can provide companies with lower-cost and more convenient financing channels, thereby improving the availability of company financing to a certain extent. On the other hand, the widespread application of financial technology in digital payment systems helps to establish corporate credit records, thereby improving the availability of corporate formal financing through data driven [12]. With the help of digital payment systems and the relevance of various financing channels, financial technology can ease the credit constraints of enterprises to a certain extent [13]. Relevant empirical studies have proved the effect and mechanism of financial technology in alleviating corporate financing constraints [4,12]. As a result, hypothesis H2 is proposed.

Hypothesis H2: Financial technology can effectively alleviate the financing constraints of big data companies.

It is generally believed that corporate financing constraints will restrict the growth of corporate performance to a certain extent, thereby inhibiting the development of related industries. Rajan and Zingales [14] selected sample data from 41 countries and empirically examined the relationship between financing constraints and industrial growth. They found that financing constraints have a significant negative impact on industrial growth. Based on the research of Rajan and Zingales, Xie and Zhang [15] further empirically analyzed the relationship between financing constraints, foreign direct investment and industrial growth, and the results showed that financing constraints had a significant negative impact on industrial growth. In addition, Yang et al. [16] showed that corporate financing constraints are an important reason for the low-end evolution of strategic emerging industries. As a result, combined with hypothesis H2, hypothesis H3 is proposed.

Hypothesis H3: Financial technology can indirectly promote the development of the big data industry by alleviating the financing constraints of big data companies.

Financial technology may have different impacts on the big data industry in different development stages. In initial stage, due to insufficient infrastructure, laws and regulations, low coordination between departments, untimely financial supervision, and increased financial risks, the cost of financial technology development is relatively high while the process of it is far from

satisfactory [17]. Under this circumstance, the demand of financial technology for big data technology products and technical services in the financial industry is relatively limited. The effect that financial technology eases the financing constraints of big data companies by broadening financing channels, reducing financing costs, and improving financing efficiency is not strong enough, and the indirect effects of financial technology on the big data industry are relatively limited. In the middle and advanced stage, with sound infrastructure, laws and regulations, financial risk is under control, and the linkage between financial technology and the big data industry is enhanced continuously [17], the direct and indirect effects of financial technology on the big data industry become increasingly prominent. As a result, hypothesis H4a and hypothesis H4b are proposed.

Hypothesis H4a: Financial technology directly promotes the development of the big data industry with a positive threshold effect.

Hypothesis H4b: Financial technology indirectly promotes the development of the big data industry by alleviating the financing constraints of big data companies, and there is a positive threshold effect.

3. Research Design

3.1. Empirical Model Setting

Economic behavior has dynamic characteristics for the fact that it has continuity and inertia, and is affected by factors such as preference. The dynamic panel data model introduces the dynamic lag term of the explanatory variable into the static panel data model to reflect the dynamic lag effect. Due to the correlation between the dynamic lag term of the explained variable and the individual effect, the endogeneity of the coefficient estimate is formed [18]. We select the dynamic panel data model to test the direct effect of financial technology on the big data industry, and the dual logarithmic model is set as follows:

$$\ln Dldb_{it} = \alpha_1 + \beta_1 \ln Dldb_{it-1} + \delta_1 \ln FinTech_{it} + \theta_1^k \ln X_{it}^k + u_{i1} + \mu_{it1} \quad (1)$$

where i indicates region, t indicates year, $Dldb_{it}$ indicates big data industry development level, $Dldb_{it-1}$ indicates the dynamic lag term of big data industry development level, $FinTech_{it}$ indicates financial technology development level, X_{it}^k indicates the k th control variable, u_i is the individual effect, and μ_{it} is random disturbance term.

The following three double logarithmic models are set up to test the indirect effect of financial technology on the big data industry through the financing constraints of big data companies, according to the causal stepwise regression test method of intermediary effects [17]:

$$\ln SA_{it} = \alpha_2 + \beta_2 \ln SA_{it-1} + \delta_2 \ln FinTech_{it} + \theta_2^k \ln X_{it}^k + u_{i2} + \mu_{it2} \quad (2)$$

$$\ln Dldb_{it} = \alpha_3 + \beta_3 \ln Dldb_{it-1} + \delta_3 \ln SA_{it} + \theta_3^k \ln X_{it}^k + u_{i3} + \mu_{it3} \quad (3)$$

$$\ln Dldb_{it} = \alpha_4 + \beta_4 \ln Dldb_{it-1} + \delta_4 \ln SA_{it} + \delta_5 \ln FinTech_{it} + \theta_4^k \ln X_{it}^k + u_{i4} + \mu_{it4} \quad (4)$$

where SA_{it} is the financing constraint of big data companies, and SA_{it-1} is the dynamic lag term of the financing constraints of big data companies.

The mediating effect is tested as follows: the first step is to test formula (1). We can say financial technology directly promote the development of the big data industry if the regression coefficient δ_1

is significant. If not, the mediating effect test is over. The second step is to test formula (2). We can say financial technology significantly affect the financing constraints of big data companies if the regression coefficient δ_2 is significant. If not, the mediating effect test is over. The third step is to test formula (3). We can say big data corporate financing constraints significantly affect the big data industry, and the mediation effect test is passed if the regression coefficient δ_3 is significant. If not, the mediating effect test is over. Finally, we test formula (4). Big data corporate financing constraints have complete mediation effect if the regression coefficient δ_3 is not significant, while the regression coefficient δ_4 is significant. Big data corporate financing constraints have a partial mediation effect if both the regression coefficients δ_4 and δ_3 are significant.

The following two threshold effect models are set up to examine the different effects of financial technology and big data enterprise financing constraints on the development of the big data industry under different financial technology development level. Firstly, the double logarithmic model is set as follows to examine the different effects of financial technology on the development of the big data industry under different financial technology development level:

$$\begin{aligned} \ln Dldb_{it} = & \alpha_5 + \beta_5 \ln Dldb_{it-1} + \delta_6 \ln FinTech_{it} (\ln FinTech_{it} \leq \gamma_1) \\ & + \delta_7 \ln FinTech_{it} (\ln FinTech_{it} > \gamma_1) + \theta_5^k \ln X_{it}^k + u_{it5} + \mu_{it5} \end{aligned} \quad (5)$$

Secondly, the double logarithmic model is set as follows to examine the different effects of big data enterprise financing constraints on the development of the big data industry under different financial technology development level:

$$\begin{aligned} \ln Dldb_{it} = & \alpha_6 + \beta_6 \ln Dldb_{it-1} + \delta_8 \ln SA_{it} (\ln FinTech_{it} \leq \gamma_2) \\ & + \delta_9 \ln SA_{it} (\ln FinTech_{it} > \gamma_2) + \theta_6^k \ln X_{it}^k + u_{it6} + \mu_{it6} \end{aligned} \quad (6)$$

where γ_1 and γ_2 are the threshold for the development level of financial technology.

3.2. Variable Selection

(1) Explained variable: big data industry development level (Dldb)

Due to the lack of big data industry statistics and considering that the electronic information industry is the basic industry among big data industry, this article refers to the literature [19] and uses the industrial scale and product type of the electronic information industry to approximate those of the big data industry. According to the connotation of the development of the big data industry, relevant research results [20-23], and the compilation principle of the "China Electronic Information Industry Comprehensive Development Index" issued by the Operation Monitoring and Coordination Bureau of the Ministry of Industry and Information Technology, following the selection principles of scientific, objective, systematic, performance, functionality, dynamics, relative independence, feasibility (or operability), and comparability, the evaluation index system is constructed from three dimensions of industry scale, product type, and infrastructure, including three primary indicators and 17 secondary indicators, which is shown in Table 1. The entropy weight method [24] is used to determine the index weight (see Table 1), and the TOPSIS method [25] is used to evaluate big data industry development level in 30 provinces (autonomous regions and municipalities) in China from 2013 to 2019 (Evaluation results are available on request).

Table 1. Big data industry development level evaluation index system.

Destination layer	Criterion layer	Index layer (unit)	Index weight		
Big data industry development level	Industry scale	Number of enterprises above designated size (enterprise)	0.043		
		Main business income (billion yuan)	0.053		
		Total profit (billion yuan)	0.064		
		Main business cost (billion yuan)	0.050		
		Total asset (billion yuan)	0.060		
		Total liability (billion yuan)	0.064		
	Product Type (Export)	Infrastructure	Communication equipment (thousand dollars)	0.089	
			Computer (thousand dollars)	0.081	
			household appliances (thousand dollars)	0.115	
			Electronic components (thousand dollars)	0.094	
			Electron device (thousand dollars)	0.073	
			Electronic material (thousand dollars)	0.042	
		Infrastructure	Infrastructure	Electronic equipment (thousand dollars)	0.107
				Mobile phone base station (base station)	0.015
				Mobile phone exchange capacity (thousand)	0.014
				Length of long-distance optical cable line (kilometer)	0.017
				Internet broadband access port (thousand port)	0.018

(2) Core explaining variable: financial technology development level (FinTech)

This article refers to the design ideas of Huang et al. [12], Tian and Zhang [17], and use the provincial digital inclusive finance index issued by the Digital Finance Research Center of Peking University(<https://idf.pku.edu.cn/yjcg/zsbg/485016.htm>) as a proxy variable for the level of financial technology development in China’s 30 provinces (autonomous regions and municipalities).

(3) Mediating variable: big data enterprise financing constraints (SA)

Enterprise financing constraints refer to the difference between internal financing cost and external financing cost caused by market incompleteness (asymmetric information, agency cost, etc.), which are generally measured by enterprise behavior characteristics such as investment-cash flow sensitivity [26]. The financing constraint index calculated based on enterprise-level data [27] is not applicable for regional data, as a result, this article draws on the method of Harrison and McMillan [28] and uses a single variable to measure the level of financing constraints of regional big data companies. Considering that current structure of corporate financing is still dominated by indirect financing, namely, bank loans, which often require fixed assets or intellectual property as collateral [29]. There is a certain negative correlation between collateral and bank loan cost, so as enterprise financing constraints. Therefore, we use the reciprocal of the sum of fixed assets and intangible assets of the regional electronic information industry to approximate the level of financing constraints of regional big data enterprises. The larger the reciprocal is, the greater the level of financing constraints of regional big data companies.

(4) Control variable

We select the basic support capacity of big data industry development, regional technological innovation capacity, the degree of opening, and the degree of government connection as the control variables. Among them, the regional per capita GDP (Pgdp) and the proportion of regional tertiary

industry (Pti) are used to measure the basic support capacity for the development of the big data industry. The regional technology innovation ability is measured by the intensity of regional R&D expenditure (Rds) and the number of regional patents granted (Npg). The degree of openness by the ratio of regional export value to total industrial output value (Dou). The degree of government connection by the proportion of government funds in the regional R&D expenditure (Gc) [30-32].

3.3. Research Samples and Data Sources

We take 30 provinces (autonomous regions and municipalities) in China as research object (Note: The original data in Tibet is seriously missing, so it is not listed as the research object). The selected time range is 2013-2019. Among them, the data related to the big data industry comes from the "Statistical Yearbook of China's Electronic Information Industry" and the website of the National Bureau of Statistics. The original financial technology data comes from the Peking University Digital Finance Research Center. The original data on big data enterprise financing constraints comes from the "China Electronic Information Industry" Statistical Yearbook. The original data of each control variable comes from "China Statistical Yearbook" and "China Science and Technology Statistical Yearbook". Since the provincial digital inclusive finance index released by the Digital Finance Research Center of Peking University is only updated to 2018, the provincial digital inclusive finance index in 2019 is estimated by the exponential smoothing method. The remaining missing data were estimated by means of imputation and manual imputation. The descriptive statistics of all variables are shown in Table 2.

Table 2. Descriptive statistics of variables.

Variable (unit)	Number of samples	Average	Standard deviation	Minimum	Maximum
Dldb	210	0.088	0.148	0.000	0.879
FinTech	210	237.398	57.782	118.010	377.730
SA (1/million)	210	1.644	20.450	0.001	296.472
Pgdp (thousand yuan)	210	57.700	26.130	23.150	140.210
Pti (%)	210	0.482	0.089	0.342	0.810
Rds (%)	210	0.017	0.011	0.005	0.062
Npg (grant)	210	56526.173	78508.547	502	478082
Dou (%)	210	0.326	0.345	0.025	1.595
Gc (%)	210	0.241	0.136	0.069	0.573

4. Empirical Analysis

4.1. Benchmark Regression

We use the system generalized moment (SYS-GMM) method in Stata16.1 to estimate the coefficient of formula (1) (benchmark regression). In order to choose between a fixed-effects model and a random-effects model, a Hausman test is first performed before the benchmark regression. The Hausman test results show that the P value is 0.0006<0.01, that is, the null hypothesis of random effects is rejected at the 1% significance level. Therefore, the fixed effects model is selected for benchmark regression. The results of the benchmark regression are shown in Regression I in Table 3.

It can be seen from Regression I in Table 3 that the regression coefficient of financial technology to the big data industry is positive and significant at 10% significance level. The results of the Arellano-Bond autocorrelation test accept the null hypothesis that there is no first-order autocorrelation in the residual series. The Hansen over-identification test results accept the null hypothesis of the validity of the instrumental variables, indicating that the setting of formula (1) is reasonable and the instrumental variables are efficient. Therefore, accept the null hypothesis H1: Financial technology can directly promote the development of the big data industry.

The regression coefficient of the dynamic lag of the big data industry is negative, but not significant, indicating that the dynamic lag effect of the big data industry is not yet obvious, which may be related to the short development history of the big data industry. Among the control variables, the regression coefficients of the proportion of regional tertiary industry, the intensity of regional R&D expenditures, the ratio of regional export value to total industrial output value, and the proportion of government funds in regional R&D expenditures are significantly positive under the significance level of 5%, 5%, 5%, and 10% respectively, indicating that these control variables can significantly promote big data Industrial Development. In addition, the regression coefficients of regional GDP per capita and the number of regional patent grants are both positive, but not significant, indicating that the impact of regional per capita GDP and regional patent grants on the development of the big data industry is not yet obvious.

4.2. Intermediate Effect Test

Under the framework of the dynamic panel data model, the causal stepwise regression test method [17] is used to test the intermediate effect of big data enterprise financing constraints. Step 1 is to use equation (1) to test the impact of financial technology on the big data industry, and get Regression I in Table 3. The results show that the regression coefficient of financial technology on the big data industry is significantly positive at significance level of 10%. Step 2 is to use formula (2) to test the impact of financial technology on big data enterprise financing constraints, and get Regression II in Table 3. The results show that the regression coefficient of the constraint is significantly negative at significance level of 10%, indicating that financial technology is effective in alleviating big data enterprise financing constraints, that is, accepting the null hypothesis H2: Financial technology can effectively alleviate the financing constraints of big data companies. Step 3 is to use equation (3) to test the impact of big data enterprise financing constraints on the big data industry, which is shown in the Regression III in Table 3. The results show that the regression coefficient of big data enterprise financing constraints to the big data industry is significantly negative at a significance level of 10%, indicating that alleviating big data enterprise financing constraints will promote the development of the big data industry. Step 4 is to use formula (4) to test the impact of financial technology and big data enterprise financing constraints on the big data industry, and obtain the Regression IV in Table 3. The results show that the regression coefficient of financial technology to the big data industry is significantly positive at significance level of 5%, however, the regression coefficient of big data enterprise financing constraints to the big data industry is significantly negative significance level of 5%, indicating that big data enterprise financing constraints have intermediate effect partly, the ratio of the intermediate effect to the total effect is: $(-4.0716) \times (-0.1194) / 1.7595 = 27.63\%$, that is, accepting the null hypothesis H3: Financial technology can indirectly promote the development of the big data industry by alleviating big data enterprise financing constraints.

Table 3. Regression results of benchmark regression and intermediate effect test.

Variable	Regression I	Regression II	Regression III	Regression IV
	DlbdI	SA	DlbdI	DlbdI
Lag1	-0.1198 (0.3480)	0.0157 (0.9080)	0.0207 (0.9060)	-0.0842 (0.3640)
FinTech	1.7595* (0.0590)	-4.0716* (0.0710)		1.8812** (0.0120)
SA			-0.1078* (0.0500)	-0.1194** (0.0360)
Pgdp	0.8583 (0.3150)	-1.4893 (0.4110)	0.2828 (0.5290)	1.7066* (0.0600)
Pti	2.7963** (0.0210)	6.3937** (0.0480)	0.9414 (0.2610)	3.2920* (0.0750)
Rds	1.6306** (0.0240)	-2.9760** (0.0280)	-0.1744 (0.5520)	0.1178 (0.9070)
Npg	0.1293 (0.6960)	-1.1776** (0.0300)	0.5989** (0.0120)	0.1942 (0.5670)
Dou	0.6120** (0.0170)	0.5350 (0.2970)	0.6324** (0.0140)	0.6632** (0.0120)
Gc	0.4335* (0.0620)	4.8790 (0.1280)	0.2336 (0.6300)	0.4160 (0.3180)
_cons	-7.9334** (0.0130)	-1.7637 (0.8240)	-9.6530*** (0.0070)	-18.1407** (0.0190)
AR(1)	-1.93 (0.0540)	-3.13 (0.0020)	-1.75 (0.0810)	-1.72 (0.0850)
AR(2)	-1.63 (0.1030)	0.92 (0.3580)	-1.18 (0.2390)	-1.41 (0.1600)
Hansen test	26.94 (0.9660)	25.22 (0.9860)	24.76 (0.9840)	19.08 (1.0000)

①***P<0.01, **P<0.05, *P<0.1, and the value in parentheses is the P value. ②Lag1 corresponds to the lagging period of the explained variable.

4.3. Threshold Effect Test

Under the framework of the dynamic panel data model, formulas (5) and (6) are used to test the different effects of financial technology and big data enterprise financing constraints on the development of the big data industry under different financial technology levels. First, we use equation (5) to test the different effects of financial technology on the development of the big data industry under different financial technology levels (recorded as regression V). Second, we use equation (6) to test the different effects of big data enterprise financing constraints on the development of the big data industry under different financial technology levels (denoted as regression VI). We test the existence of the threshold effect before the threshold effect regression. For Regression V, the P value of the single-threshold test is 0.067, so the null hypothesis is rejected,

indicating that there is a threshold. The P value of the double-threshold test is 0.244, so the null hypothesis is accepted, indicating that there is no dual threshold. Therefore, there is a single threshold in Regression V. For Regression VI, the P value of single-threshold test is 0.050, so the null hypothesis is rejected, indicating that there is a threshold. The P value of double-threshold test is 0.122, so the null hypothesis is accepted, indicating that there is no double threshold. Therefore, regression VI also exists single threshold. The single-threshold likelihood ratio function diagrams of Regression V and Regression VI are shown in Figure 1 and Figure 2.

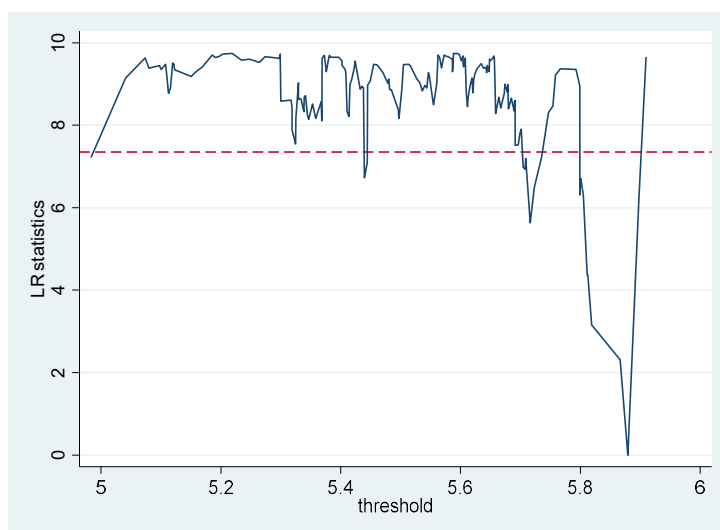


Figure 1. Single-threshold likelihood ratio function diagram of Regression V.

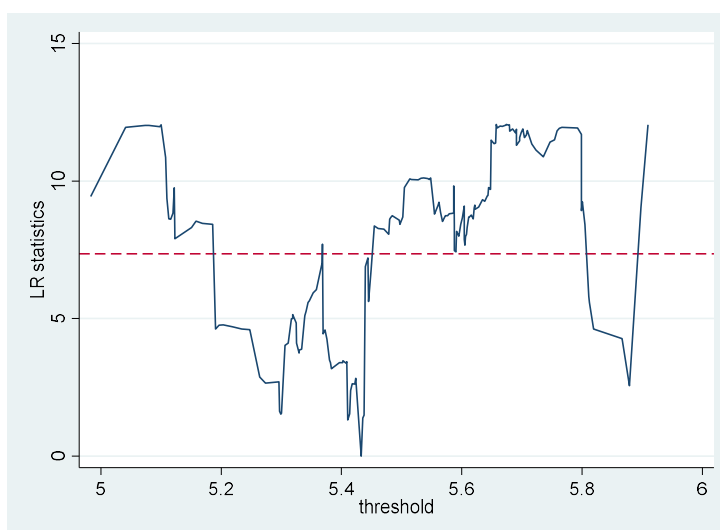


Figure 2. Single-threshold likelihood ratio function diagram of Regression VI.

We use formula (5) to perform threshold effect regression, and get Regression V in Table 4, the results show that when the development level of financial technology is lower than 5.8790, the regression coefficient of financial technology to the big data industry (2.0884) is significantly positive at significance level of 1%, indicating that financial technology can significantly promote the development of the big data industry. When the development level of financial technology is higher than 5.8790, the regression coefficient of financial technology to the big data industry (2.1684) is

significantly positive at significance level of 1%, indicating that financial technology can more significantly promote the development of the big data industry. It shows that there is a bottleneck in financial technology's direct promotion of the development of the big data industry. When the development level of financial technology breaks through this bottleneck, the direct effect of financial technology on the big data industry is significantly enhanced. Therefore, we accept the null hypothesis H4a: Financial technology directly promotes the development of the big data industry with a positive threshold effect.

Table 4. Regression results of threshold effect.

Variable	Regression V			Regression VI		
	Coefficient	t value	P value	Coefficient	t value	P value
Lag1	-0.0413	-0.80	0.423	-0.0237	-0.45	0.654
FinTech (FinTech $\leq\gamma_1$)	2.0884***	3.40	0.001			
FinTech (FinTech $>\gamma_1$)	2.1684***	3.55	0.001			
SA (FinTech $\leq\gamma_2$)				-0.1761***	-3.01	0.003
SA (FinTech $>\gamma_2$)				-0.0362	-0.58	0.560
Pgdp	1.2243**	1.98	0.049	0.6450	1.30	0.196
Pti	-2.7037	-1.41	0.162	-1.2723	-1.53	0.128
Rds	0.2532	0.67	0.502	0.2317	0.59	0.558
Npg	0.2176	1.05	0.294	0.4759**	2.35	0.020
Dou	0.2764**	2.08	0.039	0.5457***	3.61	0.000
Gc	-0.4650	-1.53	0.128	-0.3860	-1.41	0.162
_cons	-16.1841***	-3.98	0.000	-8.9509***	-2.66	0.009
Threshold	5.8790 [5.8665, 5.8978]			5.4328 [5.3962, 5.4353]		

①***P<0.01, **P<0.05, *P<0.1. ②Lag1 corresponds to the lagging period of the explained variable. ③The confidence interval is shown in square brackets.

We use equation (6) to perform threshold effect regression, and get regression VI in Table 4. The results show that when the development level of financial technology is lower than 5.4328, the regression coefficient of big data enterprise financing constraints to the big data industry is significantly negative at significant level of 1%, indicating that the alleviation of big data enterprise financing constraints can significantly promote the development of the big data industry. When the development level of financial technology is higher than 5.4328, the regression coefficient of big data enterprise financing constraints to the big data industry is negative, but not significant, indicating that the relief of big data enterprise financing constraints no longer significantly promotes the development of the big data industry. It shows that there is also a bottleneck in financial technology's indirectly promotion the development of the big data industry by alleviating big data enterprise financing constraints, when the development level of financial technology breaks through this bottleneck, although the indirect effect of financial technology on the big data industry is enhanced, there are many internal and external causes of big data enterprise financing constraints [33], leading to the result that the increase in the indirect effect of financial technology on the big data industry may be smaller than the increase in the direct effect of financial technology on the big data industry . There are many internal and external causes of big data enterprise financing constraints [33]. The

increase in the indirect effect of financial technology on the big data industry may be less than the increase in the direct effect of financial technology on the big data industry, that is, compared with the direct effect, the indirect effect of financial technology on the big data industry is relatively weakened. Therefore, we reject the null hypothesis H4b: Financial technology indirectly promotes the development of the big data industry by alleviating the financing constraints of big data companies, and there is a positive threshold effect.

4.4. Robustness Inspection

In order to test the robustness of the regression results of the dynamic panel data model, this article starts from the econometric model and uses the static panel data model to re-estimate the coefficients of formulas (1)-(6). Regression I shows that the regression coefficient of financial technology to the big data industry is significantly positive at significance level of 5%. Regression II shows that the regression coefficient of financial technology to big data enterprise financing constraints is significantly negative at significance level of 5%. Regression III shows that the regression coefficient of big data enterprise financing constraints to the big data industry is significantly negative at significance level of 10%. Regression IV shows that the regression coefficient of financial technology to the big data industry is significantly positive at significance level of 5%, while the regression coefficient of big data enterprise financing constraints to the big data industry is significantly negative at significance level of 10%. Regression V shows that when the development level of financial technology is lower than 5.7323, the regression coefficient of financial technology to the big data industry (2.0363) is significantly positive at significance level of 5%. When the development level of financial technology is higher than 5.7323, the regression coefficient of financial technology to the big data industry (2.1143) is significantly positive at significance level of 5%. The regression VI shows that when the development level of financial technology is lower than 5.2972, the regression coefficient of big data enterprise financing constraints to the big data industry is significantly negative at significance level of 5%. When the development level of financial technology is higher than 5.2972, the regression coefficient of big data enterprise financing constraints to the big data industry is negative, but not significant. Comparing the coefficient estimation results of the dynamic panel data model and the static panel data model, it can be found that the regression coefficient signs of important variables are the same, and the significance is slightly different, indicating that the regression results of the dynamic panel data model are relatively robust.

5. Conclusions, Discussions and Policy Recommendations

5.1. Conclusions

(1) Results of Regression I (benchmark regression) show that the regression coefficient of the development level of financial technology (FinTech) to the development level of the big data industry (Dlbd) is 1.7595, and the P value is $0.0590 < 0.10$, indicating that under significance level of 10%, if FinTech increase by 1%, Dlbd will increase by 1.7595%. The regression coefficient of the dynamic lag item (Lag1) to the development level of the big data industry (Dlbd) is -0.1198, and the P value is 0.3480, indicating that Lag1 has no significant effect on Dlbd. Financial technology can directly promote the development of the big data industry, but the dynamic lag effect of the big data industry is not yet obvious.

Among the control variables, the regression coefficient of the proportion of the regional tertiary industry (Pti) to the development level of the big data industry (Dlbd) is 2.7963, and the P value is $0.0210 < 0.05$, indicating that under significance level of 5%, if Pti increase by 1%, Dlbd will increase by 2.7963%. The regression coefficient of regional R&D investment intensity (Rds) to Dlbd is 1.6306, and the P value is $0.0240 < 0.05$, indicating that under significance level of 5%, if Rds increase by 1%, Dlbd will increase by 1.6306%. The regression coefficient of the ratio of regional export value to total industrial output value (Dou) to Dlbd is 0.6120, and the P value is $0.0170 < 0.05$, indicating that under significance level of 5%, if Dou increase by 1%, Dlbd will increase by 0.6120%. The regression coefficient of the proportion of government funds in the regional R&D expenditure (Gc) to Dlbd is 0.4335, and the P value is $0.0620 < 0.10$, indicating that under significance level of 10%, if Gc increase by 1%, Dlbd will increase by 0.4335%. The regression coefficient of the regional per capita GDP (Pgdp) on Dlbd is 0.8583, and the P value is 0.3150, indicating that Pgdp has no significant impact on Dlbd. The regression coefficient of the number of regional patent grants (Npg) to Dlbd is 0.1293, and the P value is 0.6960, indicating that Npg has no significant impact on Dlbd. The basic support capacity for the development of the big data industry, the regional technological innovation capacity, the degree of openness, and the degree of government connection can significantly promote the development of the big data industry to varying degrees.

(2) The regression II shows that the regression coefficient of the development level of financial technology (FinTech) on big data enterprise financing constraints (SA) is -4.0716, and the P value is $0.0710 < 0.10$, indicating that if FinTech increase by 1%, SA will fell by 4.0716%. Financial technology can effectively alleviate big data enterprise financing constraints, which is like the research results of literature [4] and [12]. Regression III shows that the regression coefficient of SA to the development level of the big data industry (Dlbd) is -0.1078, and the P value is $0.0500 = 0.05$, indicating that under significance level of 5%, if SA drop by 1%, Dlbd will increase by 0.1078%. The alleviation of big data enterprise financing constraints will promote the development of the big data industry, which is like the research results of literature [14], [15] and [16]. The results of regression I, regression II and regression III show that big data enterprise financing constraints have an intermediary effect, and financial technology can indirectly promote the development of the big data industry by alleviating big data enterprise financing constraints.

Regression IV shows that the regression coefficient of the development level of financial technology (FinTech) to the development level of the big data industry (Dlbd) is 1.8812, and the P value is $0.0120 < 0.05$, indicating that under significance level of 5%, if FinTech increase by 1%, Dlbd will increase by 1.8812%. At the same time, the regression coefficient of big data enterprise financing constraints (SA) to Dlbd is -0.1194, and the P value is $0.0360 < 0.05$, indicating that under significance level of 5%, if SA decrease by 1%, Dlbd will increase by 0.1194%. Big data enterprise financing constraints have a partial intermediary effect, and the intermediary effect accounts for 27.63% of the total effect.

(3) Regression V shows that when the development level of financial technology (FinTech) is lower than 5.8790, the regression coefficient of FinTech to the development level of the big data industry (Dlbd) is 2.0884, and the P value is $0.001 < 0.01$, indicating that under significance level of 1%, if FinTech increase by 1%, Dlbd will increase by 2.0884%. When FinTech is higher than 5.8790, the regression coefficient of FinTech to Dlbd is 2.1684, and the P value is $0.001 < 0.01$, indicating that under significance level of 1%, if FinTech increase by 1%, Dlbd will increase by 2.1684%. There is a positive

threshold effect in the direct promotion of the development of the big data industry by financial technology, which is like the research results of the literature [17].

The regression VI results show that when the financial technology development level (FinTech) is lower than 5.4328, the regression coefficient of the big data enterprise financing constraint (SA) on the big data industry development level (Dlbd) is -0.1761, and the P value is $0.003 < 0.01$, indicating that under significance level of 1%, if SA drop by 1%, Dlbd will increase by 0.1761%. When FinTech is higher than 5.4328, the regression coefficient of SA to Dlbd is -0.0362, and the P value is 0.560, indicating that the impact of SA on Dlbd is not significant. Financial technology indirectly promotes the development of the big data industry by alleviating big data enterprise financing constraints, and there is a reverse threshold effect.

5.2. Discussions

We select relevant data from 30 provinces (autonomous regions and municipalities) in China from 2013 to 2019, and use dynamic panel data models, intermediary effect testing methods, and threshold effect models to empirically test the direct promotion of financial technology to the development of the big data industry, the indirect promotion of financial technology to the development of the big data industry by alleviating big data enterprise financing constraints, and the threshold effect of financial technology in promoting the development of the big data industry. Compared with literature [4] and [12], this article extends the research on financial technology to ease enterprise financing constraints by studying how it promote industrial development. Compared with literature [14], [15] and [16], This article expands the research on alleviating enterprise financing constraints and promoting industrial development to alleviating enterprise financing constraints and promoting industrial development through financial technology. Compared with the literature [17], this article expands the intermediary effect and the threshold effect of financial technology on economic growth by improving the efficiency of financial resource allocation to the intermediary effect and threshold effect of financial technology that affect the development of the industry by alleviating enterprise financing constraints. This paper analyzes the impact of financial technology on the development of the big data industry and its mechanism in depth, which is of great significance for clarifying the interaction mechanism between financial technology and the big data industry and accelerating the integrated development of the finance and big data industry.

Due to the difficulty of data acquisition and the limitation of cognition, many shortcomings still exist, which need to be improved in the future. Future research directions are as follows: First, establishing a comprehensive evaluation index system for the development level of regional financial technology, and using a comprehensive evaluation method based on fuzzy sets to evaluate the development level of regional financial technology. Second, establishing a complete evaluation of the development level of the regional big data industry, which uses a comprehensive evaluation method based on fuzzy sets to evaluate the development level of regional big data. Third, exploring the construction of a more scientific and reasonable method for measuring the financing constraint level of regional big data companies, and improving the convincing power of the empirical analysis results. Fourth, testing the normality of the panel data. If the panel data is skewed normal, use the skewed normal panel data model for empirical analysis. Fifth, selecting more control variables that have a stronger impact on the development of the big data industry to improve the convincing power of the empirical analysis results. Sixth, considering the spatial spillover effects of financial technology, and

establishing a spatial measurement model to measure the direct, indirect, and total effects of financial technology on the big data industry.

5.3. Policy Recommendations

Based on the research conclusions above, combined with the spirit of relevant departmental documents, the following policy recommendations are put forward:

(1) In terms of direct effects, first, encourage financial institutions to actively use big data, artificial intelligence, and other technologies to deeply analyze customer financial needs and create smart financial products and services. Second, promote the transformation of traditional financial entity outlets to marketing and experience smart financial outlets, and improve the operating efficiency of financial outlets. Third, speed up the improvement of the credit process and credit evaluation models of enterprises in key areas. Fourth, optimize the mobile payment technology architecture system and increase technology-enabled payment services. Fifth, improve the financial business risk prevention and control system. Sixth, actively explore the innovation of financial big data application and further expand the demand for big data technology products and technical services in the financial industry.

(2) In terms of indirect effects, first, accelerate the application of mobile Internet, big data, cloud computing, Internet of Things, artificial intelligence, and other emerging cutting-edge technologies in the financing of big data companies, and adhere to the balanced development of online and offline, and provide multi-level and all-round financing services for big data companies. Second, vigorously promote the construction of credit information sharing platforms to realize cross-level, cross-department, and cross-regional interconnection, improve the acquisition, analysis, and application capabilities of big data enterprise financing-related data, and reduce information asymmetry, reduce financing costs, improve financing efficiency, and effectively alleviate the financing constraints faced by big data companies.

Funding: This research was funded by the Regional Project of National Natural Science Foundation of China, grant number 71861003.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

- [1] Sun Xuran, Wang Kangshi, Wang Jinfeng. Fintech, Competition and Bank Credit Structure: Based on the Perspective of SME Financing[J]. *Journal of Shanxi University of Finance and Economics*, 2020, 42(6): 59-72.
- [2] Jin Hongfei, Li Hongji, Liu Yinlu. Financial Technology, Banking Risks and Market Crowding Effect[J]. *Financial Research*, 2020, 46(5): 1-14.
- [3] Liao Min. The current status and future trends of global financial technology regulation[J]. *New Finance*, 2016(10): 12-16.
- [4] Wei Chenglong, Guo Feinan. Research on Fintech Innovation and Mitigation of Corporate Financing Constraints—Based on the Calculation and Empirical Analysis of Fintech Index[J]. *Price theory and practice*, 2020(1): 163-166.
- [5] Zhu Junjie, Wang Yanxi, Zhang Zeyi. The Influence of the Development of Financial Technology on the Upgrading of my country's Industrial Structure[J]. *Science and Technology Management Research*, 2017, 37(19): 31-37.

- [6] Chen Deyu, Tang Yonggang, Zhang Shaohe. Empirical analysis of industrial structure transformation and upgrading, financial technology innovation and regional economic development[J]. *Science and Technology Management Research*, 2018, 38(15): 105-110.
- [7] Zheng Nanlei. Fintech: the commanding heights of the future development of the financial industry[J]. *Securities Market Herald*, 2017(1): 1-6.
- [8] Chishti S, Barberis J. *The Fin-Tech Book: The Financial Technology Handbook for Investors, Entrepreneurs and Visionaries*[M]. Chichester, UK: John Wiley & Sons, Ltd, 2016.
- [9] Arner D, et al. The development of financial technology: a new model after the financial crisis[J]. *New Finance*, 2018(5): 9-15.
- [10] Qiao Haishu, Huang Jianxuan. Research on Financial Technology Development Momentum Index[J]. *Financial Forum*, 2019, 24(3): 64-80.
- [11] Yosepha S Y. The Role of Fintech Encourages the Export of Small Medium Enterprises in Indonesia[J]. *Journal of Social and Development Sciences*, 2018, 9(3): 66-77.
- [12] Huang Rui, Lai Xiaobing, Tang Song. How does financial technology affect corporate financing constraints? — — Dynamic effects, heterogeneity characteristics and macro-micro mechanism inspection[J]. *International Finance Research*, 2020(6): 25-33.
- [13] Yin Z, Gong X, Guo P, et al. What Drives Entrepreneurship in Digital Economy? Evidence from China[J]. *Economic Modelling*, 2019, 82: 66-73.
- [14] Rajan R G, Zingales L. Financial dependence, and growth[J]. *American Economic Review*, 1998, 88(3): 559-586.
- [15] Xie Qiaoxin, Zhang Yu. An Empirical Analysis of the Impact of Financing Constraints and FDI Inflows on Industrial Growth: Taking Zhejiang Province as an Example[J]. *Technical economy*, 2014, 33(12): 54-58+79.
- [16] Yang Yuanyuan, Yu Jinping, Yang Dongxu. Are financing constraints hindering the high-end of strategic emerging industries? [J]. *Economic Review*, 2018(5): 60-74.
- [17] Tian Xinmin, Zhang Zhiqiang. Financial Technology, Resource Allocation Efficiency and Economic Growth——Analysis Based on the Threshold Effect of China's Financial Technology[J]. *Statistics and Information Forum*, 2020, 35(7): 25-34.
- [18] Bai Zhonglin. *Econometric Analysis of Panel Data*[M]. Tianjin: Nankai University Press, 2008.
- [19] Pang Lujing, Zhang Mu. Research on the Coordinated Development of China's Provincial Big Data Industry and Financial Agglomeration Coupling [J]. *Science and Technology Management Research*, 2020, 40(15): 209-216.
- [20] Tang Zhongfu, Gu Peiliang. Comprehensive evaluation of the development level of high-tech industry[J]. *Economic Theory and Economic Management*, 2003(10): 23-28.
- [21] Yang Jianhua, Lu Bo. Research on the Evaluation Index System for the Development of Regional Electronic Information Industry[J]. *Journal of Irbin University of Technology (Social Science Edition)*, 2005(4): 56-60.
- [22] Ren Weihong, Huang Lucheng. The Evaluation Model and Application of the Development Level of R&D Industry Based on Entropy[J]. *Technological progress and countermeasures*, 2009, 26(3): 109-111.
- [23] Wang Hailong, Liu Jia. Evaluation and model analysis of the development level of high-tech industries in my country's provinces and regions[J]. *Technological progress and countermeasures*, 2011, 28(22): 113-117.
- [24] Qiu Wanhua. *Management Decision and Applied Entropy*[M]. Beijing: Machinery Industry Press, 2002.
- [25] Yue Chaoyuan. *Decision Theory and Method*[M]. Beijing: Science Press, 2003.
- [26] Kaplan S, Zingales L. Do investment-cash flow sensitivities provide useful measures of financing constraints? [J]. *Quarterly Journal of Economics*, 1997, 112(1): 169-215.
- [27] Hadlock C J, Pierce J R. New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index[J]. *Review of Financial Studies*, 2010, 23(5): 1909-1940.
- [28] Harrison A E, McMillan M S. Does direct foreign investment affect domestic credit constraints? [J]. *Journal of International Economics*, 2003, 61(1): 73-100.
- [29] Wang Feibo, Xie Qiaoxin. FDI inflow, financing constraints and export spillover effects[J]. *Science and Technology Management Research*, 2014, 34(22): 97-101.
- [30] Shen Junxin, Li Shuang, Zhang Jingyang. Research on the Factors Influencing the Development Capability of Big Data Industry — —Based on the fsQCA Method[J]. *Science and Technology Management Research*, 2019, 39(7): 140-147.
- [31] Fu Yongping. An Empirical Study on the Key Factors Influencing the Development of China's Strategic Emerging Industries[J]. *Journal of Donghua University (Natural Science Edition)*, 2019, 45(4): 605-611.

- [32] Fan Xiaoli, Huang Lingxiang, Lu Jing, Wang Liyan. Agglomeration Development of Strategic Emerging Industries and Analysis of Influencing Factors[J]. *Statistics and Decision*, 2017(14): 139-143.
- [33] Ma Shuqin, Wang Jianghang. A Review of Frontier Research on Financing Constraints and Heterogeneous Enterprise Exports[J]. *International trade issues*, 2014(11): 164-176.



Copyright © 2021 by the authors. This is an open access article distributed under the CC BY-NC 4.0 license (<http://creativecommons.org/licenses/by-nc/4.0/>).