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Chapter: Economic Development, Finance, Marketing and Sectoral Development

Regional disparities and spatial spillovers: the impact of fintech on manufacturing productivity in China

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Annotation. *As China's financial industry enters a new digital era, the scope of financial technology services to the real economy has expanded and deepened. This paper adopts spatial econometrics to examine the impact of FinTech on manufacturing productivity, specifically on manufacturing technology progress and efficiency improvement. The following conclusions are drawn. First, FinTech development levels in China vary, with the highest level in the east, followed by the central region, and is the lowest in western China. Second, China's total factor productivity presents clear spatial autocorrelation characteristics. Third, the development of FinTech can improve the manufacturing total factor productivity nationwide, and this effect occurs mainly through efficiency improvements, and the influence of technological progress is not significant. This study helps elucidate the possible spatial correlation effects of FinTech on manufacturing total factor productivity in terms of geographic location or socioeconomic factors. We also provide a reference for national policy departments to formulate differentiated interregional FinTech strategies.*

Keywords: fintech technology, manufacturing industry, TFP, spatial metrology, China.

JEL classification: O33, O14, C21.

Introduction

According to data published online by Statista, the revenue of the global FinTech industry has been rising over the past five years, the penetration rate of FinTech in the traditional financial industry has been expanding globally, the development level of FinTech has been improving, the overall scale of industrial investment and financing has continued to increase, and the growth scale of the FinTech in the East Asian region has continued to rise. In 2021, the global market size of the FinTech industry reached $146.2 billion, with a compound growth rate of 12.8% over the past five years. China's FinTech development

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history is relatively short, and there is a huge market gap. In light of the development of online opportunities brought by the pandemic, most financial institutions and internet companies have poured into the FinTech industry during this key period of digital transformation of traditional industries and asset digitization, reinvigorating China's FinTech industry. According to the data from Saidi Consultant's White Paper on FinTech Development, China's FinTech market size grew from 2016 to 2020 at a rate of approximately 10%. In 2022, the overall market size of China's FinTech reached approximately 542.3 billion yuan.

The manufacturing industry is a core pillar of the real economy. In 2010, China became the world's largest manufacturing country, but the advantage of low-cost labour that drove the rise of China's manufacturing sector is fading as industrialization accelerates and the population ages. Due to the lack of core competitiveness, rising costs, and other problems, China's manufacturing industry is faced with the dual dilemma of "high-end return" from developed countries and "middle and low-end diversion" from developing countries. China's manufacturing industry urgently needs to improve total factor productivity to increase its core competitiveness. In recent years, the rapid development of a new generation of information technologies such as big data, cloud computing, and the Internet of Things has provided new pathways for growing the manufacturing industry. Moreover, the manufacturing industry is inherently capital intensive and heavily reliant on complex supply chains. The rapid development of a new generation of information technologies provides new pathways to alleviate the financing constraints of manufacturing supply chains and accelerate intelligent upgrading. The People's Bank of China issued the FinTech Development Plan (2019-2021) and FinTech Development Plan (2022-2025), putting forward guidelines on FinTech development in the new era and clarifying its purpose of serving the real economy. Therefore, the marginal contributions of this paper lie in the following three aspects. First, we adopt spatial econometrics to capture the spatial dependence of productivity. Second, we not only examine the impact of FinTech on manufacturing productivity but also further decompose this impact into technological progress and efficiency improvement to uncover the underlying "black box." Third, by constructing multiple spatial weight matrices, we empirically investigate the spatial spillover effects of FinTech, providing more objective and accurate empirical evidence for interregional FinTech strategies.

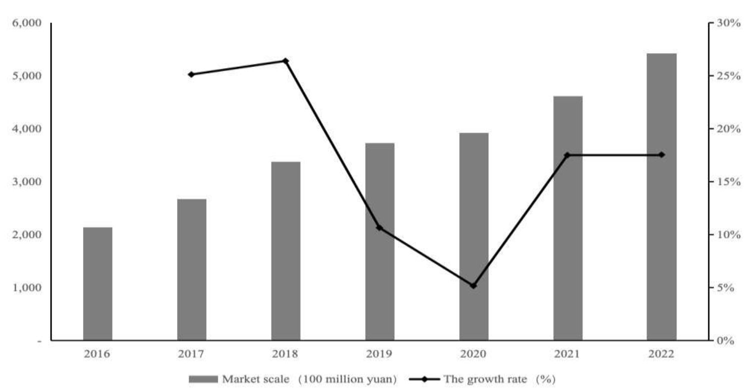
1. Literature Review

Existing research has focused mainly on the influence of internal and external factors such as R&D innovation (Grossman, Helpman, 1991), resource allocation (Hsieh, Klenow, 2009), and the open market environment on total factor productivity (Griffith *et al*., 2004). In addition, some studies have investigated this issue from the perspective of technology input and productivity. The positive role of information technology on productivity has been verified by many scholars (Cardona *et al*., 2013; Mithas *et al*., 2012; Wang *et al*., 2024), but some scholars still find that there may be no obvious correlation between the input of technology or information technology and productivity, i.e., the so-called "productivity paradox." Furthermore, some studies have verified the relationship between information technology (IT) investment and enterprise productivity. It is generally believed that technology investment may not lead to an improvement in enterprise productivity (Beccalli, 2007; Dong *et al*., 2020; Shu, Strassmann, 2005).

In the n FinTech literature, some studies focus on the measurement and development characteristics of FinTech and its influencing factors (Pollari, 2016). There are three main methods for measuring the development level of FinTech, and the main method for measuring the regional FinTech development level is to adopt the number of regional FinTech companies as an alternative variable (Phan et al., 2020). The second method is the text-mining method, which is applied to construct a regional overall FinTech development level index (Cheng, Qu, 2020). In the third method, China's Digital Financial Inclusion Index released by Peking University Digital Finance can be used directly to replace the regional FinTech development level (Ding *et al.*, 2022). In addition, there is some literature on the impact of the application of FinTech on social entities. Among them, more studies focus on the banking level. FinTech has an impact on traditional banking. Similarly, there are two different perspectives on this topic. One view holds that FinTech can effectively improve the efficiency of commercial banks. As an entity that is closely tied to the real economy, banks have strong complementarity with the FinTech industry. Through the technology spillover channel, banks can apply relevant technologies and increase related research investment, subsequently promoting their own transformation, upgrading, and technological progress (Berger, 2003). Among them, the risk control system based on big data, blockchain, and other technologies can effectively help banks efficiently analyse information and trade quickly, which can then significantly enhance their profitability and risk prevention (Dynan *et al.*, 2006; Lee *et al.*, 2021).

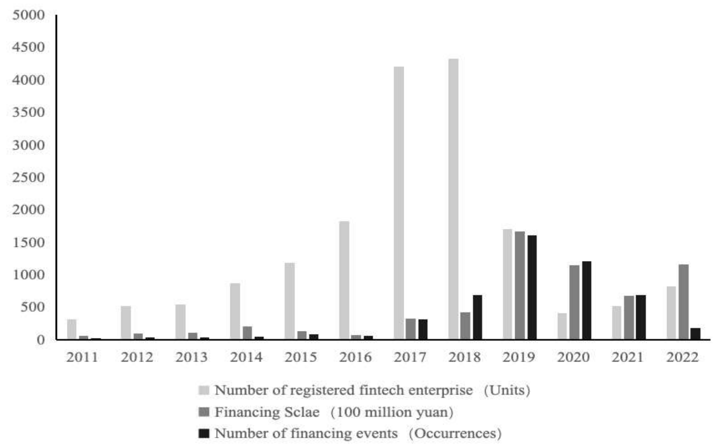
2. The Development of Financial Technology in China

From the perspective of China's FinTech development, its development history is relatively short, and there is a large market gap. Accompanied by the development opportunities brought online by the pandemic, most financial institutions and online companies entered the FinTech industry during a key period of the digital transformation of traditional industries and asset digitization, thus reinvigorating China's FinTech industry. As shown in *Figure 1*, according to the data from Saidi Consultant's White Paper on FinTech Development, from 2016 to 2020, China's FinTech market size grew at rate of approximately 10%. In 2022, China's overall FinTech market size reached approximately 542.3 billion yuan. As shown in Figure 2, according to the main indicators of China's FinTech development from 2011-2022, the number of FinTech registered enterprises, financing scale, and financing events all maintained steady growth during 2011-2016. During 2016-2018, due to booming economic conditions and tolerant government policies, FinTech saw rapid development, with all three of its indicators experiencing rapid growth. However, in 2019, the market began to eliminate small and micro FinTech enterprises, and a large number of M&A and investment activity occurred among various financial enterprises for the sake of cost and efficiency. The subsequent three consecutive years of the pandemic, i.e., 2020, 2021, and 2022, further tested the liquidity and technological strength of China's FinTech enterprises, eliminating a large number of FinTech enterprises. However, at the same time, the remaining FinTech companies withstood being tested by the market, gained a larger market share, and attracted more investors, resulting in the emergence of scale effects in the FinTech industry.



Source: created by the authors.

Figure 1. **Market Size and Growth Rate of China's FinTech Industry**



Source: created by the authors.

Figure 2. **Overview of FinTech Development in China**

FinTech is strongly correlated with China's current financial inclusion practices. Therefore, to measure the level of FinTech development, the China Digital Financial Inclusion Index was compiled by the Institute of Digital Finance Perking University at the provincial level in 2021 and is used here as a proxy indicator. ArcGIS software was used to draw *Figure 3*. The Digital Financial Inclusion Index is based on the massive amount of data from Ant Financial Services, which reacts to and portrays China's financial inclusion development in terms of factors such as coverage breadth, usage depth, and the degree of digital support services. It also has a certain reference significance in reflecting the development level and degree of balance of China's FinTech.

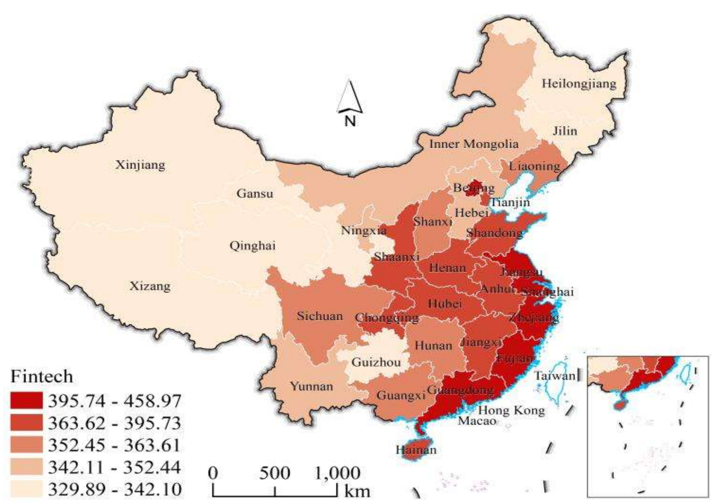


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Figure 3. **FinTech Development in Various Provinces and Cities in China**

From the regional spatial perspective, the development level of FinTech in China is generally decentralized and spatially clustered within regions, with a pattern of "strong in the east and weak in the west, more in the south and few in the north." Specifically, in terms of the distribution of cities where FinTech enterprises are located, the number of applications from enterprises in major cities such as Beijing, Shanghai, Guangzhou, Shenzhen, and Hangzhou accounted for 82% of the total, while the development of FinTech has also shown a stepwise change from the southeast coast toward inland. As shown in Figure 3, China's FinTech enterprises are concentrated mainly in Beijing-Tianjin-Hebei, the Yangtze River Delta, and Guangdong-Hong Kong-Macao. Meanwhile, Chengdu-Chongqing and the middle reaches of the Yangtze River have experienced strong development momentum in recent years, which has led to a gradual clustering effect in the FinTech industry. According to "China's Top 100 FinTech Enterprises (2023)" released by the Zhongguancun Internet Finance Institute, the number of FinTech enterprises continues to grow, the development potential of FinTech is gradually being realized nationwide, and spillover effects of the FinTech industry have gradually materialized. The evident geographical clustering and regional disparities in FinTech development strongly suggest that spatial dependencies cannot be ignored. Consequently, it is both necessary and appropriate to employ spatial econometric models to rigorously test the impact of FinTech on manufacturing productivity in the following empirical analysis.

3. Theoretical Analysis and Research Hypotheses

The rapid development of information and communication technologies (ICT) has provided a technological foundation for FinTech, and research on FinTech has gradually shifted from the regional level to a spatial and geographical perspective.

3.1 The Role of FinTech in Boosting Regional Manufacturing Productivity

The mechanism between regional financial technology and the total factor productivity of the manufacturing industry can promote the improvement of total factor productivity by promoting the long tail market. According to the long tail theory, the market scale of the tail non-popular market located at the two ends of the normal curve with small demand and great differentiation will exceed that of the popular market located at the head of the normal curve. Due to the limitations of physical outlets, the traditional financial service model is more inclined to the "28 Law," pouring limited resources and energy into a small number of high-end customers and neglecting to exploit the long tail market. However, the emergence of financial technology provides another possibility for overcoming the "28 Law" service dilemma and improving inclusive financial services. Relying on underlying technological innovations such as big data, cloud computing, artificial intelligence, and blockchain, financial technology profoundly reconstructs the financial infrastructure in the fields of current trading rules and technologies, payment and settlement systems, and regulation and supervision systems and generates new business models, technical applications, business processes, and innovative products at the level of financial service supply, thereby enabling the formation of new financial formats. New financial business models, such as smart investment, insurance technology, equity crowdfunding, and mobile payment, enable the transformation of financial services from offline to online, expand the service boundary from only high-end to be more inclusive, and provide diversified financial services for long-tail demand groups. Specifically, with intelligent and real-time collecting, analysing, decision-making, and sharing the basic big data of financial institutions and non-financial enterprises and supported by decentralized distributed ledger technology, FinTech can guarantee the security of enterprise information and data and reduce credit risk. This can significantly lower information asymmetry costs in the long-tail market, expand the coverage of financial services for manufacturing enterprises under strong siphon effects, enhance the identification of innovative but credit-constrained manufacturing firms, and strengthen the efficient allocation of financial resources to technology-intensive enterprises, thereby promoting the total factor productivity of manufacturing enterprises (Wang, Shao, 2024). Theoretically, gains in TFP can be driven by either technological change (TC), i.e., expanding the production frontier, or efficiency change (EC), i.e., moving closer to the frontier. Given that FinTech primarily reduces transaction costs, optimizes capital allocation, and improves management workflows through digitalization, its immediate impact is likely to be manifested more significantly in efficiency improvement rather than breakthrough technological progress, which typically requires long-term R&D accumulation. In view of this, Hypothesis 1 is proposed.

Hypothesis 1: At the intraregional level, FinTech contributes to the improvement of regional total factor productivity.

3.2 Spatial Spillover Effects of FinTech

At the interregional level, FinTech innovation promotes regional total factor productivity under the effect of spatial knowledge spillovers. The application of knowledge spillover theory at the spatial level is manifested in the process of unconscious knowledge exchange and dissemination between geographic locations, i.e., spatial knowledge spillover. Specifically, there are two main pathways through which total factor productivity can be increased by utilizing spatial knowledge spillover in FinTech innovation. The first pathway is based on the network effect, which accelerates the spatial spillover of explicit knowledge through FinTech innovation and further increases regional total factor productivity. The innovative behaviour of FinTech that is supported by a series of technologies, such as big data, cloud computing, artificial intelligence and blockchain, is characterized by technical knowledge.

The second pathway is based on the flow effect of personnel. Through the flow of talent with FinTech innovation knowledge between regions, the acceleration of technical knowledge absorption, reasonable personnel allocation, and technology docking, it can expand the spatial overflow channels of tacit knowledge and ultimately expanding regional total factor productivity. In view of this, Hypothesis 2 is proposed.

Hypothesis 2: At the interregional level, FinTech can promote the cross-regional transmission of knowledge, i.e., spatial knowledge spillover occurs, which promotes the growth of the total factor productivity of manufacturing enterprises in surrounding areas.

4. Sample and Methodology

4.1 Spatial Econometric Model

In the face of extremely complex economic systems or the interaction among factor variables, especially spatial autocorrelation and spatial heterogeneity in cross-sectional data, the linear regression model of classical econometrics will inevitably be biased in terms of measurement, while spatial econometrics establish a statistical and econometric relationship between geographic location and spatial connections and identify and measure the patterns and determinants of spatial change by statistical and measurement methods, which to a certain extent avoids the bias of measurement results (Anselin, 1988). To portray complex and variable spatial interactions, spatial correlations, and spatial heterogeneity grounded in reality, two major types of modelling systems, namely, the spatial panel lag model (SLM) and the spatial panel error model (SEM), have been developed.

The SLM is set up in the following form:

$$y_{it} = \alpha_i + \rho \times \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}^T \beta + \varepsilon_{it} \tag{1}$$

The SEM is set up in the following form:

$$y_{it} = \alpha_i + x_{it}^T \beta + u_{it}, \quad u_{it} = \lambda \times \sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \tag{2}$$

In Equations (1) and (2), y_{it} is the explained variable; x_{it} is the K-dimensional explanatory variable; α_i is the individual effect; $W = (w_{ij})$ is the spatial weight matrix; ρ is the spatial autoregressive coefficient of the model; λ is the spatial autoregressive coefficient of the disturbance term in the model; u_{it} and ε_{it} are the disturbance terms of the model; and β is the regression coefficient of the model. Anselin *et al*. (2008) specifically categorize general spatially dynamic panel data models into Pure Space Recursive Models, Time-space Recursive Models, Time-space Simultaneous Models, and Time-space Dynamic Models.

Pure Space Recursive Models are set up in the following form:

$$y_{it} = \rho \times \sum_{j=1}^{N} w_{ij} y_{jt-1} + x_{it}^T \beta + \varepsilon_{it} \tag{3}$$

Time-space Recursive Models are set up in the following form:

$$y_{it} = \phi y_{it-1} + \rho \times \sum_{j=1}^{N} w_{ij} y_{jt-1} + x_{it}^T \beta + \varepsilon_{it} \tag{4}$$

Time-space Simultaneous Models are set up in the following form:

$$y_{it} = \phi y_{it-1} + \rho \times \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}^T \beta + \varepsilon_{it} \tag{5}$$

Time-space Dynamic Models are set up in the following form:

$$y_{it} = \phi y_{it-1} + \rho \times \sum_{j=1}^{N} w_{ij} y_{jt} + \gamma \times \sum_{j=1}^{N} w_{ij} y_{jt-1} + x_{it}^T \beta + \varepsilon_{it} \tag{6}$$

The diversity of spatial panel model settings has also caused difficulties in applied research on how to choose the specific settings of spatial panel econometric models. A widely adopted method in applied research is the robust LM test proposed by Anselin *et al*. (1996) for spatial panel modelling. In practice, the sample values of the LM test or robust LM test statistics of multiple static panel models can be calculated separately, and the specific setting form of the model can be judged according to the significance of the LM test or robust LM test statistics. Another issue regarding the model setting is the handling of individual effects in the model. Pace and LeSage (2008) extended the Hausmann test principle of the general panel model to the static spatial panel model and proposed the following spatial Hausmann test statistic:

$$H = D^T [Var(D)]^{-1} D \tag{7}$$

where *D* is the difference between the coefficients estimated by the Spatial Fixed Effects (SFE) model and the Spatial Random Effects model (SRE), i.e., $D = [\hat{\rho}, \hat{\beta}^T]^T_{SRE}$. Pace and LeSage prove that the limiting distribution of the spatial Hausmann test statistic is the χ^2 distribution with *K+1* as degrees of freedom. By using the significance of the spatial Hausmann test statistics, it is possible to judge whether the model should be a fixed-effect static spatial panel model or a random-effect static spatial panel model.

4.2 Spatial Weighted Matrix

Spatial statistics and spatial econometrics often use a spatial weight matrix to describe the spatial location relationship between spatial units and measure spatial dependence; thus, the spatial weight matrix is the core element of spatial data analysis and spatial econometric modelling. A spatial weight matrix is actually a quantitative method to quantify the location of spatial units, spatial structural characteristics, and interrelationships of spatial units. Specifically, it is a method to quantify the relative spatial location and spatial interaction influence of spatial unit i on spatial unit j in geographic space. This influence can produce different effects according to different setting methods. In terms of setting methods, spatial weight matrices can be divided into three main categories: spatial weight matrices based on geographic adjacency, spatial weight matrices based on spatial distance, and spatial weight matrices based on socioeconomic structure.

4.3 Variables Selection

The sample data used in this paper are the panel data of 31 provincial administrative regions in mainland China from 2011 to 2021, which are obtained from the China Statistical Yearbook, China Industry Statistical Yearbook, China Statistical Yearbook on Science and Technology, and Almanac of China's Finance and Banking for the relevant years. The reason for choosing the year 2011 as the starting point of the sample time is mainly because FinTech in China began to develop rapidly in 2011. The related variables are described below:

Explained variables. This paper adopted the nonparametric method to measure the TFP of manufacturing industries in 31 provincial-level regions in China. Currently, the most widely used nonparametric measure is the Malmquist Productivity Index (MPI) proposed by Fare et al. (1994), which, in addition to the advantages of the general nonparametric method, can further decompose the MPI into EC and TC. In the specific calculation, the total output value of the manufacturing industry is taken as the output indicator, the number of manufacturing employees and fixed asset investment are taken as the input indicators, and the data envelopment analysis method is utilized to calculate the MPI and its decomposition results for the 31 provincial-level administrative regions in mainland China during the period of 2011-2021.

Core Explanatory Variables. FinTech is the core explanatory variable in the model. In this paper, the Baidu search index of FinTech-related keywords in each provincial administrative area from 2011 to 2021 is manually organized and summarized into FinTech index. The specific steps are as follows. First, drawing on the analytical framework for commercial banks' credit business targeting micro and small enterprises, this study identifies the core FinTech keywords specifically associated with these lending activities, considering the data availability of the Baidu Search Index. After all the Baidu search indices for each of the above keywords are collected, the indices are summarized from four perspectives: technology, capital payment, intermediary service model, and direct address. The technology perspective includes big data, cloud computing, artificial intelligence, and blockchain. The capital payment perspective covers mobile payments, third-party payments, and biometric payments. The intermediary service model perspective consists of peer-to-peer lending, crowdfunding, and digital banking. The direct address perspective involves FinTech and financial technology. The entropy method is used to determine the weights, and multiple indices are synthesized into a comprehensive index. Finally, the index synthesized by the entropy value method is divided by the number of residents in each province to measure the level of FinTech development in each province.

Control variables. In this paper, the variables R&D input, technological innovation, economic foundation, and the market environment are used as control variables in the model. R&D input includes R&D investment intensity and R&D personnel size. In the specific calculation, this paper measures the regional R&D investment intensity (rd) and the number of R&D personnel (re) based on the R&D investment and the share of regional R&D personnel to that of the national figure. For the level of regional technological innovation, this paper uses the logarithm of the regional high-tech industry's technological transformation expenditure (Invtr) and technology introduction expenditure (Invft). The economic foundation includes the economic growth level (Growth), human capital level (Hum), openness level (Open), and capital intensity (Cap). The economic growth level is measured using the logarithm of GDP per capita in each region, human capital level is measured using the regional indicator of years of education per capita, openness level is measured using the ratio of total imports and exports to the GDP of each region, and capital intensity is measured using the ratio of capital stock to labour force, with capital stock adjusted by the perpetual inventory method with a base period of 1952. Table 1 shows the descriptive statistics of the variables in the model.

Table 1. Summary Statistics of the Main Variables

Variable	Obs	Mean	Std.Dev.	Min	Max
MPI	341	1.0739	0.2284	0.62	2.59
EC	341	0.9995	0.1117	0.63	1.51
TC	341	1.0811	0.2483	0.84	2.77
Fin-tech	341	0.1701	0.1254	0.002	0.6109
rd	341	0.0323	0.0596	0.00001	0.3338
re	341	0.0322	0.0597	0.00001	0.3599
Invtr	341	13.2463	1.8567	2.3978	15.7866
Invft	341	10.1861	2.4333	1.6094	14.5629
Growth	341	10.8619	0.4466	9.7058	12.1225
Hum	341	9.1858	1.1348	4.2219	12.8769
Open	341	0.2489	0.2788	0.0069	1.4861
Cap	341	15.9232	7.8991	1.3027	55.6637

Source: created by the authors.

Table 1 shows the descriptive statistics of the variables in the model. As indicated in *Table 1*, the core explanatory variable (FinTech) and the dependent variable (MPI) exhibit substantial differences between their maximum and minimum values, alongside noticeable standard deviations. This descriptive evidence confirms that significant regional heterogeneity and developmental imbalances exist across Chinese provinces during the sample period, underscoring the need to account for spatial dependence in the subsequent regression analysis.

5. Empirical Results

5.1 Benchmark Regression Results

The spatial econometric models constructed in this paper are the SLM and the SEM. Since it is difficult to judge in advance which model can be fitted more efficiently, the Lagrangian Model (LM) is usually used for testing. If the LM (error) is found to be more statistically significant than the LM (Lag) in the spatial dependence test, then it can be determined that the SEM is more appropriate for empirical analysis, and vice versa for the SLM. If the LM fails to test, then further comparison between robust-LM (Lag) and robust-LM (Error) is needed. The results of the LM test and the spatial Hausman test for the spatial panel model with MPI and the decomposition results with EC and TC as the explained variables, respectively, are presented in *Table 2*.

Table 2. Test Results of the Spatial Panel Model

Variable	Spatial Weights Matrix based on Geographic Adjacency			Spatial Weights Matrix based on Spatial Distance		
	MPI	EC	TC	MPI	EC	TC
LM(Err)	0.4361	0.2727	0.5379	0.6638	0.6638	0.8907
LM(Lag)	3.9016**	33.6774***	30.9597***	25.2359***	28.9949***	27.4210***
R-LM(Err)	0.2774	0.1011	0.2252	0.3679	0.3243	0.4661
R-LM(Lag)	2.9433*	26.8066***	24.2060***	18.6641***	20.3594***	19.3561***
Hausman test	21.6241***	24.4381***	26.5958***	22.6152***	25.8333***	27.1863***

Note: values in parentheses indicate robust standard errors. *p<0.10, **p<0.05, and ***p<0.01.

Source: created by the authors.

As seen from the test results in Table 2, the LM statistics of the SLM and SEM are obtained under the Geographic Adjacency Weights Matrix with the Malmquist Productivity Index (MPI), Efficiency Change (EC), and Technological Change (TC) as the model's explained variables, and the test results show that both the LM statistics and robust LM statistics of SLM are significant at more than the 10% significance level, while the LM statistics and robust LM statistics of SEM are not significant. Similar test results are obtained under the geographic distance weights matrix. Therefore, the SLM is chosen in the following spatial panel econometric model. And based on the Hausman test results in Table 2, fixed effects are shown in the individual effects in the model.

Based on the test results of the spatial panel model, this paper establishes the following SLM with MPI, EC, and TC as the explained variables and under the two forms of the spatial weights matrix, namely, the Geographic Adjacency Weights Matrix and Geographic Distance Weights Matrix:

$$\begin{aligned} MPI_{it} = \alpha_i + \rho \times \sum_{j=1}^{N} w_{ij} MPI_{jt} + \beta_1 Fin\text{-}tech_{it} + \beta_2 rd_{it} + \beta_3 re_{it} + \beta_4 Invtr_{it} \\ + \beta_5 Invft_{it} + \beta_6 Growth_{it} + \beta_7 Hum_{it} + \beta_8 Open_{it} + \beta_9 Cap_{it} + \varepsilon_{it} \end{aligned} \tag{8}$$

$$\begin{aligned} EC_{it} = \alpha_i + \rho \times \sum_{j=1}^{N} w_{ij} MPI_{jt} + \beta_1 Fin\text{-}tech_{it} + \beta_2 rd_{it} + \beta_3 re_{it} + \beta_4 Invtr_{it} \\ + \beta_5 Invft_{it} + \beta_6 Growth_{it} + \beta_7 Hum_{it} + \beta_8 Open_{it} + \beta_9 Cap_{it} + \varepsilon_{it} \end{aligned} \tag{9}$$

$$\begin{aligned} TC_{it} = \alpha_i + \rho \times \sum_{j=1}^{N} w_{ij} MPI_{jt} + \beta_1 Fin\text{-}tech_{it} + \beta_2 rd_{it} + \beta_3 re_{it} + \beta_4 Invtr_{it} \\ + \beta_5 Invft_{it} + \beta_6 Growth_{it} + \beta_7 Hum_{it} + \beta_8 Open_{it} + \beta_9 Cap_{it} + \varepsilon_{it} \end{aligned} \tag{10}$$

In this paper, Equations (8)–(10) are estimated using the Maximum Likelihood (ML) method based on the panel data of 31 provincial administrative regions in mainland China from 2011 to 2021, and the model estimation results are shown in *Table 3*.

Table 3. Results of Panel Spatial Lag Model Estimation

Variable	Spatial Weights Matrix based on Geographic Adjacency			Spatial Weights Matrix based on Spatial Distance		
	MPI	EC	TC	MPI	EC	TC
ρ	0.7306*** (0.2236)	0.2392*** (0.0679)	0.8893*** (0.2758)	0.8754*** (0.2717)	0.5471*** (0.1418)	0.9324*** (0.2790)
Fin-tech	0.0972*** (0.0219)	0.1145*** (0.0301)	0.1603 (0.1614)	0.0365*** (0.0073)	0.1585*** (0.0427)	0.2986 (0.4669)
rd	2.1321*** (0.5088)	1.5505*** (0.3173)	0.7428*** (0.1512)	0.1010*** (0.0222)	1.4064*** (0.3372)	1.4127*** (0.2878)
re	0.2861*** (0.0823)	0.6629*** (0.1748)	0.2640*** (0.0709)	1.2995*** (0.3847)	0.6083*** (0.1707)	1.7144*** (0.4493)
Invtr	0.0317** (0.0130)	0.0151** (0.0065)	0.0225** (0.0099)	0.0372** (0.0173)	0.0151** (0.0068)	0.0465*** (0.0141)
Invft	0.0115* (0.0065)	0.0071* (0.0041)	0.0085* (0.0049)	0.0127* (0.0072)	0.0076* (0.0042)	0.0080* (0.0044)
Growth	1.54e-06* (8.56e-07)	1.63e-06* (9.39e-07)	1.81e-07* (1.04e-07)	1.34e-06* (7.43e-07)	1.59e-06** (7.36e-07)	2.57e-07* (1.4e-07)
Hum	0.0415*** (0.0130)	0.00007*** (2.09e-05)	0.0441*** (0.0138)	0.0232*** (0.0063)	0.0170*** (0.0045)	0.0662** (0.0281)
Open	0.1147*** (0.0317)	0.1129*** (0.0326)	0.0713*** (0.0196)	0.1997*** (0.0526)	0.1442*** (0.0444)	0.0460*** (0.0145)
Cap	0.0068** (0.0029)	0.0021*** (0.0006)	0.0051*** (0.0014)	0.0070** (0.0031)	0.0002*** (5.42e-05)	0.0080*** (0.0020)
R-squared	0.5521	0.4292	0.6208	0.5475	0.4795	0.6553
Log（L）	175.4286	291.4505	309.6537	189.1962	298.9828	254.6139
Obs	341	341	341	341	341	341

Note: values in parentheses indicate robust standard errors. *p<0.10, **p<0.05, and ***p<0.01.

Source: created by the authors.

The estimation results in Table 3 indicate that the spatial coefficients based on any of the spatial weight matrices are positive and that all of them pass the 1% significance test, which indicates that the total factor productivity of the manufacturing industry in China has clear spatial correlation. This is because, on the one hand, the resource factor has the economic characteristics of scarcity and profitability. As resource factors can flow freely, factors with lower productivity in manufacturing will automatically flow to regions with higher efficiency and productivity, thus further promoting the productivity of regions with higher manufacturing TFP. Regions with lower manufacturing TFP will see a decline in their production level due to the outflow of production factors. On the other hand, manufacturing enterprises in low-TFP regions can learn from manufacturing enterprises in high-TFP regions to improve their productivity to gain a latecomer advantage. At the same time, due to the rapid development of modern communication technology, information transfer and sharing are very convenient, thus strengthening the learning effect and knowledge spillover effect among regions. The spatial dependence of TFP in the manufacturing industry also indicates the rationality of applying spatial econometric models to measure the impact of Fin-tech on TFP in the manufacturing industry. Under both the Geographic Adjacency Weights Matrix and the Geographic Distance Weights Matrix, the spatial econometric models show that FinTech significantly contributes to the improvement of manufacturing TFP.

The estimation results in *Table 3* also show the effects of FinTech on technological progress and efficiency improvement. From *Table 3*, the impact of FinTech on technological progress is positive under both the Geographic Adjacency Weights Matrix or the Geographic Distance Weights Matrix, but the promotion effect does not pass the significance test. According to the estimation results in *Table 3*, the empirical results from the spatial econometric model constructed based on any of the weight matrices are consistent, and the development of FinTech has a significant facilitating effect on the improvement of efficiency, and all of the coefficients pass the 1% significance test. Therefore, the results of the above analysis reveal that the development of FinTech has played a significant role in promoting China's overall TFP mainly through the efficiency improvement pathway, but the technological progress pathway is not significant. The reasons behind this may be twofold. On the one hand, R&D activities and technological breakthroughs entail high risks and long return cycles. Under conditions of economic uncertainty or information asymmetry, some manufacturing enterprises may divert FinTech-supported funds to smooth short-term operational cash flows or ease immediate debt burdens rather than invest in long-term technological innovation. On the other hand, the transformation rate of innovation achievements in China's manufacturing sector still needs improvement. Even if funds are allocated to R&D, the inherent uncertainty of technological innovation may lead to a lag in observable productivity gains. Therefore, although enterprises relying on technological progress can promote TFP to a certain extent, the effect is not particularly significant. In contrast, the increase in TFP is very significant for enterprises through improving efficiency. In addition, the spatial coefficients in the two tables are also positive through the significance test, which also verifies the spatial dependence of regional manufacturing TFP, as shown in *Table 3*.

5.2 Robustness Test

(1) Replacement of the measurement index of the FinTech development level. This paper refers to Ding *et al*. (2022) for the measurement of FinTech and uses the “FinTech*” of the Digital Financial Inclusion Index compiled by the Institute of Digital Finance at Peking University to measure the level of fintech development in each province. Models (11)–(13) are re-estimated, and the model estimation results are shown in *Table 4*.

As seen from the estimation results in *Table 4*, the empirical conclusions presented in this paper remain robust after replacing the measures. Specifically, the Peking University index comprehensively captures the coverage breadth and usage depth of digital finance, making it a highly valid alternative proxy. The estimation results demonstrate that the coefficients of FinTech on both MPI and EC remain significantly positive at the 1% level, which is entirely consistent with the baseline regression results in *Table 3*, further confirming that FinTech primarily boosts manufacturing TFP through the efficiency improvement pathway.

(2) Replacement of the spatial weight matrix. To verify the robustness of the empirical results in the previous section of this paper, we replace the spatial weight matrix set based on geographic factors with the spatial weight matrix based on economic-social relations and re-estimate Equations (11)–(13). The results of the model estimation are shown in Table 5.

As seen from the estimation results in *Table 5*, the empirical results of the previous section of the paper remain robust when using the spatial weights matrix based on economic-social relations.

Table 4. The Model Estimation Results of Replacing the Measurement Indicators

Variable	Spatial Weights Matrix based on Geographic Adjacency			Spatial Weights Matrix based on Spatial Distance		
	MPI	EC	TC	MPI	EC	TC
ρ	0.4240***	0.7794***	0.3157***	0.1583***	0.5627***	0.5840***
	(0.1079)	(0.2266)	(0.0947)	(0.0450)	(0.1636)	(0.1596)
Fin-tech*	0.0355***	0.5049***	0.4197	0.0650***	0.7937***	0.6296
	(0.0083)	(0.1490)	(0.6703)	(0.0150)	(0.2411)	(1.2995)
rd	1.7871***	1.6052***	1.2017***	1.1852***	1.4901***	1.3287***
	(0.5013)	(0.4727)	(0.3348)	(0.3596)	(0.4477)	(0.3786)
re	0.6747***	0.7445***	0.2990***	0.7714***	0.7313***	0.6412***
	(0.2119)	(0.2069)	(0.0804)	(0.2053)	(0.2264)	(0.1628)
Invtr	0.0294**	0.0456**	0.0517**	0.0186**	0.0702**	0.0740**
	(0.0121)	(0.0189)	(0.0228)	(0.0080)	(0.0312)	(0.0341)
Invft	0.0011*	0.0043*	0.0075*	0.0032*	0.0041*	0.0049*
	(0.0006)	(0.0025)	(0.0044)	(0.0017)	(0.0024)	(0.0028)
Growth	1.42 e-06*	1.95 e-06*	1.46 e-06*	1.42 e-06*	1.28 e-06*	1.27 e-06*
	(8.34e-07)	(1.17e-06)	(8.63e-07)	(8.20e-07)	(7.15e-07)	(7.29e-07)
Hum	0.0843**	0.0402**	0.0367**	0.0492**	0.0549**	0.0163**
	(0.0421)	(0.0177)	(0.0184)	(0.0206)	(0.0238)	(0.0074)
Open	0.2605***	0.3259***	0.9058***	0.3839***	0.2097***	0.1151***
	(0.0078)	(0.0857)	(0.2535)	(0.1136)	(0.0611)	(0.0351)
Cap	0.0071**	0.0020**	0.0065**	0.0007**	0.0069**	0.0060**
	(0.0031)	(0.0008)	(0.0030)	(0.0003)	(0.0031)	(0.0025)
R-squared	0.6268	0.6130	0.5083	0.4924	0.4520	0.5452
Log（L）	132.6421	265.3987	153.8600	166.7672	280.1769	162.3849
Obs	341	341	341	341	341	341

Note: values in parentheses indicate robust standard errors. *p<0.10, **p<0.05, and ***p<0.01.

Source: calculated by the authors.

Table 5. Model Estimation Results of Replacing the Spatial Weight Matrix

Variable	Spatial Weights Matrix based on the Socioeconomic Structure		
	MPI	EC	TC
ρ	0.7426***	0.4923***	0.9602***
	(0.1662)	(0.1170)	(0.2278)
Fin-tech*	0.0693***	0.9833***	0.6608
	(0.0144)	(0.2357)	(1.6409)
rd	1.7862***	1.4534***	1.2041***
	(0.4953)	(0.4283)	(0.3250)
re	0.1681***	0.5420***	0.6619***
	(0.0449)	(0.1726)	(0.1744)
Invtr	0.0059**	0.0454**	0.0116**
	(0.0025)	(0.0191)	(0.0050)
Invft	0.0093*	0.0032*	0.0052*
	(0.0053)	(0.0018)	(0.0029)
Growth	1.17 e-06*	1.40 e-06*	1.76 e-06*
	(6.6e-07)	(7.32e-07)	(9.92e-07)
Hum	0.0862**	0.0308**	0.0432**
	(0.0380)	(0.0129)	(0.8983)
Open	0.2453***	0.8091***	0.7855***
	(0.0751)	(0.2568)	(0.2231)
Cap	0.0079**	0.0041**	0.0035**
	(0.0033)	(0.0018)	(0.0016)
R-squared	0.5544	0.6725	0.5865
Log（L）	111.4214	163.1688	220.4267
Obs	341	341	341

Note: values in parentheses indicate robust standard errors. *p<0.10, **p<0.05, and ***p<0.01.

Source: calculated by the authors.

To further verify the robustness of the benchmark regression results, this paper employs a dynamic spatial panel model to address potential endogeneity issues. In empirical analysis, endogeneity may stem from reverse causality, as regions with higher total factor productivity in manufacturing tend to attract more FinTech resources and from unobserved omitted variables. Existing studies typically adopted dynamic spatial panel models to address the endogeneity problem, and the estimation of dynamic spatial panel models can be broadly categorized into two types. First, the spatial correlation is removed before estimation, and then traditional panel estimation techniques are used. The main methods for removing spatial correlation from the data are the Griffith method (Griffith, 2000) and the Getis method (Getis, Griffith, 2002). Another type of way to estimate dynamic spatial panel models is to improve the traditional ML estimation methods. Elhorst (2005) draws on the idea of estimating non-spatial dynamic panel models and proposes to estimate the dynamic spatial panel model through unconditional maximum likelihood estimation. First, first-order differences are used to eliminate fixed effects, and then the product of the density function of first-order difference observations for each spatial unit is used to construct the unconditional maximum likelihood function of the first-order difference model. Hsiao *et al*. (2002) show that this approach is more asymptotically efficient. In view of this, this paper draws on the research of Elhorst (2005) to estimate the model using the unconditional maximum likelihood method, thus addressing the endogeneity problem to some extent. Different estimation methods can be used for different assumptions of the explanatory variables, and the most commonly used methods are the BS approximation and the NB approximation, and the latter is chosen in this paper. The estimation results of the dynamic spatial panel model for national data are shown in *Table* 6.

Table 6. Results of Dynamic Panel Spatial Model Estimation

Variable	Spatial Weights Matrix based on Geographic Adjacency			Spatial Weights Matrix based on Spatial Distance		
	MPI	EC	TC	MPI	EC	TC
ϕ	0.1823***	0.1525***	0.1434***	0.1315***	0.1045***	0.1216***
	(0.0472)	(0.0441)	(0.0405)	(0.0351)	(0.0318)	(0.0354)
ρ	0.8550***	0.9412***	0.6934***	0.1124***	0.7054***	0.8284***
	(0.2697)	(0.2641)	(0.1950)	(0.0335)	(0.2018)	(0.2274)
Fin-tech	0.0019***	0.7831***	0.1032	0.0888***	0.3742***	0.2992
	(0.0005)	(0.2439)	(0.7961)	(0.0265)	(0.0995)	(0.3016)
rd	1.6891***	1.6920***	1.6909***	1.1872***	1.7805***	1.8188***
	(0.4915)	(0.4638)	(0.4494)	(0.3763)	(0.4456)	(0.5586)
re	0.7273***	0.2302***	0.5431***	0.9058***	0.1949***	0.7999***
	(0.2288)	(0.0718)	(0.1679)	(0.2598)	(0.0510)	(0.2441)
Invtr	0.0145**	0.0655**	0.0913**	0.0664**	0.0882**	0.0811**
	(0.0064)	(0.0289)	(0.0426)	(0.0292)	(0.0406)	(0.0367)
Invft	0.0024*	0.0067*	0.0063*	0.0066*	0.0093*	0.0082*
	(0.0013)	(0.0041)	(0.0038)	(0.0038)	(0.0052)	(0.0044)
Growth	1.65 e-07*	1.24 e-07*	1.55 e-07*	1.15 e-07*	1.92 e-07*	1.17 e-07*
	(9.68e-08)	(6.95e-08)	(8.97e-08)	(6.64e-08)	(1.08e-07)	(6.86e-08)
Hum	0.0805**	0.0513**	0.0256**	0.0831**	0.0095**	0.0617**
	(0.0347)	(0.0226)	(0.0113)	(0.0370)	(0.0039)	(0.0259)
Open	0.6013***	0.7617***	0.2725***	0.7653***	0.8191***	0.2446***
	(0.1620)	(0.2339)	(0.0717)	(0.2081)	(0.2120)	(0.0710)
Cap	0.0056**	0.0029**	0.0002**	0.0021**	0.0050**	0.0053**
	(0.0024)	(0.0012)	(8.41e-05)	(0.0009)	(0.0022)	(0.0023)
R-squared	0.5386	0.4399	0.6927	0.7549	0.6780	0.6427
Log（L）	0.3749	0.9645	0.6351	0.9350	0.4544	0.2601
Obs	341	341	341	341	341	341

Note: values in parentheses indicate robust standard errors. *p<0.10, **p<0.05, and ***p<0.01.

Source: calculated by the authors.

From the estimation results of the dynamic spatial panel model in *Table 6*, it can be seen that under the Geographic Adjacency Weights Matrix and Geographic Distance Weights Matrix, FinTech has a significant positive effect on the productivity and efficiency improvement of the regional manufacturing industry, but the impact on the technological advancement of the regional manufacturing industry is not significant, and the empirical results of this paper, as previously described, are still robust.

6. Discussion

This study examines the intricate relationship between FinTech development and manufacturing productivity in China, integrating regional disparities and spatial spillover considerations. Based on these foundations, a spatial lag model (SLM) is developed to capture the dynamic interactions and spatial dependencies among different provincial administrative regions. Initially, a comprehensive framework focused on the Malmquist Productivity Index (MPI) and its decomposition into efficiency change (EC) and technological change (TC) is formulated to uncover the underlying mechanisms of productivity growth. Using various spatial weight matrices, the study derives empirical trajectories for FinTech's impact, establishing a baseline understanding of how digital financial inclusion reshapes the real economy. Recognizing that regional manufacturing industries and financial markets do not operate as independent entities, the study introduces spatial auto-correlation and knowledge spillovers to facilitate inter-regional coordination. Analytical results demonstrate that FinTech development successfully mitigates financing constraints and operational frictions, significantly elevating the overall total factor productivity across the manufacturing sector.

These empirical outcomes align with the long-tail theory, mitigating the traditional financial service dilemma commonly referred to as the "28 Law" in resource allocation. By leveraging underlying technologies such as big data, cloud computing, and blockchain, FinTech effectively lowers information asymmetry costs, expanding the service boundary to long-tail demand groups. Additionally, the analysis underscores the significance of uncovering the "black box" of productivity. The findings reveal that FinTech’s current promotion of manufacturing productivity is overwhelmingly driven by efficiency improvements rather than breakthrough technological progress. This shapes the strategic decisions of manufacturing enterprises, suggesting that in the current stage, FinTech primarily optimizes capital allocation and management workflows rather than immediately expanding the technological frontier, which typically requires long-term R&D accumulation and higher risk tolerance. Furthermore, the verified spatial spillover effects highlight that FinTech innovation not only enhances local manufacturing performance but also strengthens the competitive positioning of surrounding regions through network effects and the cross-regional flow of technical personnel.

In summary, this study provides insights into how digital financial innovations can bridge the gap between traditional financial resource allocation and the optimal productivity performance of the manufacturing industry. While contributing to the theoretical advancement of spatial knowledge spillovers and the structural decomposition of total factor productivity, the findings emphasize the necessity of targeted, cross-regional FinTech coordination strategies. Empirical validation and model extensions, such as exploring the impact using micro-level firm data, investigating the heterogeneous effects across different manufacturing sub-sectors, or evaluating the long-term delayed effects of FinTech on core technological progress, are recommended for future research.

Conclusions and Recommendations

Based on the quantitative analysis of the development of FinTech in various regions of China, this paper empirically examines the impact of FinTech on China's TFP by constructing FinTech evaluation indexes and utilizing econometric models with spatial effects. The results of this study reveal that the level of development of FinTech varies across different regions in China, with the highest level of development in the east, the middle in the centre, and the lowest in the west. China's TFP exhibits significant spatial autocorrelation characteristics, indicating that the factor utilization of a region and its spatially related regions interact. The development of FinTech can promote the manufacturing TFP nationwide, and this impact is exerted mainly through the efficiency improvement pathway, and the effect generated through the pathway of technological progress is not significant.

Based on the empirical results, this paper proposes the following policy recommendations. First, to promote the synergistic development of regional FinTech and maximize spatial spillover effects, the government should establish cross-provincial FinTech cooperation zones and data-sharing platforms. The eastern region should be encouraged to leverage its innate advantages to drive the development of neighbouring regions through knowledge diffusion and talent mobility. Moreover, policymakers should provide targeted digital infrastructure investments for the central and western regions to expand their capacity to absorb these technology spillovers.

Second, the state should formulate relevant resource utilization strategies and plans at the overall level and develop differentiated strategies according to the characteristics of regions in terms of resource endowment to improve the allocation efficiency and utilization efficiency of factors. Moreover, policy-making departments should also consider spatial connections between regions, reasonably increase the exchange and sharing of production technology, knowledge, and experience among regions, and promote the efficient flow of innovative talent.

Third, the government and banking and investment institutions should pay more attention to the investment of FinTech. FinTech entities can sign an agreement in advance to clarify the application scope of FinTech to constrain the application of financing by enterprises. The government should also strictly supervise the allocation of FinTech to reduce resource waste and mismatch. Finally, the government should construct intermediary FinTech services and information platforms and actively develop FinTech. Specifically, the government should build FinTech information platforms to play a bridging role. Moreover, the government should improve the laws and regulations of the information service platform and provide policy support for the construction and improvement of the network platform.

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REGIONINIAI SKIRTUMAI IR ERDVINIS POVEIKIS: FINTECH ĮTAKA GAMYBOS NAŠUMUI KINIJOJE

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Santrauka. Kinijos finansų sektoriui žengiant į naują skaitmeninę erą, išsiplėtė ir pagilėjo finansinių technologijų paslaugų apimtis realiajai ekonomikai. Šiame straipsnyje, taikant erdvinę ekonometrijos analizę, nagrinėjamas finansinių technologijų (FinTech) poveikis gamybos produktyvumui, ypač gamybos technologijų pažangai ir efektyvumo didinimui. Tyrimo metu prieita prie tam tikrų išvadų. Pirma, FinTech išsivystymo lygis Kinijoje skiriasi regioniškai: jis aukščiausias rytuose, mažesnis centriniuose regionuose ir žemiausias vakarų Kinijoje. Antra, bendras Kinijos gamybos veiksnių produktyvumas pasižymi aiškiomis erdvinės autokoreliacijos savybėmis. Trečia, FinTech plėtra gali pagerinti bendrą gamybos veiksnių produktyvumą visoje šalyje, jos poveikis daugiausia grindžiamas efektyvumo didėjimu, o technologinės pažangos įtaka nėra reikšminga. Šis tyrimas ne tik padėjo išsiaiškinti galimą FinTech erdvinės koreliacijos poveikį bendram gamybos gamybos veiksnių produktyvumui atsižvelgiant į geografinę vietą ar socialinius ir ekonominius veiksnius, bet ir sudarė sąlygas pateikti naudingą nuorodą nacionalinę politiką formuojantiems departamentams, kad jie galėtų formuluoti diferencijuotas tarpregionines FinTech strategijas.

Reikšminiai žodžiai: finansinių technologijų technologijos; gamybos pramonė; našusis produktyvumas (TFP); erdvinė metrologija; Kinija.