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Research article

The impact and mechanism of fintech on green total factor productivity

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Abstract: The key to balancing economic transformation and improving quality development is financial supporting green development. The relationship between financial technology (fintech) and green development has gradually emerged recently. Based on the data of 35 major cities in China from 2015 to 2019, the fintech development index and green total factor productivity (GTFP) are obtained by adopting web crawler technology and Bootstrap-SBM-GML model respectively; further, the impact of urban fintech level on GTFP is also revealed by taking the financial support policy index (FSP) as the instrumental variable. The empirical research shows the following results. First, the level of fintech and financial support policy indicators show a steady upward trend in the study period; whereas the tendency of GTFP is not obvious. Second, the urban fintech level has a significant promoting effect on GTFP through FE, MM-QR and 2SLS models. Specifically, the promoting effect mainly comes from the promotion of technological change (TC) of the GTFP decomposition index; the promoting effect will be greater in the lower cities of green development level. Third, industrial structure upgrading (UIS) and technological innovation (TI) play an intermediary role in the green development effect of fintech. Four, the green development effect of fintech is heterogeneous. Specifically, the green development effect of fintech on GTFP is larger in the central and western regions and low-level cities; whereas it is smaller in the eastern part regions and high-level cities.

Keywords: financial technology (fintech); green total factor productivity (GTFP); financial support policy; instrumental variable; mediating role; heterogeneity

JEL Codes: E44, E47, G28, P34

1. Introduction

Financial technology (hereinafter expressed by “fintech”) recently has grown rapidly, which influences greatly in many fields. According to the Financial Stability Board (FSB), fintech refers to financial innovation brought by technology. The integration of technology and finance has brought huge benefits to multiple parties and also attracted more attention to the financial sector. For example, global investment in fintech companies reached US $38.1 billion in 2017 and 57 billion in the first half of 2018 alone (KPMG, 2018). However, the academic circles still have different opinions on the role of fintech.

On the one hand, fintech fundamentally has disruptive advantages, because it brings diversified and continuous growth to major innovations for the current financial system and other infrastructures (Zavolokina et al., 2016; Deng and Cheng, 2019). Fuster et al. (2019) found that fintech can shorten 20% processing time for the lenders; as well as their targets are not only on the less creditworthy customers through a study of the mortgage market. Vallee et al. (2019) denoted that young people are more interested in P2P loans because they are less likely to use traditional credit channels by comparing the differences between traditional banking and P2P loans in the emerging fintech sector. Crowdfunding and robot-advising belong to the fintech services. Specifically, crowdfunding is a reliable way to understand both customers’ needs before production and an important source of funding (Chemla and Tinn, 2020); robot-advising can diversify investors’ portfolio decisions and reduce irrational biases in investment behavior (D’Acunto et al., 2019). In addition, fintech also involves algorithmic trading, especially high-frequency trading (HFT). Hendershott et al. (2013) declared that algorithmic trading can narrow the price gap and reduce adverse selection through research on the improvement of market quality, which can improve the liquidity of the market.

On the other hand, fintech involves more uncertainty and risk than traditional electronic banking or trading. The risks of fintech are not only limited to privacy security, but also related to legal, financial and time loss risk. Chen et al. (2019) proved that fintech innovations are generally valuable for innovators and the whole financial industry; however, it has a negative impact on the industry when this disruptive innovation technology comes from a new non-financial firm. Because fintech is usually unregulated, some institutions’ behaviors such as speculation, financial fraud and hacking may have the potential to cause social harm and loss of funds (Sobehart, 2016; Lorente and Schmukler, 2018; Ryu and Chang, 2018). The profitability of the popular P2P loan model recently is highly dependent on intermediate loans with high balance sheet risk (Demirguec-Kunt et al., 2015). From the perspective of payment, emerging anonymous electronic currencies such as Bitcoin are developing rapidly, and it plays a facilitating role for money laundering, tax evasion and financing of illegal activities (Lorente and Schmukler, 2018).

In contrast to the most previous research direction on fintech, this paper focuses on the green development effect of fintech. To begin with, factors of resources and environment have an important impact on output. China is in a specific historical development period with its rapid economic growth, especially the industrial economy, heavily depends on resource consumption and environmental pollution, so it has a practical significance to explain green production by total factor productivity. In past studies, green total factor productivity (GTFP) is one of the most important indicators referred as the level of green production (Li et al., 2021; Wang et al., 2021; Yang et al., 2021). Different from the parametric method, DEA does not require the functional form of the model to be set up in advance, and various inputs and outputs can be considered (Johnes, 2006). Then, scholars from the world pay much attention to green production. They have obtained abundant findings especially on GTFP. Cui et al. (2019) found that environment control policies, resource input structure, foreign direct investment and energy type structure have significant effects on GTFP growth; whereas technological innovation has little impact on GTFP for the industrial sector. The development of GTFP was constrained by the low economy and infrastructure allocation efficiency in current major Chinese provinces, but it is promoted by government expenditure (Liu and Xin, 2019). Moderate fiscal decentralization can improve GTFP; whereas excessive fiscal decentralization becomes an obstacle to GTFP (Song et al., 2018). Lu et al. (2021) declared that regional GTFP has significant characteristics of spatial autocorrelation and spatial clustering by constructing the SBM-ML model. More specifically, manufacturing agglomeration has a noticeable negative impact on regional GTFP, and also has a negative spatial spillover effect on surrounding areas without crowding effect; besides, the agglomeration of producer services significantly increases the level of regional GTFP, generates positive spatial spillover effect on the surrounding areas, and leads to crowding effect. Based on the above, although there are abundant conclusions of previous studies through GTFP, attention on green production issues is still limited except for Chinese scholars (Chen et al., 2018).

Fintech currently has not yet reached the expected growth, but the growth rate of its scale and market share is also stupendous. Because fintech is innovative, the attitudes of various economic entities are unpredictable; at the same time, future development is difficult to predict. Therefore, this paper may be more informative by gaining some insight into its historical impact. This paper aims to determine the direction and size of the green development effect of fintech by analyzing the impact of fintech on GTFP.

The specific contributions in this paper are as follows. First, the spatial and temporal evolution characteristics of urban fintech level, GTFP, and financial support policy indicators (FSP) are investigated from two dimensions of time and space. Secondly, the impact of urban fintech level on GTFP is studied. Based on fixed effect regression (FE), fixed effect panel quantile (MM-QR), and two stage least square (2SLS) model, we find that urban fintech level plays a significant role in promoting GTFP, which mainly from the promotion of technological progress (TC) of GTFP decomposition indicator. Thirdly, the transmission mechanism of urban fintech level promoting GTFP is studied. That is, industrial structure upgrading (UIS) and technological innovation (TI), as mediating variables, increased to promote the green development effect of fintech. Fourthly, it studies the heterogeneity of urban characteristics and attributes promoted by the level of urban fintech. Specifically, fintech has a greater impact on the green development of low-level cities in central and Western China, while it has a smaller impact on the green development of eastern and high-level cities.

The remainder of this paper is arranged as follows: Section 2 introduces the research hypothesis, empirical model, and data sources based on the analysis of the relationship among fintech, GTFP, and FSP. Section 3 analyzes the measurement and statistics description of independent variable Fintech, dependent variable GTFP, and instrumental variable FSP. Then, the impact of the fintech level on GTFP is empirically analyzed in Section 4. Section 5 is the additional analysis by considering the transmission mechanism (industrial upgrading effect and technological innovation effect) and the heterogeneity based on urban characteristics (region and development level) respectively. Lastly, section 6 concludes our paper.

2. Research design

2.1. Research hypotheses

The understanding of fintech in previous studies was polarized. Some scholars hold that fintech causes the increase of economic risk and market volatility; whereas other studies mainly agree that fintech is the driving force for diversity and sustained growth. However, there is a lack of research on fintech in the area of green development. Fintech promotes financial development, which helps companies reducing financing costs; broadening financing channels, and having more funds to invest in new equipment and projects. Financial intermediaries in developed financial markets can effectively solve the problem of information asymmetry and provide low-cost funding (Zhong and Li, 2020). Firms can update technology and investment environment projects with low-cost funding (Liao and Drakeford, 2019; Zhong et al., 2019). Financial development facilitates eco-friendly innovations and energy-efficient technologies which in turn reduce energy consumption and pollutant emissions (Jalil and Feridun, 2011). In general, we believe that fintech can promote the development of green finance by reducing the financing cost of enterprises and investing in environmental innovation activities, so as to solve the financing gap of green sustainable development technology. Therefore, the following hypothesis is proposed:

Hypothesis 1: *The promotion effect of upward fintech level on GTFP is mainly reflected in the improvement of technological change.*

Fintech plays a primary role in the financial industry and financial enterprises, which are not mainly engaged in polluting production. That means fintech does not play a direct role in green development. Therefore, it is necessary to deeply analyze the mechanism of the impact of fintech on GTFP. On the one hand, a high level of fintech development has the following advantages, such as promoting a rapid information flow, accelerating the integration of information and technology, and promoting the transferring and transformation of new technologies, which ultimately provide a basis for improving GTFP. Technological innovation and introduction are also important sources of GTFP progress. On the other hand, fintech promotes industrial upgrading and makes capital flow to production enterprises with higher efficiency and profits, which contributes to pollutant treatment and resource conservation. Based on the above, it is reasonable to hypothesize that:

Hypothesis 2: *Industrial structure upgrading and technological innovation play a mediating role in promoting the effect of fintech on GTFP.*

Previous studies have shown that GTFP and its related roles have differences in provincial and urban attribute characteristics (Song et al., 2018; Liu and Xin, 2019; Zhong and Li, 2020; Lu et al., 2021). This paper mainly studies the most developed cities in China, such as Beijing and Shanghai and many other underdeveloped inland cities. Cities with different attribute characteristics have significant differences in these aspects of financial volume, financial efficiency, and fintech level, and their unbalanced production mode and green development. Based on the above, we can reasonably infer that there is a heterogeneous relationship between fintech and GTFP among cities with different regions and development levels. Therefore, we formulate the following hypothesis:

Hypothesis 3: *There is heterogeneity in the role of fintech on GTFP in terms of urban attribute characteristics.*

2.2. Model construction

Based on the above basic hypotheses, a fixed-effect panel regression model is constructed to verify the impact of fintech level on GTFP. The basic form of the regression model is as below:

$$GTFP_{it} = \alpha_0 + \alpha_1 * Fintech_{it} + \alpha_2 * X_{it} + \eta_i + \varepsilon_{it} \quad (1)$$

where *i* represents the individual city; and t represents time; *GTFP* (green total factor productivity) is the dependent variable; *Fintech* is an independent variable; *X* is a covariable that may affect the *GTFP* of a city; it means the level of foreign trade, government intervention, environmental protection, and enterprise profitability for a city *i* in the period of *t*; η_i denotes the individual fixation effect; ε_{it} is the error term.

On the one hand, the above model mainly studies the impact of Fintech on conditional expectations of GTFP, which is also a regression of the mean, and the impact of Fintech on the entire conditional distribution. On the other hand, the mean regression of OLS is susceptible to the influence of outlier because the objective function of minimization is the sum of squares of residuals ($\sum_{i=1}^{n} e_i^2$). Koenker and Bassett declared that the quantile regression not only provides the conditional distribution of comprehensive information, but also acts as the objective function of minimization by using the residual error absolute value of the weighted average (eg. $\sum_{i=1}^{n} |e_i|$); therefore, it is not susceptible to the influence of extreme values (Koenker and Bassett, 1978). Koenker (2004) proposed a fixed-effect panel quantile regression with moderating effect. The existing literature of quantile studies assumed that a single effect only causes a parallel (positional) shift in the distribution of the response variable, and not for the entire distribution (Koenker, 2004; Canay, 2011); namely, it does not take unobserved individual heterogeneity into account. To solve this problem, a new MM-QR method to investigate the impact of the fintech level on GTFP is used (Machado and Silva, 2019), which has advantages in estimating panel data models with individual effects and eliminating endogenous problems (Lee et al., 2021).

In addition, when the above benchmark model is used to analyze the influence of fintech on GTFP, the endogenous of fintech variables needs to be discussed. Specifically, on the one hand, fintech may improve GTFP through industrial structure upgrading and capital accumulation channels; On the other hand, GTFP in turn also influences the level of fintech through the effects of technology and structure. Taking the appropriate tool variables as a core independent of fintech can effectively solve the endogenous problem. This tool variable should highly correlate with endogenous variables, but it does not directly affect dependent variables. Based on this understanding, the urban financial policy (FSP) is adopted as the tool variable of fintech finally.

The reason why financial policy can be used as an instrumental variable of the fintech level may be based on the following aspects. On the one hand, financial policy is related to the level of fintech, which can meet the hypothesis of correlation of effective instrumental variables(Hering and Poncet, 2014). On the other hand, local government work reports generally occur at the beginning of the year; whereas economic activities run through the whole year, which can effectively avoid the endogenous problems caused by “reverse causality”, thus, it satisfied the exogenous assumption of effective instrumental variables (Broner et al., 2012). In order to further discuss the impact of government fintech on GTFP, appropriate government financial policy variables need to be built; and the corresponding model should be set. Then, based on the text analysis method, the score is comprehensively evaluated as the proxy variable, which comes from types and quantity of financial related policy reports in the sample city government documents of urban financial policy. The specific analysis method is shown in section 3.2.

In order to better quantitatively investigate the impact of China's urban fintech level on GTFP, the two-stage least squares regression model (2SLS) is set as below.

$$Fintech_{it} = \beta_0 + \beta_1 * FSP_{it} + \beta_2 * X_{it} + \eta_i + \varepsilon_{it} \tag{2}$$

$$GTFP_{it} = \gamma_0 + \gamma_1 * Fintech_{it} + \gamma_2 * X_{it} + \eta_i + \varepsilon_{it} \tag{3}$$

where *i* represents the city individual; *t* denotes time; *FSP* is a variable of urban financial support policy, which is acted as an instrumental variable to solve the endogeneity of fintech level in the 2SLS model. Other variables are set as the same as the baseline model (1).

2.3. Data sources

The sample data is drawn from 35 selected cities in China covering the period from 2015 to 2019 with 175 samples, which including 4 municipalities, 5 cities with separate state plans and 26 provincial capitals. Fintech is the theme of this paper, so the data period of this paper revolves around the emergence of financial technology. Although the contents of fintech and other relative words have already appeared around 2008, there is little information online to collect before 2015, so it is impossible to establish a fintech index before 2015 in this paper. A brief introduction of variables is as follows: (1) The dependent variable is dynamic GTFP and its decomposition index, which is measured by the DEA model based on Bootstrap-SBM-GML. The input-output index includes capital stock, labor force, electricity consumption, GDP, and waste discharge. (2) The independent variable is Fintech, and the data comes from the web crawler. (3) The instrumental variable is the FSP Indicator, which comes from the content analysis of city government websites. (4) The mediating variables are industrial structure upgrading (UIS) and technological innovation (TI), namely, the proportion of the output value of the tertiary industry in GDP and the market value of the high-tech industry in the total market value of listed companies. What needs to be explained here is that the reason why "the market value of the high-tech industry in the total market value of listed companies" is chosen as the index of technological innovation in this paper is to reflect not only the high-tech innovation level of the city, but also the aggregation degree of high-tech innovation level (like the idea of location entropy). (5) Control variables are levels of foreign trade, government intervention, environmental protection, and enterprise profit. Among them, the level of foreign trade is measured by the ratio of urban import and export volume to urban GDP; the degree of government intervention is measured by the ratio of urban energy conservation and environmental protection fiscal expenditure to general public budget fiscal expenditure; the level of environmental protection is measured by the ratio of the market value of urban environmental protection enterprises to the market value of urban listed companies, and the level of enterprise profitability is measured by the ratio of total profits of the above enterprises with designated size to urban GDP. The above data all come from China Statistical Yearbook, City Statistical Bulletin, and WIND database except for special instructions.

3. Measurement of variables and descriptive statistics

3.1. Measurement of independent variable: Fintech

There is little literature on quantitative research on fintech indicators among the previous studies. According to the research of Chuntao Li, we extract 48 keywords related to fintech based on the relevant important news and conferences, such as "13th Five-Year Plan for National Science and Technology Innovation"; "Big Data Industry Development Plan (2016–2020)"; "China's fintech operation report (2018)", which includes EB storage, NFC payment, differential privacy technology, big data, etc. Then we search these cities plus keywords on Baidu after matching these cities of prefecture-level and municipalities in China with keywords. The web crawler technology is used to the source code in the Baidu information page and many search results are extracted. Finally, the total search amount is obtained by summing up all the keyword search results, which is used as an indicator to measure the level of fintech development at the prefecture-level city or municipality. Figure 1 reports the trend of the Fintech index for each city is in a state of steady growth during the study period.

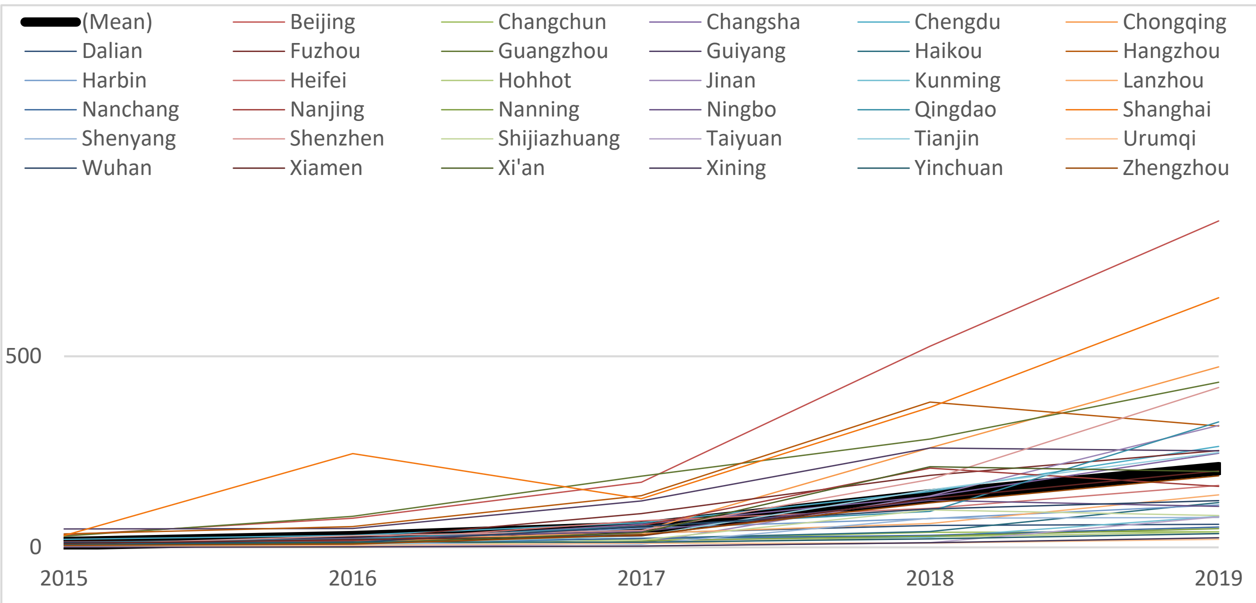

Figure 1. Trend line of fintech index.

3.2. Measurement and analysis of dependent variable: GTFP

In this paper, the dependent variable of GTFP is measured by the data envelops analysis (DEA) of the SBM-GML model based on 2000 times Bootstrap. Among them, SBM is a distance function, which is also known as "Slacks-based Measure Directional Distance". GML is a panel data model. DEA, which was proposed in 1978, is used to evaluate the relative efficiency of decision groups with multiple inputs and outputs (Charnes et al., 1978). The distance function of the basic model consists of CCR and BCC without focus on the "Slack" phenomenon. Later, Tone proposed the SBM model in 2001 and the super-efficiency model of the SBM in 2002 respectively. The super-efficiency SBM model not only considers slack variables, but also sorts the decision-making units (DMUs) whose efficiency value is greater than 1 (Tone, 2001, 2002). The index of Malmquist-TFP was first introduced by Malmquist (1953) and later developed by Caves (1982). It measures the change of TFP between two periods, and makes the directional distance function of containing undesirable outputs introduced into the Malmquist index in order to support the analysis of undesirable outputs. Oh (2010) included the production unit in the global reference set and constructed the global-Malmquist-Luenberger (GML) index so as to facilitate intertemporal comparison and overcome the problem of infeasible solution.

The general method of DEA only measures the static efficiency of DMU by taking input-output ratio; however, the model of Malmquist index which is based on DEA can analyze the dynamic efficiency variation trend of DMU according to the panel data; and further, provide more robust and in-depth support for GTFP estimation by making use of decomposition analysis of DEA-Malmquist index. For example, the productivity index of Malmquist can be decomposed into the product of the technical efficiency change index (EC) and the technological change index (TC) (Färe et al., 1992). Specifically, the technical efficiency change index (EC) can be extended to the product of the pure technical efficiency change index (PEC) and scale efficiency change index (SEC) (Färe et al., 1994). Färe said: "We use an enhanced decomposition of the Malmquist index developed in Rolf Fare et al. (1994). This enhanced decomposition takes the efficiency-change component calculated relative to the constant-returns to scale technology and decomposes it into a pure efficiency-change component (calculated relative to the variable-returns technologies) and a residual scale component which captures changes in the deviation between the variable-returns and constant returns-to-scale technology." It can be shown in Equation (4):

$$GTFP = EC(CRS) * TC(CRS) = PEC(VRS) * SEC(CRS, VRS) * TC(CRS) \tag{4}$$

where *GTFP* index is the dynamic index of green total factor productivity, reflecting the variation scale of *GTFP* in different cities in different periods. *CRS* means a constant return to scale, and *VRS* means a variable return to scale. Technical efficiency change index (*EC*) refers to the deviation between "actual output" and "best practical output" under the given production function; namely, the efficiency is higher as the deviation becomes smaller. It measures the level of input resource allocation, management efficiency, and the accumulation of production experience. The technology change index (*TC*) measures technological invention (mainly green technology), the fundamental innovation of production and operation system and technological improvement, which refers to the frontier movement of production function under the given input of production factors. Between two indicators derived from *EC*, the *PEC* index measures the change proportion of pure technical inefficiency in the decision-making unit, which represents the green production technical efficiency affected by management and technology factors; and the index of *SEC* judges the scale efficiency level of decision-making unit and denotes the production efficiency affected by production scale factors. Equations (5) to (8) introduces the specific composition of each index:

$$EC(CRS) = \frac{D_c^{t+1}(X^{t+1}, Y^{t+1})}{D_c^t(X^t, Y^t)} \tag{5}$$

$$TC(CRS) = \left[\frac{D_c^t(X^{t+1}, Y^{t+1})}{D_c^{t+1}(X^{t+1}, Y^{t+1})} * \frac{D_c^t(X^t, Y^t)}{D_c^{t+1}(X^t, Y^t)}\right]^{\frac{1}{2}} \tag{6}$$

$$PEC(VRS) = \frac{D_v^t(X^{t+1},Y^{t+1})}{D_v^t(X^t,Y^t)} \tag{7}$$

$$SEC(CRS,VRS) = \frac{D_v^t(X^t,Y^t)}{D_c^t(X^t,Y^t)} * \frac{D_c^{t+1}(X^{t+1},Y^{t+1})}{D_v^{t+1}(X^{t+1},Y^{t+1})} \tag{8}$$

where (X^t,Y^t) and (X^{t+1},Y^{t+1}) mean the input and output vectors at time t and $t+1$ respectively; D_c^t 、 D_c^{t+1} are distance functions based on constant returns to scale in the period of t and $t+1$ respectively; namely, means the compression ratio of the actual output of decision-making unit (X,Y) to the optimal output. D_v^t and $D_v^{t+1}$are distance functions based on the variable return to scale in periods t and $t+1$. D_c^t; D_c^{t+1}; D_v^t and D_v^{t+1} can be obtained by the DEA method. If $EC > 1$, the efficiency is improved; If $EC = 1$, there is no change in efficiency; If $EC < 1$, the efficiency is reduced. The meanings of *TC* and *SEC* have the same criteria as EC.

Based on the above, capital stock, employment number, and total electricity consumption of sample cities are selected as input indexes. Specifically, GDP is the expected output that represents the total output; Waste-water discharge is the undesired output which denotes the pollution discharge. The specific input-output settings are shown in Table 1 as below.

Table 1. Measurement of input and output index by GTFP.

First grade indicators	Second grade indicators	Third grade indicators
Input index	Capital	Capital stock
	Labor	Employment
	Energy	Power consumption
Output index	Desirable output	GDP
	Undesirable output	Wastewater discharge

The capital stock is an indirect variable that needs to be calculated. The perpetual inventory method is used to calculate the capital input.

$$K_t = K_{t-1}(1-\delta) + I_t/P_t \tag{9}$$

where K_t and K_{t-1} are the actual capital stock in the year t and t–1 respectively. I_t is the investment amount in the current year, which selects the total investment in fixed assets as the capital investment of GTFP of each city; P_t denotes the price index of fixed assets investment in the current year, which uses the GDP deflator of prefecture-level city because there are no statistics on the price index of urban fixed assets investment. δ is the current depreciation rate, which is usually taking 9.6% as its general practice. Figure 2 reports the trend of the GTFP index of each city during the inspection period; however, it is difficult to directly observe the relationship between its index and the level of fintech based on the inconspicuous change trend.

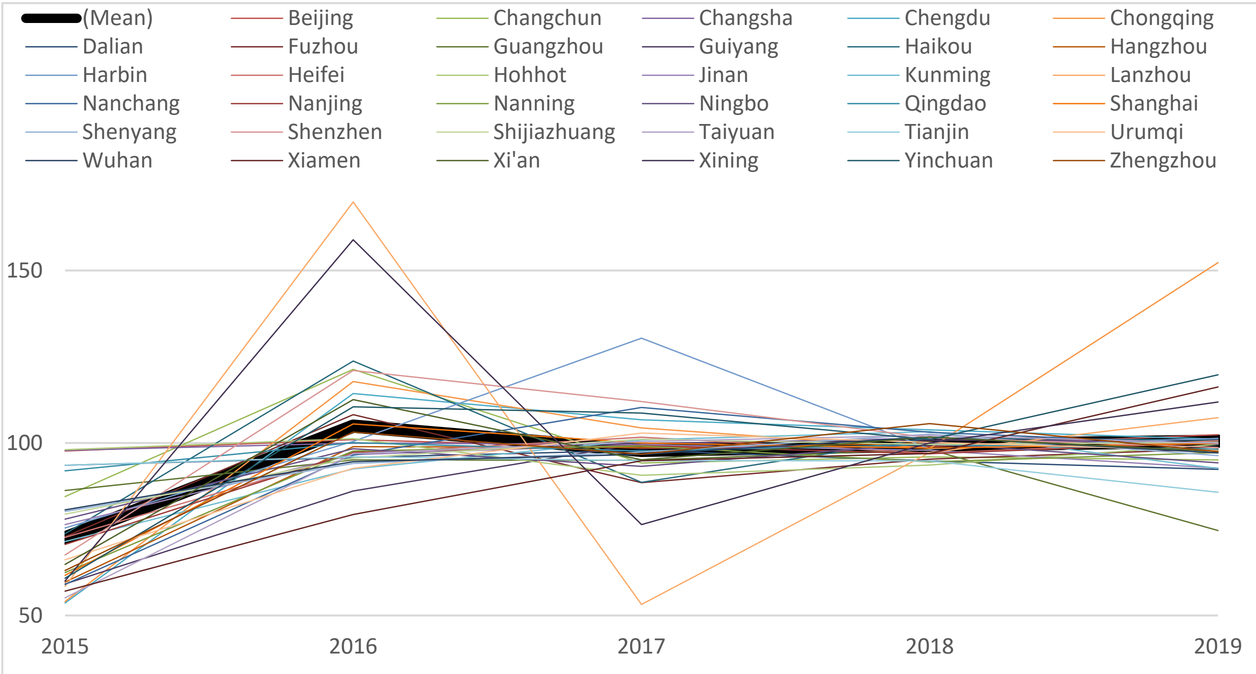

Figure 2. Trend line of GTFP index (%).

3.3. Measurement of instrumental variable: financial support policy

The necessity and feasibility of taking financial support policies (FSP) as instrumental variables have been explained in section 2.2. This section is going to illustrate the construction method of indicators of FSP in detail. First, all the policy documents from the local government websites for the sample cities during the investigation period 2015–2019 are extracted. Secondly, according to the content, the policy documents related to financial support are extracted and divided into seven policy types, namely, financial support, compound policy, single policy, tax-free and tax reduction, regional construction, honor and special training. These specific contents and scores are summarized in Table 2 and Equation (10). Finally, additional processing is carried out after score classification. There are three treatments. One is giving extra points if the policy document supports the city's specific financial construction with "siphon effect" on financial development; the second one also gains extra points if the policy document contains mandatory constraint indicators to reflect policy strictness; The third one is policies in the continuation period can add scores in the continuation year, but in consideration of the decay of policy effectiveness and influence, a decline coefficient of 0.8 is added to them. Table 3 shows the results of the detailed content and score. Figure 3 reports the trend of indicators of FSP for each city during the inspection period. The mean value of FSP indicators has increased steadily from 76.42 in 2015 to 177.35 in 2019, which preliminarily estimates their positive correlation with the fintech level.

$$\begin{aligned} FSP_{it} = {} & Fund\ support\ point_{it} + Compound\ policy\ point_{it} + Single\ policy\ point_{it} \\ & + Tax\ exemption\ and\ reduction\ point_{it} + Regional\ construction\ point_{it} \\ & + Advanced\ commendation\ point_{it} + Financial\ training\ point_{it} \end{aligned} \tag{10}$$

Table 2. Policy classification and scoring.

classification	explanation	score
Fund support	Fund support policy for financial institutions with clear amount	100
Compound policy	Including three or more specific financial support policies	60
Single policy	Including one or two specific financial support policies	20
Tax exemption/reduction	Specific preferential tax policies for financial institutions	40
Regional construction	(not fully covered) financial construction of single region, financial center and free trade zone, etc	20
Advanced commendation	Commendation and reward for advanced units and individuals	5
Financial training	Notice on holding special financial training lectures	5

Table 3. Additional treatment of policy scoring.

additional classification	additional score
Construction of urban financial center	20 added
Mandatory indicators	10 added
Duration	decline factor 0.8

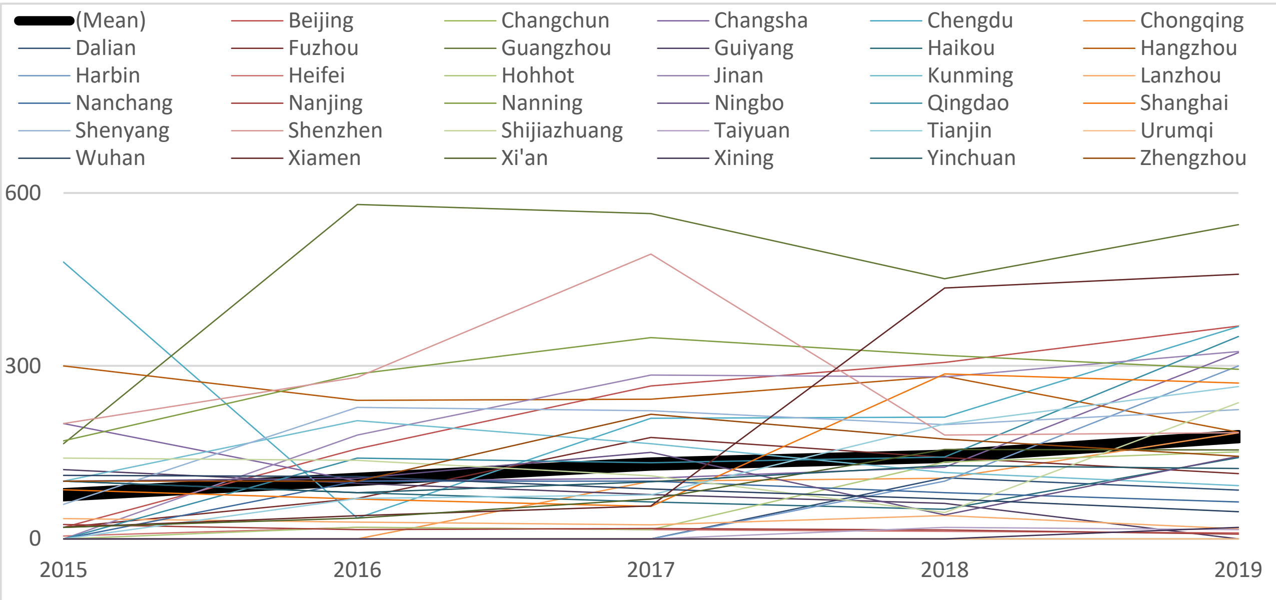

Figure 3. Trend line of financial support policy index.

3.4. Descriptive statistics

Table 4 shows the descriptive statistics of all variables. Specifically, the descriptive statistics of cities in the east, central and western regions are shown respectively for the differences among different regions. Simultaneously, the descriptive statistics of cities with high, medium and low GDP are also revealed for the differences among cities with different levels of development. Besides, all kinds of urban variables are different from different perspectives. Based on this, the heterogeneity of the impact of fintech on GTFP based on the urban differences with different dimensions is going to be analyzed in section 5.

Table 4. Descriptive statistics.

	Item	summary	eastern	central	western	high GDP	middle GDP	low GDP
	N	175	80	45	50	59	58	58
GTFP (%)	Mean	94.99	94.09	95.70	95.79	96.38	94.47	94.10
	Min	53.21	57.06	55.10	53.21	53.63	63.04	53.21
	Max	169.82	123.73	130.38	169.82	152.28	130.38	169.82
EC (%)	Mean	99.67	99.62	99.67	99.75	99.95	99.32	99.73
	Min	83.55	83.55	88.50	86.59	83.55	86.68	86.59
	Max	113.03	109.22	107.34	113.03	109.22	107.62	113.03
TC (%)	Mean	94.90	94.25	95.72	95.20	96.11	94.87	93.70
	Min	55.14	61.56	62.05	55.14	59.92	68.90	55.14
	Max	150.23	120.86	122.37	150.23	149.87	122.37	150.23
PEC (%)	Mean	99.62	99.50	99.86	99.60	99.91	99.22	99.73
	Min	85.80	85.80	88.24	88.39	86.69	85.80	91.18
	Max	107.39	107.39	105.81	106.23	107.39	106.34	106.23
SEC (%)	Mean	100.02	100.10	99.79	100.10	100.03	100.09	99.94
	Min	86.97	86.97	92.55	91.68	86.97	94.71	91.68
	Max	109.67	106.13	102.53	109.67	106.13	103.41	109.67
Fintech	Mean	85.09	119.28	47.88	63.86	159.52	56.77	37.68
	Min	0	0	1	0	3	0	0
	Max	854	854	246	472	854	319	260
Financial support policy	Mean	125.90	169.95	70.41	105.38	188.81	99.32	88.50
	Min	0	0	0	0	0	0	0
	Max	580	580	323	480	580	325	459
Industrial structure upgrading	Mean	58.05	60.42	54.71	57.27	60.68	53.78	59.65
	Min	40.6	45	40.6	42.9	45.9	40.6	41.2
	Max	83.5	83.5	75.1	72.6	83.5	75.1	79.2
Technological innovation	Mean	0.63	0.72	0.28	0.79	0.70	0.55	0.63
	Min	0	0	0	0	0	0	0
	Max	4.01	3.16	2.45	4.01	2.80	3.16	4.01
Foreign trade	Mean	4.01	55.00	16.63	17.09	53.21	25.38	23.99
	Min	0.91	5.10	2.73	0.91	5.10	2.03	0.91
	Max	156.57	156.57	48.57	62.80	156.57	77.81	149.14
Government intervention	Mean	3.16	3.23	3.02	3.18	2.82	3.32	3.36
	Min	0	0	0	0	0	0	0
	Max	10.06	7.72	3.02	6.67	7.28	10.06	7.43
Environmental protection	Mean	6.11	4.98	8.24	6.01	6.96	4.92	6.45
	Min	0	0	1.49	0	1.21	4.92	0
	Max	33.22	33.22	25.99	22.77	33.22	21.02	25.99
Enterprise profitability	Mean	3.25	3.98	3.61	1.74	4.06	4.14	1.52
	Min	−0.89	0.58	−0.42	−0.89	1.88	0.87	−0.89
	Max	13.21	13.21	8.49	6.65	9.30	13.21	6.52

4. Empirical results

4.1. GTFP and fintech

The panel fixed effect FE model and the quantile MM-QR model of the benchmark are used to analyze the impact of fintech on GTFP and its decomposition indicators. According to Equation (1), the estimated results are shown in Tables 5 to 7 as below.

Table 5. The estimation results for the fixed effect model of GTFP.

	GTFP			
	(1)	(2)	(3)	(4)
Fintech	0.026^{**}	0.031^{***}	0.039^{***}	0.038^{**}
	(2.58)	(2.91)	(2.94)	(2.59)
Foreign trade	−	−0.057	−	−0.232
Government intervention	−	0.419	−	0.128
Environmental protection	−	0.127	−	0.054
Enterprise profitability	−	−0.029	−	−0.087
Controls	No	Yes	No	Yes
City FE	No	No	Yes	Yes
N	175	175	175	175

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-statistics.

Table 5 shows empirical results that fintech significantly promotes urban GTFP when simply considering the relationship between fintech and GTFP. Specifically, green total factor productivity increases by about 0.026 with every 1 increase in fintech index. Besides, the promotion effect of fintech on GTFP is still significant by adding fixed urban individuals and control variables.

Table 6. The estimation results for the fixed effect model of decomposition efficiency.

	EC	TC	PEC	SEC
Fintech	0.006	0.035^{***}	0.004	0.002
	(1.30)	(2.95)	(1.20)	(0.88)
Foreign trade	−0.055	−0.211	−0.058	0.002
Government intervention	0.088	0.030	0.076	0.007
Environmental protection	0.315	−0.239	0.261	0.055
Enterprise profitability	0.079	−0.136	−0.096	0.179
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
N	175	175	175	175

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-statistics.

Table 6 shows the impact of fintech on the decomposition index of GTFP is significantly different. The promotion effects of fintech on EC and its decomposition indexes of PEC and SEC are not significant. Besides, the promoting effect of Fintech on TC is significant and its coefficient is almost the same as that of GTFP. Based on this, fintech mainly improves urban GTFP by promoting green technology progress in production, whereas it has little effect from the perspective of green technology efficiency.

Table 7. The estimation results for the MM-QR model.

		FE	Q10	Q25	Q50	Q75	Q90
GTFP	(1)	0.038**	0.067	0.046	0.033	0.025	0.016
		(2.59)	(1.08)	(1.12)	(0.56)	(0.34)	(0.17)
EC	(2)	0.006	0.026*	0.015	0.015	−0.005	−0.012
		(1.30)	(1.80)	(1.59)	(0.56)	(−0.90)	(−1.53)
TC	(3)	0.035***	0.048**	0.040***	0.033**	0.029	0.024
		(2.95)	(2.04)	(2.84)	(2.30)	(1.58)	(0.93)
PEC	(4)	0.004	0.017	0.010	0.001	−0.003	−0.007
		(1.20)	(1.56)	(0.66)	(0.02)	(−0.06)	(−0.11)
SEC	(5)	0.002	0.009	0.005	0.002	0.002	−0.004
		(0.88)	(0.72)	(0.64)	(0.36)	(−0.49)	(−0.91)
Controls		Yes	Yes	Yes	Yes	Yes	Yes
City FE		Yes	Yes	Yes	Yes	Yes	Yes

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively. The values in brackets are T or Z-statistics.

Table 7 shows the impact of fintech on GTFP and its decomposition index is different under different quantiles. Specifically, taking GTFP as the dependent variable, results (1) shows the promotion effect of fintech on GTFP is universal, but this effect becomes smaller with significant decrease when the GTFP is improving. Adopting EC as the dependent variable, result (2) shows the impact of fintech on green technology efficiency is different; namely, fintech plays a significant role in cities with low green technology efficiency; whereas the role of fintech continues to decline, or even has a negative effect with the rise of EC. Results (4) and (5) show the decomposition index PEC and SEC of EC are similar to the regression results of EC, which indicates that the impact of fintech on pure technical efficiency and scale efficiency is basically the same. In general, the lower the green production capacity of cities, the greater the role that fintech can play in promoting green production. Therefore, the policy should guide financial technology to pay more attention to the areas with weak green production capacity, in order to achieve the maximum benefit through the minimum improvement.

4.2. Regression results of instrumental variables: financial support policy point

Tables 8 and 9 show the regression results of 2SLS for the instrumental variables. Through investigation of the correlation between instrumental variables and endogenous variables, the RKF test statistics of the first stage are 34.864 and 28.373 respectively, and the P value was 0, which indicates that there is no weak instrumental variable problem.

Table 8. The estimation results for the first stage of 2SLS.

	(1)		(2)	
	Coef.	Std. Err.	Coef.	Std. Err.
Financial support policy	0.567***	0.096	0.490***	0.092
	(5.90)		(5.33)	
Controls	No		Yes	
City FE	Yes		Yes	
N	175		175	

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-statistics.

From the first-stage regression results in Table 8, whether it adds control variables or not, the correlation between instrumental variables and fintech level is a significant positive with passing the significance test of 1%, which indicates that cities with stronger financial support policies have higher fintech level. The regression results of the first stage meet the requirement of the correlation hypothesis of instrumental variables.

Table 9. The estimation results for the second stage of 2SLS.

	GTFP	EC	TC	PEC	SEC
Fintech	0.049*	0.010	0.042*	0.005	0.006
	(1.58)	(1.03)	(1.67)	(0.64)	(1.20)
Controls	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
N	175	175	175	175	175

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are Z-statistics.

The second-stage regression results in Table 9 show that the significant level of GTFP is decreased although the regression results are still positive. In addition, from the regression results of the decomposition indicators, fintech has a significant impact on technological progress (TC) in the GTFP, but this significant impact decreases by adding instrumental variables. Besides, there is no significant impact of fintech on technical efficiency (EC) in the GTFP composition. From the above, the 2SLS regression results with addition FSP as instrumental variables are consistent with the results of the fixed-effect regression model, which indicates that the conclusion is still significant after removing partial endogeneity. Based on the above, Hypothesis 1 is proved.

4.3. Robustness tests

To begin with, this empirical regression has the disadvantage of fewer samples. Based on this, more asymptotic and effective estimator can be obtained by Bootstrap sampling (Li et al., 2021). Based on the fixed-effect regression model and 2SLS model, 2000 repeated samples are conducted with regression coefficients. The regression results are shown in Table 10.

Table 10. The estimation results for the bootstrap test.

	FE		2SLS	
Fintech	0.039***	0.038**	0.048*	0.049
	(2.63)	(2.32)	(1.28)	(1.05)
Controls	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes
Bootstrap	2000	2000	2000	2000

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are Z-statistics.

Table 10 shows the direction and significance of the impact of urban fintech on GTFP are basically consistent with the previous conclusions. The authenticity of the empirical results is not affected by the small sample size, and its conclusions are still robust.

In addition, the robustness analysis is carried out by adjustment of the dependent variables. The measurement method of GTFP adopts the DEA model based on the Bootstrap-SBM-GML. The sample cities of GTFP are measured by three envelopment analysis models, namely CCR-GML, BCC-GML and Super-SBM-GML respectively; and its index setting of the input-output is consistent with the above section. Based on the fixed-effect regression model and 2SLS model, a regression is conducted on the adjusted GTFP with its regression results in Table 11.

Table 11. The estimation results for the dependent variables adjustment.

	CCR-GML	BCC-GML	Super-SBM-GML
Fintech	0.030**	0.028**	0.038**
	(2.70)	(2.56)	(2.52)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-statistics.

Table 11 shows the direction and significance of the impact of urban fintech on GTFP are basically consistent with the previous conclusions. The empirical results are not affected by the calculation model of the independent variable adjustment, and its conclusions are still robust.

5. Additional analysis

5.1. Mechanism Study on the Impact of fintech on the GTFP

5.1.1. The mediating role of industrial structure upgrading

The higher level of fintech development brings wider coverage rate of fintech, more advanced usage of fintech and greater degree of digitization. The information effect of the coverage rate, utilization degree and digitization data not only speed up the information flow, but also accelerates the integration speed of information and technology, as well as promotes the development of new technology and transformation. Thus, it can promote the whole industry productivity and then boost industrial structure upgrading. Simultaneously, fintech further lays stable foundation for the improvement of GTFP through the following measures, such as promoting the integrated development of the financial industry and technology industry; effectively accelerating the asset management business from virtual to real, optimizing the capital allocation structure, improving the ability of serving the real economy by traditional financial business; as well as improving the efficiency and quality of financial services to the real economy. These measures not only promote the transformation and upgrading of competitive advantages for the financial industry itself, but also improve the upgrading of related industrial structures. In order to verify this mechanism, the proportion of the output value of the tertiary industry in GDP is selected as the proxy variable for industrial structure upgrading (UIS). UIS is used as a mediating variable to examine the promotion effect of fintech on GTFP. This mediating effect model is constructed as below:

$$GTFP_{it} = \alpha_0 + \alpha_1 * Fintech_{it} + \alpha_2 * X_{it} + \varepsilon_{it} \tag{11}$$

$$UIS_{it} = \beta_0 + \beta_1 * Fintech_{it} + \beta_2 * X_{it} + \varepsilon_{it} \tag{12}$$

$$GTFP_{it} = \gamma_0 + \gamma_1 * Fintech_{it} + \gamma_2 * UIS_{it} + \gamma_3 * X_{it} + \varepsilon_{it} \tag{13}$$

where α_1 measures the impact of fintech level on urban GTFP; β_1 denotes the impact of fintech level on industrial structure upgrade; γ_1 means the direct impact of fintech level on urban GTFP, and γ_2 represents the impact of industrial structure upgrade on urban GTFP. The meaning and calculation method of variables in regression equation are consistent with that in the baseline regression by adopting the stepwise regression coefficient method. The regression results are shown in Table 12.

Table 12. The estimation results for the mediating role of UIS.

	GTFP	UIS	GTFP
	(1)	(2)	(3)
Fintech	0.038^{**}	0.011^{***}	0.028^{*}
	(2.59)	(4.23)	(1.77)
UIS	–	–	0.994^{**}
			(2.01)
Cons	99.235	62.284	37.337
Control variable	Yes	Yes	Yes
City FE	Yes	Yes	Yes

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-statistics.

Table 12 shows that the upgrading of industrial structure plays a strong partial intermediary role in the impact of fintech on urban GTFP.

Further, the robustness of the mediating effect is verified by the Sobel test, and the analysis results are consistent with the stepwise test. The total effect of fintech level on GTFP is 0.038, which equals to the direct effect of 0.028 plus the indirect effect of industrial structure upgrading of 0.011. The calculated intermediary effect accounts for 27.96% of the total effect.

5.1.2. The mediating role of technological innovation

Technological innovation and import may also be important sources for the progress of GTFP. The innovation theory means that the innovation of production technology and the transformation of production mode are the most fundamental forces of economic development (Singh et al., 2020). Because innovation can produce new products, new production methods, new markets, new supplies and new organizational forms, which constitute the internal driving force of economic growth. As a new mode of production and operation, fintech has reformed the operation mode of traditional finance. The emerging technology is the internal driving force to stimulate financial innovation. The new production mode born by fintech improves the operation efficiency of enterprises, as well as promotes the technological progress of enterprises. It also further benefits to optimizing the scale, structure and efficiency for enterprises, promoting the continuous accumulation of capital, and forming the innovation effect of fintech. Generally, the allocation of resources and funds tends to flow to enterprises with high profits and low risks, rather than to high risks and low profits enterprises. Thus, it can achieve the optimal allocation of resources; improve the production efficiency for enterprises, which benefits the effective utilization for elements and the level of pollution, as well as save resources and control costs, etc., these aspects are the important forces to promote the improvement of GTFP. In order to verify this mechanism, the proportion of market value of high-tech industry in market value of listed companies is selected as the proxy variable of technology innovation effect (TI). It should be noted that TI here is essentially different from the decomposition index TC that mentioned above. Therefore, TI is used as an intermediary variable to test its role in the promotion of urban GTFP by fintech. A mediating effect model constructed as below:

$$GTFP_{it} = \alpha_0 + \alpha_1 * Fintech_{it} + \alpha_2 * X_{it} + \varepsilon_{it} \tag{14}$$

$$TI_{it} = \beta_0 + \beta_1 * Fintech_{it} + \beta_2 * X_{it} + \varepsilon_{it} \tag{15}$$

$$GTFP_{it} = \gamma_0 + \gamma_1 * Fintech_{it} + \gamma_2 * TI_{it} + \gamma_3 * X_{it} + \varepsilon_{it} \tag{16}$$

where α_1 measures the impact of fintech level on urban GTFP; β_1 is the impact of fintech level on technological innovation effect; γ_1 represents the direct impact of fintech level on urban GTFP; γ_2 denotes the impact of technological innovation effect on urban GTFP. The meaning and calculation method of variables in the regression equation are consistent with that in the baseline regression by adopting the stepwise regression coefficient method. The regression results are shown in Table 13.

Table 13. The estimation results for the mediating role of TI.

	GTFP	TI	GTFP
Fintech	0.038^{**} (2.59)	0.001^{*} (1.22)	0.033^{**} (2.43)
TI	–	–	7.424^{**} (2.47)
Cons	99.235	0.666	94.323
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-statistics.

Table 13 shows that the technological innovation effect plays a weak partial intermediary role in the impact of fintech on urban GTFP.

Further, the robustness of the mediating effect is verified by the Sobel test, and the analysis results are consistent with the stepwise test. The total effect of fintech level on GTFP is 0.038, which equals to the direct effect of 0.035 plus the indirect effect of technological innovation of 0.003. The calculated intermediary effect accounts for 7.45% of the total effect. According to the above analysis results, hypothesis H2 is proved.

5.2. Heterogeneity Analysis of the Impact of fintech on the GTFP

Based on the results of the quantile regression mentioned above, the impact of fintech on GTFP can be understood from the perspective of green efficiency; however, a single indicator of green efficiency level cannot fully reflect all the differences in the sample cities. Therefore, the heterogeneity of the impact of fintech on GTFP from two dimensions of region and development level is analyzed as the additional analysis, so as to show the effects of exogenous factors on the impact of fintech on GTFP more comprehensively (Dong et al., 2019).

5.2.1. Heterogeneity based on regional differences

Regional factors are important to analyze problems of China's cities or provinces. According to general practice, we divided the sample cities into eastern, central and western cities based on reference to geography and climate. According to simple analysis, we found that there are great differences among the three regions; specifically, fintech is the highest in the eastern region, middle in the central region and lowest in the western region. Further, the fixed effect model is adopted for regression of cities in these three regions with the same form of Equation (1). Table 14 reports the categorical regression results.

Table 14. The estimation results for regional heterogeneity.

	Eastern	Central	Western
Mean of fintech	119.28	47.88	63.86
Fintech	0.019	0.084*	0.095*
	(1.61)	(1.67)	(1.49)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-statistics.

Table 14 shows the impact of fintech level on GTFP varies significantly among cities in different regions. The regions which are closer to inland have greater promotion effect of fintech to GTFP. Among them, the coefficient of promotion effect of fintech on GTFP is small and does not have statistical significance in the eastern cities; whereas it is significant in the central and western cities, which was larger than the overall contribution of baseline regression.

5.2.2. Heterogeneity based on development

Although the samples in this empirical research are the top economic cities in various provinces, there is still a large span in their development degree. This paper takes GDP as the proxy variable of development level. During the study period in each province, for example, Haikou has the lowest GDP value of 117.358 billion RMB in 2015, and Shanghai has the highest GDP value of 32605.43

RMB in 2019. The extreme values between them are up to 28 times. Therefore, studying the impact of fintech on GTFP from the perspective of development level is quite necessary. According to samples categories of high, medium and low GDP, we find that high-level development cities always have higher levels of fintech based on quantile references. The fixed effect model is adopted for regression in these three categories regions with Equation (1). The classified regression results are shown in Table 15.

Table 15. The estimation results for development heterogeneity.

	High GDP	Middle GDP	Low GDP
Mean of fintech	159.52	56.77	37.69
Fintech	0.016	0.039	0.186**
	(0.88)	(1.32)	(2.16)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes

Notes: *, **, *** denote significant levels of 10%, 5% and 1% respectively, and the values in brackets are T-statistics.

Table 15 shows the impact of fintech on GTFP varies significantly among cities with different levels of development. The role effect of fintech on GTFP is greater when the level of development is lower. Among them, the contribution of fintech on GTFP is not statistically significant in middle and high level cities; whereas it has a large and significant promoting effect in cities with low development level.

From the above, the role of fintech in promoting GTFP is stronger in inland cities with low-level development, which indicates that fintech can play a more important role in promoting green production in less developed regions. Therefore, Hypothesis 3 is proved.

6. Conclusions and implications

This study attempts to explore the impact of the fintech level on GTFP in Chinese cities from 2015 to 2019. Over the past 40 years of reform and opening-up, China has achieved remarkable economic growth and poverty shaking off, but the environmental problems still been criticized by international society. The relationship between finance and green development has gradually attracted people's attention currently. The study of the relationship between the fintech level and GTFP is of great significance to China and other countries in the process of economic transformation. This paper obtains fintech level indicators of 35 major cities in China by adopting web crawler technology, and then constructs GTFP for sample cities by DEA method based on Bootstrap-SBM-GML. Besides, the fintech level that affects city GTFP is analyzed empirically. Specifically, by constructing the 2SLS model, financial support policy (FSP) is selected as a tool variable, which can weaken the endogeneity of the fintech level index. Finally, mediating effects and heterogeneity based on urban attribute characteristics are taken into account. The key findings are summarized as follows:

To begin with, the level of fintech and FSP of Chinese cities show a steady upward trend in the study period; whereas the tendency of GTFP is not obvious. First, through internet crawler technology, 48 fintech keywords of sample cities in a specific year are crawled. By taking the obtained data as the fintech level indicators, the average value of each city shows significant growth with rises from 10 in 2015 to 205.8 in 2019. Second, the GTFP of the sample cities is measured based on the DEA method of the Bootstrap-SBM-GML. It shows that the average value of each city is basically in a small range of fluctuation, which requires further regression analysis on fixed cities. Third, based on subjective empowers for the government policy documents and work reports of sample cities in a specific year, we found that the average value of each city has steadily increased from 76.42 in 2015 to 177.35 in 2019 by taking FSP indicators of mentioned data.

Then, the level of urban fintech plays a significant role in promoting GTFP, mainly from the promotion of technological change (TC) of GTFP decomposition indicators, and the promotion effect is greater in cities with lower green development levels. First, the fintech level plays a significant role in promoting GTFP, which mainly promotes technological change (TC) by employing the fixed-effect model. Besides, control variables will not affect the size and significance of its effect. Second, based on the panel quantile model MM-QR regression, the promoting effect of the fintech level on GTFP decreases with the increase of GTFP level, and even loses significance in cities with high GTFP. Third, by taking FSP as a tool variable, we verify the conclusion on the effect of fintech level on GTFP remained the same with the previous results after eliminating endogeneity by adopting the 2SLS model. Both conclusions pass the robustness tests by Bootstrap and dependent variable adjustment.

Furthermore, there are two mediating mechanisms of industrial upgrading and technological innovation for the role of urban fintech level on GTFP. First, the total effect of urban fintech level on GTFP equals the direct effect of 0.028 and the indirect effect of industrial structure upgrading of 0.011. The calculated intermediary effect accounts for 27.96% of the total effect, which shows a strong intermediary effect. Second, the total effect of urban fintech level on GTFP equals the direct effect of 0.035 plus the indirect effect of technological innovation of 0.003. The calculated intermediary effect accounts for 7.45% of the total effect, which is a weak intermediary effect.

Finally, the effect of the urban fintech level on GTFP is heterogeneous, which is shown by the differences in the characteristics of the attributes. First, in the comparison of urban groups in different geographic locations, the more inland, the greater the promotion effect of fintech on GTFP; Second, in the comparison of city groups with the different development level, the lower the development level, the greater the promotion effect of fintech on GTFP. Overall, the green development effect of fintech is statistically stronger in the less developed inland areas. This may be explained that green production capacity is transferred from the advanced areas and shows a stronger green development effect on fintech although these inland areas have backward fintech foundation and slower development speed.

These conclusions offer suggestions for the fintech and green development policies for economics. Firstly, given the positive effect of fintech level on green production efficiency, countries should pay attention to the role of finance in strengthening their green development; for example, focusing more on the financial effect in the real economy; guiding the development of financial support for green industries properly. Secondly, currently, the promotion of fintech on green production efficiency only works on technological advance, but not on technical efficiency, which sounds the alarm for the formulation of industrial policy. Although the pursuit of technological change can certainly improve overall efficiency, it is extremely prone to bottlenecks and decadence. Only with the progress of green technology and production capacity, can the optimal green production state be achieved. Thirdly, based on the heterogeneous impact of the fintech on green production efficiency and the differences in the fintech level among city groups, we should take regional spatial linkages as an important decision for coordinated regional development, and strengthen the tightness of financial relations among regions as an important decision-making goal as well, especially to the development of fintech in underdeveloped inland areas. In general, according to the economic entities' situation, they need to carry out the following aspects, such as cooperating with the implementation of internal and external policies in finance, environmental protection, science and technology and supply-side; improving the pertinence of response means, gradually improving the fintech level and its green development effect, improving their production pollution in the long-term without affecting the production capacity, as well as balancing the environmental production and economic development.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

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