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Financial Technology Development and Green Total Factor Productivity

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Abstract: As a new product resulting from the deep integration of the financial industry and artificial intelligence (AI) technology, financial technology (fintech) has a significant impact on the progress of green total factor productivity (GTFP). Based on city-level data from 2011 to 2021 in China, this paper used the super-efficiency SBM model with embedded non-expected output and the GML index method to measure the GTFP levels of 283 prefecture-level and above cities and to empirically test the impact of fintech on GTFP and its underlying mechanisms. The empirical results showed that the development of fintech had significantly promoted the improvement of GTFP, and the effect was dynamically stable. Specifically, fintech had a stronger and more significant incentive effect on GTFP in its more mature stage of development. By decomposing fintech into two dimensions, it was found that the depth of fintech development had a stronger impact on GTFP with dynamic superimposed characteristics. Mechanism analysis showed that fintech development can drive the progress of GTFP by improving resource allocation efficiency, optimizing human capital, and incentivizing technological innovation channels. Moderating effect analysis revealed that financial regulation and environmental regulation have a positive moderating effect on the baseline relationship between fintech and GTFP. Further research found that the moderating effects of financial regulation and environmental regulation exhibit significant nonlinear threshold characteristics, and the driving effect of fintech on GTFP can only reach its maximum when both are within the optimal range. This study provides valuable insights for the development and optimization of fintech, the green transformation of the real economy, and high-quality development.

Keywords: financial technology; financial regulation; environmental regulation; green total factor productivity

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1. Introduction

China, as a typical developing country, has gained tremendous economic achievements and significantly improved its comprehensive national strength during more than 40 years of reform and opening up. However, objectively speaking, the rapid growth of the past decades has been based on the extensive development model that relies on the consumption of a large amount of material resources and pursues quantity and spatial expansion [1]. This extensive growth path has overemphasized the speed of economic growth while relatively neglecting the quality of economic development, which has led to numerous resource, environmental, ecological, and social problems such as tightened resource constraints, severe environmental damage, and low economic efficiency [2]. In recent years, with the profound changes in the international market environment and domestic factor endowment conditions, the previous high-input, high-consumption, and high-pollution extensive development is unsustainable, and the economic development model urgently needs to transform "rough" development with an emphasis on factor inputs into "high-quality" development that integrates environmental protection and economic efficiency improvement [3]. Green total factor productivity (GTFP), which takes into account the improvement of ecological and economic efficiency, coincides with the concept of high-quality economic development and has become an important tool to improve the quality of economic development [4]. In simple terms, GTFP refers to the efficiency level of an economic system in utilizing production factors while considering environmental factors. By incorporating environmental benefits into the calculation of total factor productivity, it reflects the performance of the economy in environmental protection and sustainable resource utilization [4]. Enhancing GTFP is of paramount importance in achieving high-quality economic development, promoting the transition to a green economy, and facilitating sustainable development in China. By improving resource efficiency and reducing environmental pressures, China can achieve a harmonious balance between economic growth and environmental protection, making positive contributions to sustainable development [5]. Recently, the Chinese government has attached great importance to the improvement of GTFP and the quality of economic development, repeatedly emphasizing the adherence to the new development concept of "innovation, coordination, green, openness, and sharing". The "14th Five-Year Plan for National Economic and Social Development and the Outline of the Long-Range Objectives for 2035" issued in March 2021 further stressed the need to "promote the green transformation of economic and social development and build a beautiful China", and made high-quality economic development the theme and key goal of economic and social development in the 14th Five-Year Plan and even in the longer term. GTFP can be considered the concentrated summary of high-quality economic development [6], which profoundly reveals the new direction and new momentum of economic development, and is of great practical significance to China in terms of accelerating the transformation of the economic development mode, as well as promoting the upgrading of economic quality, power, and even efficiency [7].

As the lifeblood of the real economy, finance is an important condition to promote innovative development and efficiency of the real economy, and an incomplete financial market is a key factor hindering the improvement of total factor productivity [8], while the integration of artificial intelligence (AI) technology with financial support can help improve the quality of financial service supply and resource allocation efficiency [9]. Generally speaking, AI is a comprehensive technological field that encompasses the integration of various technologies such as big data, cloud computing, blockchain, etc. It aims to develop intelligent algorithms and techniques that enable computer systems to perceive, understand, learn, and make decisions. In recent years, with the widespread application of AI technology, China's financial technology (fintech) has developed by leaps and bounds. According to statistics, by the end of 2021, more than 20,000 companies had applied for fintech-related patents in China, with the total number of patents reaching more than 120,000, and the number and growth rate of patents in the past five years were far higher than those of other countries [10]. From the perspective of business, China's fintech is more focused on technology "empowerment", that is, leveraging the deep integration of AI technology and financial services to upgrade financial products and business processes, solving long-standing problems in the financial market such as information asymmetry and high operating costs, and thereby reducing financial service thresholds, expanding the accessibility of financial services, and providing intrinsic motivation for improving the quality and efficiency of the real economy [9]. Can the financial industry innovation driven by the development of AI technology boost GTFP growth? In the context of economic structural transformation and upgrading, deepening financial reform, and arduous ecological and environmental protection tasks, the exploration of this issue undoubtedly has important theoretical and practical values.

At present, the academic community pays much attention to topics related to fintech or digital finance. Numerous studies have analyzed the impact of fintech on total factor productivity (TFP) from micro or macro perspectives. From a micro perspective, fintech can improve enterprise TFP through various channels, such as alleviating information asymmetry between banks and enterprises and easing financing constraints [11], improving credit resource allocation efficiency [10], enhancing enterprise revenue and financial efficiency [12], and increasing enterprise innovation capabilities [13]. From a macro perspective, the application of financial technologies such as big data and cloud computing is conducive to risk identification and management, reducing risk concentration, ensuring the stability of the financial system, and thus improving resource allocation efficiency [14]. The study by Hou Cen and Li Beiwei (2020) [15] showed that the role of fintech in improving TFP is mainly achieved through mechanisms such as enhancing technology spillover and promoting industrial structure upgrading. Additionally, Wang Xin (2015) [16] argued that internet-based financial services help to alleviate credit allocation and promote rational credit resource allocation, driving the progress of TFP. Bunea et al. (2016) [17] pointed out that fintech innovation poses certain challenges to the dominant position of traditional financial institutions, restructuring the traditional resource allocation model based on indirect financing, but traditional financial institutions can also use financial technology to optimize financial products and services, achieving a new growth curve. In recent years, with the rapid integration of digital technology and the real economy, some scholars no longer stick to the specialized category of fintech and have started to examine the influencing factors of TFP from a broader digital perspective, whose mechanisms of action can be broadly categorized as technological progress, labor efficiency improvement, and industrial agglomeration [18,19]. Throughout the existing studies, only a small amount of studies have investigated the impact of fintech or digital finance on GTFP, and it mainly focused on single causal identification, spatial spillover transmission, and regional heterogeneity [20–22], and the discussion of the underlying mechanisms is still insufficient. Therefore, it is necessary to further explore the "black box" of the mechanisms through which fintech affects GTFP and scientifically evaluate its role through empirical tests, which can help deepen the academic understanding of the economic and environmental impacts of fintech.

It is worth noting that the government's rational understanding of the ecological environment is also essential to achieve the harmonious development of the social economy and ecological environment and thus to promote the continuous progress of GTFP. In a market economy, due to the negative externalities of environmental pollution, it is difficult for economic actors to adopt systematic environmental protection strategies [23]. Therefore, environmental regulation at the government level becomes an important means to promote environmental governance and high-quality economic development [24]. Theoretically speaking, as a mandatory measure, environmental regulation can promote the development of clean environmental industries and force the green transformation of polluting industries, thus further driving GTFP [5]. In addition to actively embracing frontier technologies to help upgrade industries and transform the economy, another important reason for China's tremendous achievements in green industry development and ecological environment management in recent years is the Chinese government's high regard for environmental protection and increasingly tightening environmental regulation policies [20]. Moreover, China is a vast country, and the intensity of environmental regulations naturally varies greatly across regions. Therefore, it is necessary to ask what role environmental regulation plays in the relationship between fintech and GTFP, and whether the impact of fintech on GTFP is heterogeneous depending on the intensity of environmental regulation. The current literature does not provide a systematic response to this question. At the same time, fintech does not change its own financial logic, let alone the basic core of "risk-return" in the financial industry. Fintech innovation will also generate new risks, and with AI technology, the financial risks embedded in fintech will be transmitted more quickly and through multiple channels, which will eventually have a dampening effect on the productivity of the real sector [13]. Therefore, fintech undoubtedly has the dual attributes of both efficiency gain and risk induction. Due to the existence of this dual attribute, effective regulation is essential [9]. Financial regulation facilitates the sustainable development of fintech. Regulatory bodies establish and enforce laws and policies that require fintech companies to adhere to environmental protection and sustainable development principles while promoting GTFP. These regulations may include disclosure requirements for fintech firms to report their environmental and social impacts, ensuring that their operations and innovations do not have adverse effects on the environment [25]. In this regard, it is worth exploring the role of financial regulation in the "fintech–GTFP" relationship. This will help achieve benign development of fintech, improvement of financial regulatory models, and enhancement of the quality and efficiency of the real economy. Table 1 presents some prior studies on this topic.

Table 1. Overview of the relevant studies related to the research topic of this paper.

Author(s)	Fintech/Digital Finance	Financial Regulation	Environmental Regulation	Mechanism Effect	GTFP
[9]	Yes	No	No	Yes	No
[13]	Yes	Yes	No	Yes	No
[10]	Yes	No	No	Yes	No
[12]	Yes	No	No	Yes	No
[5]	No	No	Yes	Yes	Yes
[4]	No	No	No	No	Yes
[6]	No	No	Yes	Yes	Yes
[17]	Yes	Yes	No	Yes	No
[21]	Yes	No	Yes	No	Yes
[26]	No	No	No	No	Yes
[27]	Yes	No	No	Yes	No
[24]	Yes	No	Yes	Yes	No
[28]	Yes	No	No	Yes	No
[29]	No	No	Yes	Yes	No
[30]	Yes	No	No	Yes	No
[31]	Yes	Yes	No	Yes	No
[22]	Yes	No	No	Yes	Yes
[32]	Yes	Yes	No	Yes	No
[14]	Yes	Yes	No	No	No
This study	Yes	Yes	Yes	Yes	Yes

Compared with the existing literature, the marginal contributions of this paper are mainly in the following aspects: First, in terms of the research objective, the existing literature mainly discusses the impact of fintech or digital finance on TFP, while this paper focuses on the relationship between fintech and GTFP, and for the first time examined the dynamic effects and nonlinear effects of fintech on GTFP, thus creating an important supplement to the literature on financial functions and providing new empirical evidence for clarifying the economic effects of fintech. Second, under a unified framework, this paper explored the heterogeneity of fintech's impact on GTFP, comprehensively and systematically evaluating the linear and non-linear regulatory roles played by environmental regulation and financial supervision. This provides important empirical evidence for China in formulating refined policies to support the progress of GTFP and the upgrading of economic development quality. Third, we analyzed the mechanisms and paths of the impact of fintech on GTFP from three aspects: resource allocation, technological innovation, and human capital, further opening up the "black box" of the inherent mechanisms of financial technology, and providing new evidence for a deeper understanding of the impact of emerging financial forms on green economic development.

2. Theoretical Analysis and Research Hypothesis

Based on the existing research, this study investigated and demonstrated the impact of fintech on GTFP from two aspects: the mechanism of action and the regulatory effect. Based on this, the research hypotheses of this article were proposed. Before theoretical analysis, Figure 1 presents the basic conceptual framework and research hypotheses of this study.

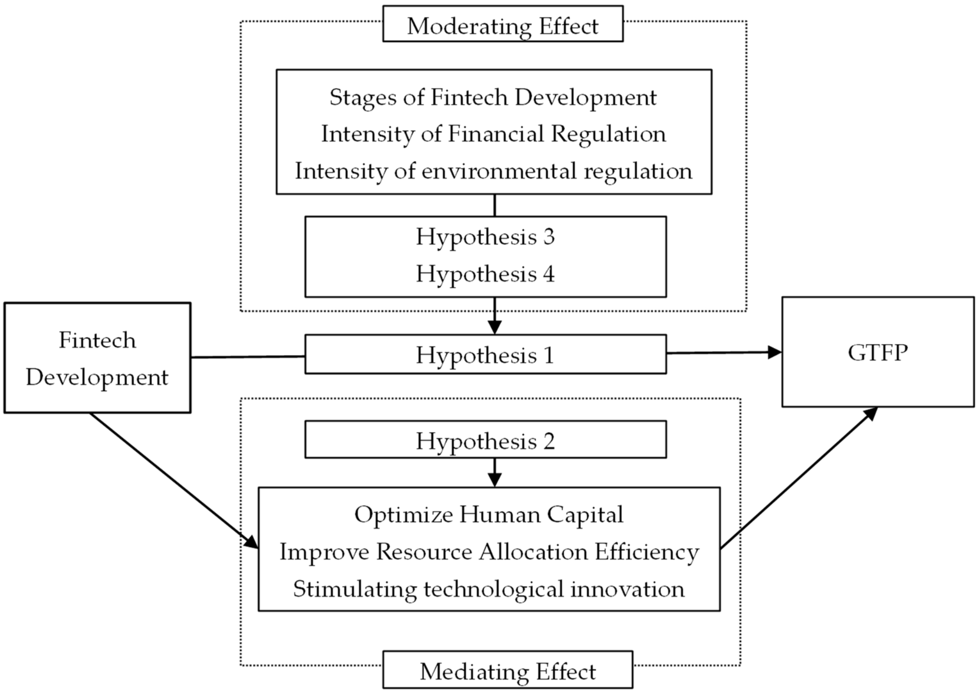

Figure 1. The conceptual framework of fintech on GTFP. Note: The framework diagram includes this study's main research questions and hypotheses.

2.1. The Mechanism of Fintech's Effects on GTFP

Green total factor productivity (GTFP), which takes environmental factors into account, is an important indicator of the quality of economic development in a country or region [4]. As resource and environmental constraints become increasingly tight and ecological carrying capacity approaches saturation, a country or region can only achieve green and sustainable development by transforming to endogenous growth that relies on GTFP [5]. Among the many factors affecting GTFP, the completeness of financial markets and their effectiveness in resource allocation are undoubtedly the key variables. A well-functioning financial market can not only provide sufficient and timely financial support for factor inputs and technological R&D of market players but also allocate capital to key segments and critical sectors of the economy, thereby improving the level of social production [12]. China's financial structure is dominated by bank-led indirect finance, coupled with the tendency toward financial system and government credit regulation, which has led to long-standing issues such as information asymmetry, structural mismatch, and distortion in resource allocation, becoming important factors hindering the improvement of GTFP [10]. However, in recent years, seizing the great opportunities brought by the rapid development of AI technologies such as big data and cloud computing, the finance sector has also strengthened its integration with AI technology. Fintech has emerged and developed rapidly, and the challenges faced by traditional financial development are expected to be reversed with the "empowerment" of fintech [9].

Fintech is the product of the deep integration of finance and AI technology. Relying on underlying AI technologies such as big data, cloud computing, and blockchain, it can effectively alleviate information asymmetry, which helps to improve resource allocation efficiency and technological innovation capabilities [31], thereby providing endogenous power for the upgrading of GTFP. Technological innovation is an important factor affecting GTFP, while financing constraints and credit allocation distortions can severely constrain technological R&D [33]. The synergistic development of fintech and traditional financial institutions can significantly increase market transparency and curb credit allocation imbalance [32], which can be beneficial in alleviating the financing constraints faced by enterprises [34]. Fintech in China has both technology spillover effects and inclusive effects, not only significantly improving the total factor productivity of commercial banks [35], but also having a stronger promotion effect for innovation in areas with less developed financial sectors [36]. The combination of AI technology and finance can also use both "incremental supplementation" and "stock optimization" to break down technological innovation barriers [13]. On the one hand, fintech can efficiently integrate financial resources, allocate them rationally to the demand side, and enrich enterprise financing methods and identify the optimal R&D paths for enterprises by providing high-quality data analysis tools and intelligent products, thereby driving the creation of new knowledge and technological iterations [37]. On the other hand, fintech can effectively drive the upgrading of traditional financial structures, improve the operation modes and pricing models of traditional financial products, and provide a favorable financial environment for innovation activities [27].

Resource allocation efficiency is also a key factor affecting GTFP. Hsieh and Klenow (2009) [38] argued that resource allocation distortion is a major constraint to factor productivity growth in China. If China's resource allocation efficiency could reach the level of the United States, its productivity would increase by 30–50%. Numerous studies have shown that fintech has significant advantages in reducing resource allocation distortions and improving resource allocation efficiency. Firstly, fintech can not only solve the trust issue between transaction parties based on the tamper-proof characteristics of blockchain, promoting the smooth completion of transactions and the rational flow of production factors [39], but also overcome information asymmetry in the transaction process through big data analysis and information processing technology, effectively matching supply and demand of funds, expanding the boundaries of financial services, and improving resource allocation efficiency [30]. Secondly, fintech, characterized by high synergy and networking, can accelerate information interconnectivity between institutions and regions, expand resource allocation boundaries, and promote the free flow of talents, capital, and technology across industries, sectors, and regions [40]. Thirdly, the innovative and integrated development of finance and AI technology can enhance the vitality and efficiency of the financial market, improve the traditional financial sector's ability to consolidate, organize, and analyze information, help the real sector overcome transaction frictions, information asymmetry and other problems, and improve the effectiveness of investment and financing decisions in the real economy [13]. Finally, fintech significantly reduces information asymmetry costs in long-tail markets by collecting, analyzing, and sharing real-time and intelligent basic information of financial and non-financial institutions, using decentralized distributed ledger technology to ensure information security and reduce trust risks, thereby expanding the scope of financial services to small and medium enterprises (SMEs). It enhances the identification of outstanding enterprises with development potential but faces budget constraints, and ultimately strengthens the allocation efficiency of financial resources for technological innovation projects [41].

Among the many factors that determine GTFP, the important role played by the accumulation level and quality of human capital cannot be overlooked [42]. Human capital condensed with educational inputs is the basis of technological innovation and naturally facilitates the development and output of green technologies [43]. At the same time, higher levels of human capital generally have stronger technology absorption capabilities, enabling better application of green technologies in economic practice [44]. Moreover, human capital affects the consumption of green products in society, and a high level of human capital tends to have a stronger tendency to consume innovative products [45], which is extremely beneficial in driving the overall progress of GTFP. Meanwhile, fintech can also drive the accumulation level and quality of human capital from multiple perspectives. First, the development of fintech has greatly expanded the customer base that can be reached by financial services, effectively reducing the financing constraint of residents and improving the availability of credit, which is conducive to stimulating the consumption propensity of residents in knowledge acquisition, education, and training [9]. Second, fintech can also provide more investment channels for low-income groups excluded by traditional finance, realize individual wealth appreciation, narrow the income gap between regions [12], and lay a solid material foundation for human capital accumulation. Third, the information technologies such as big data and cloud computing used in fintech rely on the Internet, and the Internet has a significant network effect. Fintech innovation activities can break the temporal and spatial boundaries of knowledge dissemination and accelerate knowledge exchange and communication through network effects, and market subjects can imitate advanced technologies, learn advanced knowledge, and generate new knowledge, which greatly contributes to the optimization of the human capital structure [46]. As a result, this paper proposes:

Hypothesis 1. *Fintech development contributes to GTFP enhancement.*

Hypothesis 2. *Fintech development can contribute to GTFP progress by stimulating technological innovation, improving resource allocation efficiency, and optimizing human capital.*

2.2. Nonlinear Relationship between Fintech and GTFP

As analyzed earlier, fintech has the advantages of high efficiency, low cost, and wide service range, which can promote GTFP through encouraging technological innovation, improving resource allocation efficiency, and optimizing human capital. However, the development of fintech is a gradual process with the characteristic of "one hair moves the whole body", and its impact on GTFP may be characterized by phases [21]. On the one hand, in the early stage of fintech development, due to the lack of synchronization and automation of financial regulation, the rapidly updated fintech products may have a high risk of uncertainty [19], which poses a negative impact on the real sector. With the gradual maturity of fintech and the improvement of the financial regulatory system, the service function of fintech can be gradually optimized [27], and its contribution to GTFP will be increasingly enhanced. On the other hand, with the widespread application of fintech, the marginal cost of linkage among various sectors continues to decline, while the benefits obtained by participants increase geometrically, and this effect will become more and more obvious as the level of fintech increases [47], that is, the "Metcalfe's Law" and "Moore's Law" in the internet field hold in the relationship between fintech and GTFP [27]. Therefore, this article proposes:

Hypothesis 3. *The impact of fintech on GTFP exhibits heterogeneity in different stages of its own development.*

2.3. The Moderating Effect of Fintech on GTFP

As analyzed earlier, fintech does not change the inherent logic of finance itself, nor does it change the basic rule of "risk-return" in the financial industry. Fintech is essentially a product of the deep integration of AI technology and traditional finance, and innovation is the inherent driving force of fintech, which constitutes an important component of financial risk while promoting financial development [9]. Fintech innovation will increase the probability of financial risk contagion, which may expand the risk exposure of the real sector and adversely affect GTFP. As a result, fintech has both efficiency-enhancing and risk-inducing properties, so it is a necessary task to impose effective regulation on it [27]. This matters for the effectiveness of fintech, the stability of financial markets, and the quality improvement of macroeconomic development. In fact, any financial innovation, including fintech, cannot avoid the theoretical detour of financial innovation, financial risk, and financial regulation [10]. On the one hand, strengthening financial regulation can undoubtedly help guard against systemic financial risks and enhance the positive effects of fintech; on the other hand, the uncertainty and complexity of fintech may also amplify the shortcomings of financial regulation, and inappropriate financial regulation may also fetter the release of fintech effectiveness and impede the improvement of GTFP.

To promote GTFP progress and thus achieve sustainable development in harmony with nature, the pushback effect of environmental regulation is indispensable [48]. The non-exclusivity and non-competitiveness of the environment and the negative externalities of pollution lead to market failure in environmental protection, and government environmental regulation policies are crucial to internalize environmental costs [5]. The rapid development of the internet and digital technologies has greatly expanded channels for environmental governance and social participation, effectively enhancing the effectiveness of environmental regulation [49]. Environmental regulation policies also produce an indicative effect. Under the guidance of environmental regulation, financial resources mobilized by fintech will be invested more in green and environmentally friendly, clean energy, and resource-intensive industries, which is conducive to achieving a win–win situation among ecological, economic, and social benefits and providing strong support for sustainable high-quality development [24]. However, there is no consensus among academics on the relationship between environmental regulations and GTFP. When environmental regulation reflects resource scarcity, it generates a so-called "compliance cost" where increased spending on environmental protection may crowd out production resources and reduce innovation returns, thus having a negative impact on GTFP [50]. However, the "Porter Hypothesis" argues that, under appropriate constraints on environmental regulation, firms will increase green technology development and reduce environmental pollution in the production process, partially or fully offsetting the loss of environmental regulations [51], which will significantly increase GTFP. Therefore, the impact of environmental regulation on GTFP may not be a simple linear relationship. Based on the above analysis, this article proposes:

Hypothesis 4. *Financial regulation and environmental regulation play a moderating role between fintech development and GTFP.*

3. Econometric Model, Variables, and Data

3.1. Construction of the Econometric Model

Based on the theoretical analysis and existing literature discussed earlier, this paper constructed the following baseline econometric model to investigate how the development of regional fintech affects the level of a city's GTFP:

$$GTFP_{i,t} = \alpha_0 + \alpha_1 Fintech_{m,t-1} + \sum_{k=2}^{T} \alpha_k Controls_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (1)$$

where the dependent variable is the GTFP of city i in year t, which is measured based on the super-efficiency SBM model (slack-based measure) with GML (global Malmquist–Luenberger) index method for non-expected output. The core explanatory variable $Fintech_{m,t-1}$ denotes the level of fintech development of province m in year $t - 1$, using the fintech development index as its proxy variable. To control for the influence of omitted variables, multiple city-level control variables, $Controls_{i,t}$ are included in this paper; the fixed effects for city and year are denoted by μ_i and δ_t, while $\varepsilon_{i,t}$ represents the random error term. To improve the estimation efficiency, cluster robust standard errors are used by default in the regression process. Additionally, considering that there is lag time between regional fintech development and its effects on urban GTFP, we followed an approach in a previous study [12] and used a lagged fintech development index, which can also alleviate the reverse causality problem. We focused on the coefficient of the core explanatory variable $Fintech_{m,t-1}$, and if α_1 is significantly positive, this indicates that the development of fintech can significantly enhance the level of urban GTFP, and Hypothesis 1 is supported.

3.2. Variable Definitions

3.2.1. Explained Variable

GTFP incorporates energy consumption and environmental pollution into the economic growth framework, emphasizing the green concept of coordinated development of economy, resources, and environment, which is a significant improvement to traditional total factor productivity. The academic community's measurement of GTFP mainly includes methods such as the traditional radial DEA model [52], the SBM model with undesirable outputs [26], and the stochastic frontier analysis model [53]. However, these methods have problems, mainly, ignoring slack variables, effective DMU is not easy to distinguish, and poor comparability across periods. Therefore, based on the research of Tone (2001) [26] and Oh (2010) [54], this paper uses the super-efficiency SBM model that considers energy consumption and environmental pollution, and applies the GML index of global parameter ratio to measure the GTFP of 283 cities in China, denoted as GTFP_GML. This method can overcome the three key issues of variable relaxation, efficient DMU distinguishability, and cross-period comparability, ensuring the robustness of the results. In addition, the SBM-GML approach to measure GTFP requires determining input and output indicators; for these, this paper referred to Fare et al. (2009) [55], taking labor, energy, and capital as input indicators, real GDP as the expected output indicator, and industrial SO_2 emissions, industrial wastewater emissions, and industrial smoke and dust emissions as undesirable outputs. The relevant indicators and metrics are shown in Table 2. The specific measurement method can be divided into the following three steps:

Step 1: Define the environmental technology set for measuring GTFP:

$$\mathrm{ETS} = \left\{ \left(X, \overline{Y}^g, \overline{Y}^b\right) \middle| \overline{X} \geq \sum_{\substack{j=1 \\ j\neq 0}}^{L} \lambda_j x_j ,\ \overline{Y}^g \leq \sum_{\substack{j=1 \\ j\neq 0}}^{L} \lambda_j y_j^g ,\ \overline{Y}^b \leq \sum_{\substack{j=1 \\ j\neq 0}}^{L} \lambda_j y_j^b ,\ L \leq e\lambda \leq \mu, \lambda_j \geq 0 \right\} \quad (2)$$

where the input–output pattern of each city corresponds to n inputs, s_1 is the desired outputs, and s_2 is the non-desired outputs. X represents the n-dimensional input vector, $X = (x_1, x_2, \cdots, x_n) \in R_+^n$; Y^g represents the s_1-dimensional desired output vector, $Y^g = \left(y_1^g, y_2^g, \cdots, y_{s_1}^g\right) \in R_+^{s_1}$; Y^b represents the s_2-dimensional non-desired output vector, $Y^b = \left(y_1^b, y_2^b, \cdots, y_{s_1}^b\right) \in R_+^{s_2}$; and $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_L)$ represents the L-dimensional weight vector.

Step 2: Denote the excess input vector as $s^- \in R_+^{s_n}$, denote the excess of the undesired output as $s^b \in R_+^{s_2}$, and denote $s^g \in R_+^{s_1}$ as the deficiency of the desired output. A super-efficiency SBM model with undesired outputs is introduced based on the super-efficient SBM model:

$$\begin{aligned} &\theta = \min_{\lambda,\, \overline{x},\, \overline{y}^g,\, \overline{y}^b} \frac{\sum_{i=1}^{m} \frac{\overline{x}_t}{x_{io}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} \frac{\overline{y}_r^g}{y_{ro}^g} + \sum_{k=1}^{s_2} \frac{\overline{y}_k^b}{y_{ko}^b}\right)} \\ &\text{s.t. } X \geq \sum_{\substack{j=1 \\ j=0}}^{L} \lambda_j x_j ,\ \overline{Y}^g \leq \sum_{\substack{j=1 \\ j=0}}^{L} \lambda_j y_j^g ,\ \overline{Y}^b \geq \sum_{\substack{j=1 \\ j=0}}^{L} \lambda_j y_j^b \\ &\quad \overline{X} \geq x_o ,\ \overline{Y}^g \leq y_o^g ,\ \overline{Y}^b \geq y_o^b \\ &\quad \overline{Y}^g \geq 0 ,\ \overline{Y}^b \geq 0,\ L \leq e\lambda \leq \mu,\ \lambda_j \geq 0 \\ &\quad \overline{x}_t = x_{io} + s^-(i = 1, \cdots, n),\ \overline{y}_r^g = y_{ro}^g - s^g(r = 1, \cdots, s_1),\ \overline{y}_k^b = y_{ko}^b - s^b(r = 1, \cdots, s_1) \end{aligned} \quad (3)$$

where $\overline{x}$, $\overline{y}_r^g$, and $\overline{y}_k^b$ are the target values of the input and output of the evaluated unit, and x_{io}, y_{ro}^g, and y_{ko}^b represent the corresponding original values.

Step 3: According to the non-parametric framework and based on the above super-efficiency SBM model containing the undesirable outputs, construct a non-angular and non-radial MPI:

$$GML_o^{t,t+1} = \frac{\theta_o^{t+1}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)}{\theta_o^{t}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)} \times \left[\frac{\theta_o^{g}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)}{\theta_o^{t+1}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t}\right)} \times \frac{\theta_o^{t}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)}{\theta_o^{g}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)}\right] \tag{4}$$

where $\theta_o^{t}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)$ and $\theta_o^{t+1}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)$ represent the city efficiency values at periods t and t+1, respectively; $\theta_o^{g}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)$ is the efficiency value based on global production technology and t-period input–output values; $\theta_o^{g}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)$ is the efficiency value based on global production technology and the input–output values of period t+1. $\frac{\theta_o^{g}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t+1}\right)}{\theta_o^{t+1}\left(x_o^{t+1}, y_o^{g,t+1}, y_o^{b,t}\right)}$ reflects the proximity of the frontier in period t+1 to the global frontier, and $\frac{\theta_o^{t}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)}{\theta_o^{g}\left(x_o^{t}, y_o^{g,t}, y_o^{b,t}\right)}$ reflects the proximity of frontier period t to the global frontier. $GML_o^{t,t+1}$ is the change in city GTFP from period t to t + 1. $GML_o^{t,t+1} = 1$ indicates no change in GTFP; $GML_o^{t,t+1} > 1$ indicates an increase in GTFP; and $GML_o^{t,t+1} < 1$ indicates a decrease in GTFP.

In addition, considering that the GTFP indicator used in this paper is more concerned with the reduction of the unexpected output and drawing on the work of Fare et al. (2009) [55], we further estimated the city GTFP using the directional distance function of SBM that includes the unexpected output (SBM-DDF) as a robustness test indicator, denoted as GTFP_DDF.

Table 2. Description of input and output indicators.

Input/Output	Input/Output	Indicator Description
Input	Capital input	Referring to Shan Haojie (2008) [56], taking 2005 as the base period and using the perpetual inventory method calculate the capital input, the depreciation rate was set at 10.96%/billion CNY
	Labor input	Sum of the number of unit employees, private employees, and self-employed employees in each city/10,000 people
	Energy input	Electricity consumption of each city as a proxy variable for energy consumption /10,000 TCE
Expected output	Real GDP	Real GDP of each city (based on 2005) (billion CNY)
Non-desired output	Industrial sulfur dioxide emissions	Industrial sulfur dioxide (SO_2) emissions (million tons)
	Industrial wastewater emissions	Industrial wastewater emissions (million tons)
	Industrial soot emissions	Industrial soot emissions (million tons)

3.2.2. Core Explanatory Variable

The Global Financial Stability Board (FSB) defines fintech as a technological form of integrating finance and technology into financial services, capable of effectively reducing the operational costs of the financial system and enhancing the output and service efficiency of traditional finance through emerging AI technologies such as cloud computing, big data, blockchain. According to this definition, fintech is essentially a business model, technology application, and even processes and products based on technological means to promote financial innovation. The Digital Inclusive Finance Index, jointly compiled by the Digital Finance Research Center of Peking University and Ant Financial Services Group, provides a comprehensive measurement of China's fintech business penetration, service efficiency, and depth of technology application in three dimensions: the breadth of fintech coverage, the depth of fintech use, and the degree of fintech services; thus, this index can better reflect the stage characteristics and evolution trends of China's fintech development in recent years and has been widely adopted by scholars [57,58]. Based on the above considerations, this paper selected the Digital Inclusive Finance Index (provincial level), jointly compiled by the Digital Finance Research Center of Peking University and Ant Financial Services Group in China, as a proxy variable for fintech development, denoted as Fintech_P. At the same time, in the robustness test, we also used the city-level digital inclusive finance index, denoted as Fintech_C, as a proxy variable for fintech development. To improve the accuracy and rationality of the findings, the above data were treated as logarithms.

3.2.3. Mediating and Moderating Variables

The mediating variables mainly included technological innovation, resource allocation, and human capital level. In terms of technological innovation, previous studies often used R&D investment as a proxy variable for technological innovation, but real-world technological innovation activities often have typical high-risk characteristics, and the effective transformation of R&D investment into innovation output often has greater uncertainty, which may overestimate technological innovation capabilities. In view of this, this paper selected the logarithm of the number of patents granted in each city as a measure of technological innovation. Among them, the logarithm of the total number of invention patents granted was used to measure the quality of technological innovation, which is denoted as Innova_Q; the logarithm of the total number of utility model patents and design patents granted was used to measure the quantity of technological innovation, denoted as Innoa_N. Resource allocation efficiency, following the research of Chen Yongwei and Hu Weiming (2011) [59], was measured using the absolute value of the resource mismatch index, with Capital_M representing the degree of material resource mismatch and Labor_M representing the degree of labor resource mismatch, and the larger the absolute value of the index, the more serious the degree of resource mismatch and the lower the efficiency of resource allocation. For the human capital level, based on existing research, we used the proportion of the total population with a college degree or above in each city to measure the degree of human capital accumulation, denoted as Human_E. Based on the number of students enrolled in each level of education (general higher education, general undergraduate, general secondary school, secondary vocational and technical, etc.) and referring to the method of Liu Zhiyong et al. (2018) [60], the degree of human capital structure upgrading in each city was calculated using the vector index method and denoted as Human_A.

The moderating variables included environmental regulation and financial supervision. For environmental regulation, considering data availability and following the approach of He Lingyun and Qi Xiaofeng (2022) [5], the four basic indicators of industrial wastewater discharge compliance rate, industrial sulfur dioxide removal rate, industrial soot removal rate, and comprehensive utilization rate of solid waste were selected. By standardizing and removing dimensions, the entropy method was used to calculate the weight coefficients of each basic indicator, and then the weighted sum was used to obtain the provincial environmental regulation intensity indicator, denoted as Eregulat. For financial regulation, the ratio of financial regulatory expenditure to financial industry value added in each province was taken as a proxy indicator, denoted as Fsupervis, following Tang Song et al. (2020) [13].

3.2.4. Control Variables

In order to minimize the estimation bias caused by omitted variables, based on existing research, this study incorporated multiple city-level variables into the baseline model. These included: (1) government size (Gover), measured by the proportion of government fiscal expenditure to GDP; (2) trade openness (Ecopen), measured as the ratio of total imports and exports to GDP; (3) urbanization level (Urban), calculated as the ratio of urban non-farm population to total population; (4) industrialization level (Indus), measured as the ratio of industrial added value to GDP; (5) financial development (Fincial), expressed as the ratio of total institutional deposits and loans to the city GDP; (6) industrial structure (Indstr), measured as the proportion of secondary industry output to GDP; (7) population density (Popul), expressed as the number of people (in hundreds) per square kilometer of the city; (8) greening level (Green), represented as the greening coverage rate in built-up areas; (9) foreign direct investment (Fdi), represented as the ratio of total foreign direct investment to local GDP; and (10) infrastructure (InfStra), using the road construction area per capita as a proxy variable.

3.3. Sample Selection and Data Sources

This paper used panel data from 283 prefecture-level and above cities in China from 2011 to 2021 to obtain a final sample of 3113 "city-year" observations. The fintech development index (provincial and city levels) was derived from the "Digital Inclusive Finance Index" from Peking University in China. Provincial-level data were mainly obtained from the "China Statistical Yearbook", "China Financial Statistical Yearbook", and "China Energy Statistical Yearbook"; city-level data were mainly taken from the "China City Statistical Yearbook", "China Environmental Statistical Yearbook", "China Energy Statistical Yearbook", "China Urban Construction Statistical Yearbook", and the CNRDS database. Table 3 gives the descriptive statistics of the main empirical variables in this paper. The mean value of GTFP calculated using the SBM-GML model was 1.0050 and the median value was 1.0011, indicating that the results were not significantly biased. The mean value of the fintech development index was 5.1464, which is slightly lower than its median of 5.3532, indicating a certain left skewness. The statistical information of the other control variables is consistent with previous research.

Table 3. Descriptive statistics of variables.

Variable	N	Mean	Sd	Min	P50	Max
GTFP_GML	3113	1.0050	0.0520	0.4884	1.0011	1.6335
Fintech_P	3113	5.1464	0.6595	2.9085	5.3532	6.0168
Fintech_B	3113	4.9872	0.7903	0.6729	5.2406	5.9523
Fintech_D	3113	5.1414	0.6139	1.9110	5.2459	6.0866
Innova_Q	3113	4.8298	1.7966	0.0000	4.5850	10.8770
Innova_N	3113	7.0968	1.5860	2.6391	6.9745	11.4340
Capital_M	3113	0.3764	0.3221	0.0002	0.3252	3.3634
Labor_M	3113	0.3682	0.3100	0.0007	0.2988	3.1416
Human_E	3113	0.0185	0.0242	0.0003	0.0097	0.1311
Human_A	3113	16.1950	0.6765	15.5610	15.9480	19.8252
Eregulat	3113	0.6787	0.5566	0.0000	0.4266	2.5853
Fsupervis	3113	0.0102	0.0109	0.0005	0.0064	0.1116
Gover	3113	0.2005	0.1021	0.0352	0.1746	0.8717
Ecopen	3113	0.1874	0.3045	0.0000	0.0770	4.6784
Urban	3113	0.5547	0.1472	0.0649	0.5290	0.9973
Fincial	3113	16.4050	1.1435	13.7230	16.1831	20.4202
IndStr	3113	0.4692	0.1096	0.1068	0.4754	0.8934
Indus	3113	0.4015	0.1215	0.03245	0.4056	0.8821
Popul	3113	4.3752	3.3979	0.0510	3.6530	26.4810
Green	3113	0.3942	0.0692	0.0036	0.4050	0.8925
Fdi	3113	0.0167	0.0179	0.0000	0.0114	0.2116
InfStra	3113	17.0810	7.2722	0.0005	15.6770	60.0705

4. Baseline Empirical Results and Economic Analysis

4.1. The Impact of Fintech on GTFP

Table 4 provides an empirical test of the benchmark "fintech–GTFP" relationship. The stepwise regression method was used to overcome the problem of multicollinearity. Columns (1), (3), and (5) are the OLS regression results without fixed effects. Columns (2), (4), and (6) control for the city- and year-fixed effects to mitigate omitted variable interference. The regression results show, in columns (1) and (2), considering fixed effects and control variables, whether the regression coefficients of the fintech development index (L.Fintech_P) on GTFP were positive and significant at least at the 5% confidence level. This indicates that fintech development can have a significant driving effect on GTFP: the better the regional fintech development, the higher the city's GTFP. As the control variables were gradually introduced, the estimated coefficient of the effect of fintech remained significantly positive at the 1% confidence level, and the conclusion that fintech drives city GTFP remained unchanged. From an economic perspective, taking column (6) as an example (including control variables and two-way fixed effects), the coefficient of the fintech development index was 0.0227 and significant at the 1% level. For every 1% increase in the regional fintech development index, the city GTFP increased by an average of 0.023 units. These results support Hypothesis 1.

Table 4. Baseline regression results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
L.Fintech_P	0.0178 *** (4.4721)	0.0135 ** (2.2875)	0.0136 *** (5.9293)	0.0163 *** (3.4491)	0.0145 *** (4.2998)	0.0227 *** (3.9538)
Gover			−0.0004 (−0.0419)	−0.1852 * (−1.6261)	−0.0027 (−0.2322)	−0.1845 (−1.2969)
Ecopen			−0.0052 (−1.3136)	−0.0067 (−1.1708)	−0.0043 (−1.0344)	−0.0057 (−0.9971)
Urban			0.0197 (0.0956)	−0.0765 * (−1.7174)	−0.0196 (−0.8750)	−0.0699 (−1.5111)
Indus			−0.0161 (−0.6194)	−0.0096 (−0.1849)	−0.0143 (−0.5496)	−0.0093 (−0.1823)
Fincial			0.0043 * (1.6835)	0.0051 * (1.6161)	0.0043 *** (3.6791)	0.0042 ** (2.4300)
IndStr			−0.0334 * (−1.6477)	−0.0172 ** (−2.3612)	−0.0287 ** (−2.0615)	−0.0149 ** (−2.3183)
Popul					0.0000 (0.1174)	0.0028 (0.4134)
Green					0.0055 (0.2792)	0.0270 (0.8726)
Fdi					0.0134** (2.2407)	0.2512** (2.0268)
Infstr					0.0003 *** (2.8775)	0.0006** (2.2499)
Cons	0.9135 *** (17.2697)	0.9358 (17.4054)	0.8633 *** (18.7024)	1.0972 *** (7.6931)	0.8662 *** (10.4305)	1.0370 *** (7.2836)
City fixed	No	YES	No	YES	No	Yes
Year fixed	No	YES	No	YES	No	Yes
Adj. R^2	0.5021	0.61001	0.5945	0.7271	0.6952	0.6838
N	2830	2830	2830	2830	2830	2830

Note: Values in the lower brackets of the estimated coefficients are t-statistics adjusted for robust standard errors (clustering at the city level); ***, **, and * represent passing significance tests at the 1%, 5%, and 10% confidence levels; the dependent variables in the regressions in columns (1) to (6) are GTFP_GML.

The significance and signs of the other control variables' coefficients were generally consistent with the existing literature. For example, taking column (6), which considers both fixed effects, the coefficient of government size (Gover) was negative but insignificant, which may be explained by the fact that the non-market-oriented behavior of government intervention is detrimental to the optimal allocation of resources and has a certain inhibitory effect on the increase of production efficiency. The estimated coefficients of urbanization level (Urban) and industrialization level (Indus) were also insignificantly negative, suggesting that rapid urbanization and industrial expansion without considering environmental carrying capacity may exacerbate the contradictions between humans and nature, thus having a negative effect on GTFP. The coefficient of industrial structure (Indstr) was significantly negative, suggesting that the current imbalance in industrial structure is an important factor hindering the progress of China's GTFP. The estimated coefficient of financial development (Fincial) was significantly positive, which indicates that effective financial support is indispensable in enhancing GTFP. The coefficient of trade openness (Ecopen) was significantly positive, implying that international trade is an important support for the continuous improvement of economic development quality and efficiency. Foreign direct investment (Fdi) significantly improved GTFP. Generally speaking, foreign direct investment entities are mostly multinational corporations with advanced business models and frontier technology, which can produce good demonstration effects, incentive effects, and competitive effects on host country enterprises [61], and have a significant improvement effect on GTFP [62].

We further examined the dynamic impact of fintech on GTFP. Following Chen Zhongfei and Jiang Kangqi (2021) [12], we replaced the core explanatory variable in model (1) with the lagged fintech development index, and the results are reported in panel A of Table 5. With the increase in the lagged order of fintech, the intensity of the positive effect of fintech on GTFP remained basically stable, and all of them were significant at the 1% confidence level. This indicates that the incentive effect of fintech on GTFP has a dynamic and stable trend over time, and can continue to provide strong support for GTFP.

To more accurately portray the impact of Fintech on GTFP, we decomposed the fintech development index into two symmetrical dimensions: the breadth and depth of fintech development. We explored the impact of the different dimensions of fintech development on GTFP. The breadth of fintech development was mainly characterized as the coverage of electronic accounts related to regional fintech services [63], denoted as Fintech_B. The depth of fintech development reflects the frequency and transaction volume of local actual use of fintech services, representing the service capability of fintech [13], which was denoted as Fintech_D. We replaced the core explanatory variable in model (1) with the breadth and depth of fintech development and the test results are shown in panels B and C of Table 5, respectively. It was found that the positive impact of fintech development breadth on GTFP gradually decayed with the increase of lag periods, and its significance also declined or even disappeared. Specifically, the regression coefficient of fintech at lag 2 was 0.013 and passes the 1% statistical significance test, but the positive effect at lag 3 was weaker and significant only at the 10% confidence level, and the regression coefficient at lag 4 further declined and failed the statistical significance test. In contrast, the effect of depth of fintech development on GTFP was very prominent and remained significant with increasing lag. Overall, the depth of fintech development maintained a significant promoting effect on GTFP in a relatively long time series, exhibiting obvious dynamic cumulative characteristics.

The above results indicate that although both the depth and breadth of fintech development are conducive to improving GTFP, the promotion effect of fintech development depth was even stronger. Therefore, in the construction of fintech, it is not only necessary to expand the breadth of fintech development and achieve inclusive finance but also to pay more attention to tapping the depth of fintech development to fully improve fintech service capability.

Table 5. Dynamic impact of fintech on GTFP.

Variable	**GTFP_GML**		
	(1)	**(2)**	**(3)**
Panel A Comprehensive Index of Fintech Development			
L2.Fintech_P	0.0206 *** (7.7008)		
L3.Fintech_P		0.0193 *** (7.7074)	
L4.Fintech_P			0.0211 *** (5.7433)
Controls	Yes	Yes	Yes
Year/City fixed	Yes	Yes	Yes
Adj. R^2	0.5208	0.4792	0.4654
N	2547	2264	1981
Panel B The Breadth of Fintech Development			
L2.Fintech_B	0.0130 *** (3.9277)		
L3.Fintech_B		0.0085 * (1.8621)	
L4.Fintech_B			0.0033 (0.9516)
Controls	Yes	Yes	Yes
Year/City fixed	Yes	Yes	Yes
Adj. R^2	0.3208	0.3784	0.3656
N	2547	2264	1981
Panel C The Depth of Fintech Development			
L2.Fintech_D	0.0255 ** (2.2856)		
L3.Fintech_D		0.0293 *** (3.9901)	
L4.Fintech_D			0.0313 *** (3.6856)
Controls	Yes	Yes	Yes
Year/City fixed	Yes	Yes	Yes
Adj. R^2	0.4208	0.4812	0.4665
N	2547	2264	1981

Note: Values in the lower brackets of the estimated coefficients are t-statistics adjusted for robust standard errors (clustering at the city level); ***, **, and * represent passing significance tests at the 1%, 5%, and 10% confidence levels.

4.2. Discussion and Treatment of Endogeneity

In the benchmark regression, we treated the fintech indicators with a one-period lag to minimize the impact of reverse causality on the empirical results, while controlling for factors that may simultaneously affect fintech and GTFP. However, the empirical results may have still been subject to unobservable factors or reverse causality, resulting in biased OLS estimates. To alleviate the endogeneity issues, this paper employed the instrumental variable method and GMM dynamic panel analysis.

4.2.1. Instrumental Variable Method

Drawing on the research of Xie Xuanli et al. (2018) [25] and Huang Qunhui et al. (2019) [64], the Internet penetration rate and the number of landline telephones per million people in each province of China were used as instrumental variables. The reasons are as follows: first, the Internet, as the infrastructure of fintech, is closely related to the changes in fintech. Second, the application of internet technology in China started from telephone penetration, and the development of fintech also originated from fixed telephone penetration, so regions with higher fixed telephone penetration may have a higher level of fintech development. Third, both the internet penetration rate in 1999 and the number of fixed telephones per 10,000 people in 1999 are historical data, which are obviously exogenous and have a small quantitative relationship with the current GTFP, and thus satisfy the principle of exclusivity and are suitable as instrumental variables. Since the selected instrumental variables are cross-sectional in form and cannot be directly used in panel data analysis, the final instrumental variables IV1 and IV2 were obtained by referring to Manacorda and Tesei (2020) [65] and using the time trend term reflecting the evolution of fintech multiplied by the internet penetration rate in 1999 and the number of fixed telephones per 10,000 people in 1999, respectively.

Columns (1) and (2) of Table 6 report the results of the two-stage least squares regression (TSLS) using the instrumental variables. In the first stage, the estimated coefficients of IV1 and IV2 were significant at the 1% confidence level, indicating that regions with more developed Internet and higher fixed telephone penetration rates historically also had better fintech development, consistent with the previous analysis. In the second stage, the regression coefficient of fintech was significantly positive, suggesting that after controlling for potential endogeneity, the development of fintech indeed provided a driving force for GTFP. Moreover, the coefficients of fintech were significantly higher than those in the benchmark regression in Table 4, which is consistent with previous instrumental variable estimation results. In a series of statistical tests for instrument validity, both the K-P rk LM and K-P Wald rk F tests significantly rejected the null hypothesis of under-identification and weak identification, indicating that the instrumental variables had a strong association with endogenous variables and were strong instrumental variables. The Hansen J test also failed to reject the null hypothesis of exogeneity of the instrumental variables at the 10% significance level, indicating that the instrumental variables were strictly exogenous.

4.2.2. GMM Dynamic Panel Analysis

The city GTFP may have a certain degree of persistence, i.e., serial correlation. To address this issue, the benchmark model (1) was extended as follows:

$$\mathrm{GTFP}_{i,t} = \beta_0 + \beta_1 \mathrm{GTFP}_{i,t-1} + \beta_2 \mathrm{Fintech}_{m,t-1} + \sum_{k=3}^{T} \beta_k \mathrm{Controls}_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (5)$$

The variable settings are consistent with the previous section. To overcome the possible endogeneity in the model and to reduce measurement errors, omitted variables, and other issues, the two-step system generalized method of moments (SYS-GMM) was employed to estimate the parameters of Equation (5). The results are shown in columns (3) and (4) of Table 6. The coefficients of fintech were significantly positive in both sets of regressions, indicating that the contribution of fintech to GTFP still exists when considering the serial correlation problem, and the previous conclusion is robust. In addition, the Sargan–Hansen test statistics failed to reject the null hypothesis, implying that the choice of instrumental variables was valid; the AR(1) test rejected the null hypothesis, while the AR(2) test accepted the null hypothesis, inferring that there was no serial correlation in the error terms of the original model, and thus the estimation results were not affected by the serial correlation of error terms.

Table 6. Endogeneity treatment results.

Panel A The Second-Stage Regression				
Variable	**TSLS**		**GMM Analysis**	
	(1)	**(2)**	**(3)**	**(4)**
L.GTFP			0.1073 *** (5.4649)	0.1140 *** (6.0710)
L.Fintech_P	0.0632 *** (3.7659)	0.1403 *** (3.6390)	0.0449 *** (4.2432)	0.0309 *** (2.8325)
Controls	No	Yes	No	Yes
City fixed	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
D-W-H Test (*p*-value)	27.4403 (0.000)	22.1133 (0.000)		
K-P rk LM (*p*-value)	39.1123 (0.000)	24.1961 (0.000)		
K-P wald rk F (*p*-value)	70.9419 (0.000)	36.5875 (0.000)		
Hansen/Sargan (*p*-value)	2.9897 (0.1184)	3.5917 (0.1518)	9.8577 (0.2326)	5.6650 (0.1692)
AR(1) (*p*-value)			4.2605 (0.0000)	3.0339 (0.0006)
AR(2) (*p*-value)			0.5282 (0.6041)	0.6413 (0.5251)
Adj. R^2	0.4937	0.5546		
N	2830	2830	2547	2547
Panel B The First-Stage Regression				
IV	**(1)**	**(2)**	**(3)**	**(4)**
IV1	0.1461 *** (3.3238)	0.2079 *** (6.3869)		
IV2	0.1112 *** (4.6138)	0.1383 *** (3.7475)		
F (*p*-value)	134.0743 (0.0000)	95.1193 (0.0000)		

Note: D-W-H, K-P rk LM, K-P wald rk F, Hansen/Sargan represent endogeneity, under-identification, weak identification, and overidentification test statistics, respectively; AR(1) and AR(2) are the first-order and second-order serial correlation test statistics, respectively. The accompanying probabilities corresponding to each statistic are shown in the lower parentheses. *** represent passing significance tests at the 1% confidence levels.

4.3. Robustness Test

4.3.1. Replacing the Measurement Indicators of Fintech

First, there may be significant differences in economic growth, financial development, and other aspects among different cities within the same province, which may affect the conclusions of this paper. In view of this, we replaced the core explanatory variable in the benchmark model (1) with the city-level fintech development index (Fintech_C), and the test results are reported in column (1) of Table 7. As can be seen, the positive effect of city-level fintech on GTFP remained significant. The regression results are robust.

Second, following the approach of Song Min et al. (2020) [10] and considering both the financial function and financial technology characteristics, we used the logarithm of the number of provincial fintech companies as a proxy variable for fintech development (Fintech_N), replacing the core explanatory variable in the benchmark model (1) for re-estimation; the test results are reported in column (2) of Table 7. The conclusions still held.

Table 7. Robustness test results.

Variable	(1) Fintech_C	(2) Fintech_N	(3) GTFP_DDF	(4) Exclusion of Specific Samples	(5) Winsorized
L.Fintech_C	0.0185 *** (2.9372)				
L.Fintech_N		0.0117 ** (2.2582)			
L.Fintech_P			0.0420 *** (7.4359)	0.0347 *** (3.7553)	0.0179 *** (4.3942)
Controls	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.5023	0.5041	0.5046	0.4459	0.4542
N	2830	2830	2830	2600	2830

Note: Values in the lower brackets of the estimated coefficients are *t*-statistics adjusted for robust standard errors (clustering at the city level); *** and ** represent passing significance tests at the 1%, and 5%, confidence levels.

4.3.2. Replacing the Explanatory Variable

To ensure that the benchmark regression results will not vary due to different measurement methods of GTFP, we further used the SBM directional distance function (SBM-DDF) including non-expected output to re-estimate the city-level green total factor productivity (GTFP_DDF), replacing the dependent variable in model (1) for re-testing to ensure the robustness of the benchmark results. The test results are shown in column (3) of Table 7. The results show that the benchmark results of this paper were still significantly valid.

4.3.3. Exclusion of Specific Samples

Municipalities and provincial capital cities have greater advantages in terms of fintech and GTFP, and the reverse causality problem may be more serious. In accordance with Chen Zhongfei and Jiang Kangqi (2021) [12], we excluded municipality and provincial capital city samples and re-estimated the benchmark model (1); the test results are reported in column (4) of Table 7. The results show that after excluding specific samples, the coefficient of fintech on GTFP was still significantly positive, which is consistent with the benchmark regression results.

4.3.4. Winsorize

To avoid the impact of large fluctuations in the dependent variable on the regression results, we winsorized the dependent variable at 1% and 99% levels and re-estimated the benchmark model. The results are shown in column (5) of Table 7. The test results are nearly identical to the benchmark regression results, indicating that the conclusions are reliable.

4.4. Further Analysis: Non-Linear Incentive Effect of Fintech on GTFP

As pointed out in the theoretical analysis, the impact of fintech on GTFP may exhibit heterogeneous characteristics depending on its development stage. To test this theoretical hypothesis, we constructed a dynamic panel threshold model with fintech development as the threshold variable. Considering that endogeneity may lead to biased estimation, we followed Seo and Shin (2016) [66] and adopted the first-order difference transformation generalized moment estimation method (FD-GMM), which can effectively overcome the joint endogeneity of the threshold variable and core explanatory variable. The dynamic panel threshold model was set as follows:

$$GTFP_{i,t} = \lambda_0 + \lambda_1 GTFP_{i,t-1} + \lambda_2 Fintech_{m,t-1}(Fintech_{m,t} \leq \omega) + \lambda_3 Fintech_{m,t-1}(Fintech_{m,t} > \omega) + \sum_{k=4}^{T} \lambda_k Controls_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (6)$$

Here, Fintech is both the core explanatory variable and threshold variable; ω is the threshold value to be estimated; $I(\cdot)$ is an indicator function, which takes the value of 1 when the condition in the parenthesis holds and 0 otherwise; λ is the coefficient term of the regression variable; μ_i represents the city fixed effect; θ_t represents the time fixed effect; and $\varepsilon_{i,t}$ is the random error, $\varepsilon_{i,t} \sim iid(0, \sigma^2)$. Equation (6) is a single-threshold case and can be expanded to a multi-threshold case based on sample data statistical tests and other steps.

The results of the bootstrap test and threshold value estimation are shown in panel A and panel B of Table 8. It can be observed that the fintech development index passed the double-threshold effect test, indicating that the impact of fintech on GTFP will exhibit heterogeneity as its development stage changes. Using the FD-GMM approach to estimate the dynamic panel threshold model can overcome the adverse effects of endogeneity to some extent, and the estimation results are shown in panel C of Table 8. With the development of fintech, the intensity of the positive impact of fintech on GTFP rose continuously. Specifically, when Fintech $\leq$ 5.6909, the estimated coefficient of Fintech was 0.0018 at the 5% level; when 5.6909 $<$ Fintech $\leq$ 5.8000, the coefficient of Fintech was 0.0090 and significant at the 5% level; when Fintech $>$ 5.8000, the estimated coefficient became 0.0142 and passed the 1% statistical significance test. Thus, theoretical Hypothesis 3 is confirmed.

Table 8. Dynamic panel threshold effect tests and parameter estimation.

Panel A Threshold Effect Test Results							
Variable	Threshold Effect	SupW	BS	*p*-Value	Critical Value		
					1%	5%	10%
Fintech_P	Single	80.0305 ***	1000	0.000	16.8911	12.6236	11.6284
	Double	54.8497 ***	1000	0.007	24.6122	13.6262	11.5559
	Triple	24.4906	1000	0.713	109.8550	92.7709	86.3673

Panel B Threshold Estimation Results				
Threshold Type	Threshold Value 1		Threshold Value 2	
	Threshold Estimate	95% Confidence Interval	Threshold Estimate	95% Confidence Interval
Fintech_P	5.6909	[5.6902, 5.6911]	5.8000	[5.7911, 5.8049]

Panel C Estimation Results of Dynamic Panel Threshold Model		
Variable	**Coefficient**	***p*-Value**
L.GTFP	0.1902 *** (4.0637)	0.000
$I(Fintech\_P > \omega_2)$	0.0142 *** (4.9505)	0.000
$I(\omega_1 < Fintech\_P \leq \omega_2)$	0.0090 ** (2.2511)	0.025
$I(Fintech\_P \leq \omega_1)$	0.0018 ** (2.0345)	0.044
Controls	Yes	
Hansen J (*p*-value)	47.0746 (0.151)	
Wald	9638 ***	
N	2547	

Note: **, and *** indicate significance at the 5%, and 1% confidence levels, respectively. Values in the lower brackets of the estimated coefficients are the corresponding z-statistics. L.GTFP is the first-order lag of the explained variable. The Hansen J is a test statistic for overfitting of instrumental variables, with the null hypothesis being that the instrumental variables are valid, and its corresponding *p*-value is in the parentheses below.

5. Identification Test of the Mechanism of Fintech Affecting GTFP

The theoretical analysis section mentioned that fintech development can drive GTFP through the channels of resource allocation, human capital, and technological innovation. Based on the available data, we then conducted an empirical test of the above mechanisms. Following Jiang Ting's (2022) operational suggestions for analyzing mediation effects [67], the mechanism test mainly focused on identifying the effectiveness of fintech on mediating variables. The following econometric model was constructed:

$$\mathrm{Mediator}_{i,t} = \eta_0 + \eta_1 \mathrm{Fintech}_{m,t-1} + \sum_{k=2}^{T} \eta_k \mathrm{controls}_{i,t-1} + \delta_t + \mu_i + \varepsilon_{i,t} \quad (7)$$

On the selection of mediating variables (Mediator), resource allocation efficiency proxies included the capital mismatch index (Capital_M) and labor mismatch index (Labor_M); human capital proxies included the human capital accumulation level (Human_E) and human capital structural upgrading (Human_A); and technology innovation proxies included technology innovation quantity (Innova_N) and technology innovation quality (Innova_Q). The other variables were set as described above. The detailed test results are shown in Table 8.

From columns (1)–(2) of Table 9, the regression coefficients of fintech on the capital mismatch index and the labor mismatch index were −0.0896 and −0.1145, respectively, and both were significant at least at the 5% confidence level, indicating that fintech development can effectively reduce the degree of capital and labor mismatch and produces a significant improvement in resource allocation. Hsieh and Klenow (2009) [27] believe that focusing on resource allocation efficiency is essential for enhancing TFP in a transitioning economy like China's. Relying on information technology, fintech can facilitate the effective transmission of market information, guide the allocation of factor resources across time and space, improve the efficiency of resource circulation, and greatly facilitate the exchange of factors between regions and industries, thus promoting the overall progress of GTFP.

Table 9. Mechanism test results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Capital_M	**Labor_M**	**Human_E**	**Human_A**	**Innova_N**	**Innoa_Q**
L.Fintech_P	−0.0896 ** (−2.3794)	−0.1145 *** (−2.8944)	0.0035 ** (2.5043)	0.4072 *** (3.9092)	0.1848 * (1.7179)	0.4207 *** (3.8758)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes
N	2830	2830	2830	2830	2830	2830
Adj. R^2	0.8397	0.7539	0.9599	0.9598	0.9740	0.8345

Note: Values in the lower brackets of the estimated coefficients are *t*-statistics adjusted for robust standard errors (clustering at the city level); ***, **, and * represent passing significance tests at the 1%, 5%, and 10% confidence levels.

According to the test results of columns (3) and (4) in Table 9, fintech had a significant growth-promoting effect on human capital accumulation and human capital structure upgrading, which lays a solid talent foundation for promoting environmental governance, cultivating green consumption concepts, and promoting green production, thus improving GTFP. Since human capital is an important determinant of technological innovation, fintech should have a certain "innovation-promoting" effect following the above logic. According to columns (5) and (6) of Table 9, fintech had a significant promoting effect on technological innovation (coefficients were 0.1848 and 0.4207, respectively), providing empirical support for the above speculation. Specifically, the pulling effect of fintech development on the quality of technological innovation was particularly strong. The possible reasons include:

First, fintech can enhance the ability of entities to collect, integrate, and analyze information, help them to grasp the situation of technological innovation and market potential in a timely manner, and improve the effectiveness of technological innovation decisions. Second, the development of fintech is conducive to improving market competition mechanisms [28]; under external market supervision pressure, enterprises will focus more on enhancing their core competitiveness. Both domestic and foreign researchers believe that technological innovation is crucial for improving green total factor productivity [5,20,29,60]. Therefore, financial technology can help improve GTFP by driving technological innovation.

In summary, improving resource allocation efficiency, optimizing human capital, and promoting technological innovation are important channels for fintech to drive GTFP. The empirical results support Hypothesis 2.

6. Analysis of the Moderating Effect of Fintech on GTFP

6.1. Linear Moderating Effect

The theoretical analysis mentioned that the driving effect of fintech on GTFP may be subject to the moderating influence of financial regulation and environmental regulation. Therefore, this section further explores the "fintech–GTFP" research paradigm by embedding financial regulation and environmental regulation elements. First, the linear moderating effect was examined, and the econometric model was set as follows:

$$\mathrm{GTFP}_{i,t} = \xi_0' + \xi_1' \mathrm{Fintech}_{m,t-1} + \xi_2' \mathrm{Adjuva}_{m,t-1} + \xi_3' \left(\mathrm{Fintech}_{m,t-1} \times \mathrm{Adjuva}_{m,t-1} \right) + \sum_{k=4}^{T} \xi_k' \mathrm{Controls}_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{8}$$

In Equation (8), Adjuva represents the province-level moderating variables, including financial regulation (Fsupervis) and environmental regulation (Eregulat). The meanings of the other variables are consistent with the previous sections. We focused on the coefficient signs of Fintech $\times$ Adjuva to reveal the moderating effect of financial regulation and environmental regulation on the baseline relationship between fintech and GTFP.

The regression results of Equation (8) are reported in Table 10. It was found that the cross-product term coefficient of financial regulation and fintech was significantly positive, indicating that better financial regulation is an important condition for fintech to promote GTFP. Financial regulation is conducive to reducing the financial risks arising from fintech innovation, ensuring the standardized and orderly development of fintech, and better realizing the important goal of "financial support for sustainable development of real economy". Meanwhile, the cross-product of environmental regulation and fintech had a weak contribution to GTFP (coefficient was 0.0022) and did not pass the significance test. On the one hand, this result suggests that environmental regulation does enhance the contribution of fintech to GTFP to a certain extent; on the other hand, it also reminds us that the "innovation compensation" and "cost compliance" attributes of environmental regulation itself may determine that its moderating effect is not a simple linear one [68]. If a linear model is used for fitting, it may obscure part of the truth. However, the above results preliminarily verify Hypothesis 4.

Table 10. Results of the test for linear moderation effect.

Variable	(1)	(2)
	Fsupervis	**Eregulat**
L.Fintech_P	0.0222 ** (2.2348)	0.0221 * (1.8207)
L.Fsupervis	0.0483 (0.0847)	
L.Eregulat		−0.0821 *** (−4.7927)
L.Fintech_P × L.Fsupervis	0.0111 ** (2.3615)	
L.Fintech_P × L.Eregulat		0.0022 (0.2845)
Controls	Yes	Yes
City fixed	Yes	Yes
Year fixed	Yes	Yes
N	2830	2830
Adj. R^2	0.3034	0.3141

Note: Values in the lower brackets of the estimated coefficients are *t*-statistics adjusted for robust standard errors (clustering at the city level); ***, **, and * represent passing significance tests at the 1%, 5%, and 10% confidence levels.

6.2. Nonlinear Moderating Effect

The empirical test in the previous section confirmed that financial regulation and environmental regulation have a certain moderating strengthening effect on the benchmark relationship between fintech and GTFP. However, do different intervals of financial regulation and environmental regulation make a large difference in the moderating effect and lead to a non-linear statistical characteristic of the impact of fintech on GTFP? To answer this question, we used a dynamic panel threshold model to explore the nonlinear relationship between fintech and GTFP from the perspectives of financial regulation and environmental regulation. Considering that the joint endogeneity of the core explanatory variable (fintech) and the threshold variable (financial regulation, environmental regulation) may cause estimation bias, consistent with the previous sections, the FD-GMM method that can overcome the joint endogeneity was adopted. The dynamic panel threshold model was set as follows:

$$\mathrm{GTFP}_{i,t} = \kappa_0 + \kappa_1 \mathrm{GTFP}_{i,t-1} + \kappa_2 \mathrm{Fintech}_{m,t-1}\left(\mathrm{Adjuva}_{m,t} \le v\right) + \kappa_3 \mathrm{Fintech}_{m,t-1}\left(\mathrm{Adjuva}_{m,t} > v\right) + \sum_{k=4}^{T} \kappa_k \mathrm{Controls}_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \quad (9)$$

where Adjuva is the threshold variable, including financial regulation (Fsupervis) and environmental regulation (Eregulat); fintech (Fintech) is the core explanatory variable; $I(\cdot)$ is an indicator function, which takes a value of 1 when the condition in the parentheses holds and 0 otherwise; and κ is the coefficient term of the regression variable. The other variables are consistent with the previous sections.

Using financial regulation or environmental regulation as the threshold variable, we conducted bootstrap sampling tests to determine whether threshold effects exist between fintech and GTFP. The test results are shown in panel A of Table 11. Both financial regulation and environmental regulation passed the double-threshold effect test; therefore, the double-threshold model is applicable, which also indicates that a non-linear structural transformation effect of the impact of fintech on GTFP exists based on these two threshold variables. Panel B of Table 11 further shows the threshold estimates and 5% confidence intervals for the two threshold variables.

Table 11. Threshold effect tests and threshold estimates.

Panel A Threshold effect test results							
Variable	Threshold Effect	SupW	BS	p-Value	Critical Value		
					1%	5%	10%
Fsupervis	Single	17.0446	1000	0.000	13.6705	10.1751	8.3059
	Double	24.0863	1000	0.000	12.7142	11.0066	9.0383
	Triple	14.4504	1000	0.420	39.1392	31.7894	28.0710
Eregulat	Single	29.4466	1000	0.000	19.7083	16.6235	14.4088
	Double	24.6195	1000	0.000	18.5559	15.0787	11.0093
	Triple	15.1822	1000	0.700	85.0688	76.1750	60.5853

Panel B Threshold estimation results				
Threshold Type	Threshold Value 1		Threshold Value 2	
	Threshold Estimate	95% Confidence Interval	Threshold Estimate	95% Confidence Interval
Fsupervis	0.0136	[0.0129, 0.0159]	0.0461	[0.0460, 0.0463]
Eregulat	0.4183	[0.4050, 0.4187]	1.4354	[1.4292, 1.4363]

Next, we conducted an overall estimation of the dynamic panel threshold model; the detailed results are reported in Table 12. Column (1) shows the regression results with financial regulation as the threshold variable. Financial regulation has a significant double-threshold characteristic, and the impact strength of fintech on GTFP varied significantly within different financial regulation zones. When financial regulation was below the threshold value of 0.0136, the coefficient value of fintech was 0.0144, which is weak; when financial regulation was between (0.0136, 0.0461), the regression coefficient of fintech rose to 0.1197 and was significant at the 1% level; when financial regulation crossed the maximum threshold value of 0.0461, the impact effect of fintech on GTFP remained positive but was significantly weakened and no longer significant. It can be seen that there is an optimal zone for the moderating effect of financial regulation. Weakened financial regulation may not be able to suppress the financial fluctuations or risk shocks caused by financial technology innovation, making it difficult for fintech to achieve its intended economic effects. Excessive financial regulation may weaken the vitality of the financial market, constrain financial technology innovation, distort the allocation of financial resources, and fail to leverage the function of fintech to improve economic quality and efficiency. Therefore, maintaining moderate and effective financial regulation is preferable.

Similarly, the regression results with environmental regulation as the threshold variable shown in Column (2) are also mixed, and the impact of fintech on GTFP exhibited significant heterogeneity within different environmental regulation zones. When the environmental regulation was less than 0.4183, the coefficient of fintech was 0.0620 and significant at the 10% confidence level; when the environmental regulation was in the (0.4183, 1.4354) interval, its coefficient was 0.1044 at the 1% significance level; and when the environmental regulation exceeded 1.4354, its coefficient was −0.0168 at the 10% significance level. It was easy to find that there was also an optimal range for the moderating effect of environmental regulation. The government's adoption of moderate environmental regulation policies will have a "forcing effect" and a "guiding effect" on enterprises, allowing enterprises benefiting from fintech to have enough time and energy for production equipment upgrades and increasing green technology R&D, ultimately reducing pollution emissions during the production process, thereby enhancing the level of GTFP. However, overly stringent environmental control will make economic entities exhausted in fulfilling their environmental protection responsibilities and neglect production and technological innovation, the internal and external environment for the stable operation of enterprises will face more uncertainties, and the support effect of fintech on enterprises will naturally be greatly discounted, thereby hindering the progress of GTFP.

Table 12. Estimation Results of Dynamic Panel Threshold Model.

Variable	(1)		(2)	
	Fsupervis		**Eregulat**	
	Coefficient	***p*-Value**	**Coefficient**	***p*-Value**
L.GTFP	0.1480 *** (3.2323)	0.000	0.1127 *** (4.0226)	0.000
$I(Adjuva > v_2)$	0.0146 (1.5941)	0.110	−0.0168 * (1.8914)	0.058
$I(v_1 < Adjuva \leq v_2)$	0.1197 *** (5.4812)	0.000	0.1044 *** (4.3907)	0.000
$I(Adjuva \leq v_1)$	0.0144 ** (2.0630)	0.040	0.0620 * (1.8144)	0.070
Controls	Yes		Yes	
Hansen J (*p*-value)	22.4656 (0.309)		17.7935 (0.449)	
Wald	11204 ***		9752 ***	
N	2547		2547	

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively. Values in the lower brackets of the estimated coefficients are the corresponding z-statistics. L.GTFP is the first-order lag of the explained variable. The Hansen J is a test statistic for overfitting of instrumental variables, with the null hypothesis being that the instrumental variables are valid, and its corresponding *p*-value is in the parentheses below.

In summary, the aforementioned results fully demonstrate that fintech has nonlinear threshold effects on GTFP based on financial regulation and environmental regulation. Financial regulation or environmental regulation that is too strong or too weak is not conducive to fully exploiting the promoting effect of fintech on GTFP, and only moderate financial regulation and environmental regulation policies can maximize the moderating strengthening effect of both. Thus, Hypothesis 4 is further verified. In addition, the Hansen J statistic measuring instrumental variable overfitting did not reject the null hypothesis of effective instrument variables, proving the validity of the instrument variables and the rationality of the model setting. The Wald statistic also showed that all dynamic panel threshold model estimation results were highly significant.

7. Research Conclusions and Policy Implications

7.1. Research Conclusions

Enhancing the ability of financial services to serve the real economy is crucial for achieving green transformation and high-quality development of the real economy. In the context of the continuous integration of emerging AI technology and the financial industry, exploring how the development of fintech affects GTFP undoubtedly has important theoretical value and practical significance. This paper first analyzed the relationship between fintech and GTFP from a theoretical perspective and then used the super-efficiency SBM model with embedded non-expected output and the globalization GML index method to measure the green total factor productivity of China's 283 prefecture-level and above cities from 2011 to 2021. On this basis, we empirically tested the impact of fintech on GTFP and its underlying mechanisms in a multi-dimensional manner. The main conclusions are as follows: First, the development of fintech significantly improved the level of city GTFP, and the impact effect showed dynamic stability characteristics. After endogeneity treatment and other robustness tests, the findings of the study still held.

Second, by decomposing fintech into two dimensions, depth and breadth of fintech development, it was found that both the depth and breadth of fintech development contributed to the improvement of city GTFP. However, the depth of fintech development had a stronger and dynamically cumulative effect on city GTFP, while the breadth of fintech development had a relatively weaker and dynamically decaying effect. Specifically, in the more mature stages of fintech development, fintech will have a stronger and more significant incentive effect on city GTFP.

Third, the mechanism analysis showed that financial technology promoted the progress of city GTFP through channels such as improving resource allocation efficiency, optimizing human capital, and stimulating technological innovation.

Fourth, the moderating effect test showed that financial regulation and environmental regulation had a positive linear moderating effect on the benchmark relationship between fintech and GTFP. Further research revealed that the moderating effects of financial regulation and environmental regulation have significant nonlinear threshold characteristics, and when the intensity of financial regulation and environmental regulation was too high or too low, they could not fully exert their moderating effects; only when both are in the optimal range can the driving effect of fintech on GTFP be maximized.

7.2. Policy Implications

The findings of this paper provide important policy implications for exploring the drivers of GTFP growth and thus achieving high-quality economic development.

First, given the reality that fintech can play a constructive role in improving GTFP, the Chinese government should provide policies that support the deep integration of AI technology and finance, and promote the further development of the fintech industry in a comprehensive and multifaceted manner while keeping the bottom line of risk. On the one hand, policies should encourage and improve the development of supporting industries, deepen the application of AI technology in finance, establish a balanced system of safety and efficiency for the application of technological achievements, strengthen the protection of fintech patents, continuously expand the open innovation and win–win industrial ecology, enhance the market competition efficiency of the fintech industry, and improve the survival of the fittest mechanisms. On the other hand, in the development of fintech, efforts should be made to actively expand the coverage of fintech and focus on using AI technological advantages to improve the accessibility of financial services. In addition, we should vigorously promote the in-depth construction of fintech, and comprehensively improve the quality and efficiency of financial services through technology-driven and data-empowered fintech. Meanwhile, the government should comprehensively strengthen the construction of software and hardware infrastructure to consolidate the foundation of fintech development. Specifically, the Chinese government should accelerate the intelligent upgrading and transformation of the fintech infrastructure and the cultivation of high-level scientific and technological talents, focus on promoting the research and application of key AI technologies such as big data, cloud computing, and blockchain, and assist in deepening fintech capabilities by improving the construction level of AI infrastructure, laying a solid foundation for fintech to effectively contribute to the transformation and upgrading of the real economy.

Second, policies should vigorously promote the coordinated development of fintech and green industries, and build a healthy application ecosystem of fintech to support improvement of GTFP. On the one hand, the government should encourage financial institutions to fully utilize advanced AI technologies such as big data, cloud computing, and block chain to identify green industries (e.g., clean technology, clean production models, and clean enterprises), reduce the pre-approval procedures and post-supervision costs of green credit, increase funding support for the R&D and promotion of new green and energy-saving technologies and products, and ultimately improve the level of GTFP by focusing on green technology innovation and industrial structure upgrading. On the other hand, utilizing the information identification, analysis, and supervision capabilities of fintech, the government can help micro-enterprises grasp the situation in terms of technological innovation and market potential, enhance the effectiveness of enterprise innovation decision-making and fund utilization, optimize resource allocation, and create favorable conditions for the progress of GTFP.

Third, this paper found that fintech development had a more significant contribution to GTFP in regions with moderate financial and environmental regulations. Therefore, the following suggestions are proposed: (1) Accelerate the reform of the financial supervision system, appropriately adjust the regulatory framework and improve relevant policies, and enhance the quality and efficiency of financial supervision services for fintech to meet the needs of the rapid development of fintech. At the same time, regulatory authorities should implement incentive-compatible regulatory principles, adopt sustainable, coordinated, and moderate regulatory policies, focus on process supervision, strengthen ex-ante and ex-post supervision, and improve the pertinence, timeliness, and penetration of supervision, building a firewall between finance and technology. (2) The government should grasp the intensity of environmental regulation, formulate appropriate environmental regulation policies, and avoid "campaign-style" law enforcement. Neither should excessive environmental control be imposed, nor should environmental governance be overly relaxed. Attention should be paid to the issue of "degree" in the process of formulating environmental standards, finding appropriate environmental governance methods, effectively urging enterprises to undergo green technology transformation and innovation, and enhancing the promoting effect of fintech on GTFP.

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