sustainability

Article

Can Digital Innovation Improve Green Total Factor Productivity: Evidence from Digital Patents of China

Wanying Rao and Pingfeng Liu *

School of Economics, Wuhan University of Technology, Wuhan 430070, China; rao_yanssic@163.com
* Correspondence: lpf@whut.edu.cn

Abstract: Amid intensifying global economic rivalries, China has pinpointed the digital economy and sustainable growth as key accelerators for societal and economic progress. Digital innovation (DI) plays a crucial role in propelling China's economy towards sustainable growth, by serving as the technological backbone of the digital economy. This study explores how DI influences China's GTFP through an analysis of panel data covering 30 provinces, municipalities, and autonomous regions from 2005 to 2021. The results indicate that DI greatly contributes to the enhancement of GTFP. DI can also indirectly promote GTFP by increasing the effectiveness of factor allocation efficiency including capital, labor, and technology. Heterogeneity analysis results indicate that the influence of DI on GTFP differs depending on the degree of intellectual property protection (IPP), the development of digital infrastructure construction (DIC), and the geographical location. A higher degree of IPP and developed DIC make areas better suited for the role of DI in advancing GTFP. Furthermore, in the central and eastern areas, the impact of the digital economy on the promotion of GTFP is particularly noticeable. This study offers reliable empirical evidence for the effect of DI on GTFP and contributes to China's digital economy and sustainable development.

Keywords: digital innovation; green total factor productivity; resource allocation efficiency; digital patent

Citation: Rao, W.; Liu, P. Can Digital Innovation Improve Green Total Factor Productivity: Evidence from Digital Patents of China. *Sustainability* **2024**, *16*, 3891. https://doi.org/10.3390/su16103891

Received: 8 April 2024
Revised: 2 May 2024
Accepted: 3 May 2024
Published: 7 May 2024

1. Introduction

As China's economic aggregate continues to grow, it has entered a new normal era. In 2022, the Gross Domestic Product (GDP) of China escalated to 120 trillion yuan, constituting close to 18% of the world's economic output, with an average annual growth exceeding 14% since the reform and opening-up, achieving significant accomplishments in economic construction. However, the evaluation of the economy in the new era should not be confined solely to speed indicators, improving the quality of economic expansion is a vital component. The emergence of phenomena described as "imbalanced, uncoordinated, and unsustainable" stemming from previous rough modes of development, has positioned environmental pollution and the limitations of ecological sustainability as primary constraints on economic progress [1]. As reported by the National Bureau of Statistics of China, the global GDP of China accounted for about 18% in 2021, but its energy consumption exceeded 26%, and the carbon dioxide emissions have reached as high as 31% (http://www.stats.gov.cn/, accessed on 5 April 2024). Indeed, the Chinese government has consistently placed a high emphasis on sustainable development, viewing it as a crucial notion closely linked with the broader economy. It represents a strategic move to address limitations pertaining to the environment and resources, signifying a fundamental transition in the model of development, and it stands as a necessary decision in the pursuit of sustainable and superior-quality growth [2]. Hence, the strategic challenge lies in advancing green high-quality development that harmonizes economic efficacy with environmental advantages, given the limitations of factor endowments, and in improving the overall productivity of all factors involved. GTFP merges considerations of energy usage and environmental degradation with traditional measures of productivity, highlighting the concurrence of economic growth and environmental conservation [3,4]. Employing this metric to gauge green high-quality development presents considerable value for research.

The contemporary digital economy is marked by swift advancements and comprehensive incorporation of emergent technologies, such as artificial intelligence, big data analytics, cloud computing, blockchain, and quantum communication into the tangible economy. This integration has spurred the development of numerous novel goods and business strategies, increasingly solidifying their effect on economic expansion. In recent years, the Chinese authorities have significantly focused on advancing the growth of the digital economy. China's digital economy, experiencing a nominal growth rate of 10.3% annually, escalated to 50.2 trillion yuan, therefore becoming the second largest in the world in 2022. This represents about 41.5% of China's total GDP (http://www.cac.gov.cn/2023-05/22/c_1686402318492248.htm, accessed on 5 April 2024). The State Council of China's "14th Five-Year Plan for Digital Economy Development" emphasized the creation of a new growth pathway. This pathway is aimed at enhancing total factor productivity via technological advancements while fostering technological innovation through practical applications (https://www.gov.cn/zhengce/content/2022-01/12/content_5667817.htm, accessed on 5 April 2024). Furthermore, the plan advocates for a development approach that is both innovation-led and integrated, highlighting the critical role of innovation as the cornerstone of the digital economy and its capacity to continually unleash data's intrinsic value. Presently, DI has arisen as a field rich in resources for innovation, characterized by its widespread impact and varied application contexts, marking it a central area of technological progress [5–7]. The emerging model of DI integrates digital technology with crucial supplementary resources, platforms for sharing knowledge, and activities driven by knowledge. This integration seeks to reconfigure existing innovation resources and processes [8]. Theoretically, DI is beneficial for the development of fresh, knowledge-intensive business structures because it accelerates the linkage and recombination of factors, encourages the creation of innovative combinations of productive elements, and enhances the distribution of resources across these factors [9]. Nevertheless, the present situation of DI within China faces a multitude of obstacles, including those related to technological research and development (R&D), talent cultivation, innovation transformation, and digital governance. The insufficiencies in competitiveness within the high-tech sector [10], the shortage of digital talents [11], and the inability to convert DI results into tangible productivity [12], along with inadequate measures for safeguarding data security and privacy [13], represent significant barriers that might impair the efficacy of DI in China. In addition, numerous studies have indicated that the uncoordinated development of multiple fields such as technology, economy, policy, and environment will hinder the growth of GTFP. The bottleneck of core technology innovation, the insufficient combination of the digital economy and the traditional real economy, and the energy consumption of technological innovation might impede the progress of the GTFP. Therefore, considering the space and potential for the development of DI, whether and how DI positively contributes to GTFP in China is the main issue that is worth considering.

Regarding the circumstances of the evolving landscapes of the digital and low-carbon economies, marked by the elevated barriers, costs, and replicability of digital technologies [14], the investigation into optimizing DI for greater economic advantages emerges as a pivotal concern. Currently, the Chinese economy is shifting from a period of swift expansion to one defined by high-quality advancement. Achieving superior economic growth necessitates embracing green development. Improving GTFP is not only essential as a key route to high-quality growth but is also a crucial benchmark for evaluating economic advancement's quality. The existing limitations present an opportunity for potential breakthroughs in this research domain. The purpose of this study is to look at the effects of DI on GTFP, providing empirical evidence to support the theoretical mechanisms through which DI empowers economic development and offering valuable insights into promoting regional DI and sustainable growth in China.

The contributions of this study can be encapsulated as follows: Firstly, it conducts a systematic analysis on the quantitative effects of DI on GTFP, thereby bridging the gap between empirical data and theoretical reasoning. Unlike previous research that predominantly focuses on qualitative analysis, this paper enhances the understanding of the economic effects of DI by examining its influence on GTFP. Furthermore, this research offers theoretical backing for utilizing DI to enhance regional environmental sustainability and acts as a reference for future studies in this area. The study delves into the connection between DI and GTFP, focusing on the allocative efficiency of labor, capital, and technology. This broadens the field of study concerning the digital economy and sustainable growth, substantially enriching the body of existing literature. Lastly, it explores the differential impacts of IPP, DIC, and regional heterogeneity. Hence, this study enhances the understanding of the link between DI and GTFP with clearer policy ramifications.

The organization of the following parts of this article is structured as follows: Section 2 outlines the literature review and theoretical analysis. Section 3 describes the measurement model and data description. We show the estimation results in Section 4 and analyze the influence mechanism and heterogeneity in Section 5. Section 6 proposes our discussion. Finally, Section 7 outlines the conclusion and policy recommendations.

2. Literature Review and Theoretical Analysis

2.1. Literature Review on DI and GTFP

There are abundant studies on DI and GTFP, which can be divided into these main aspects. On the one hand, several studies indicate that DI has a profound impact on enhancing GTFP. DI plays a crucial role in mitigating information asymmetry [15], optimizing processes in production and business [16], fostering the transition and advancement of industries [17], affecting the distribution of resources [18], and elevating the efficiency of financing [19]. Regarding research subjects, the emphasis predominantly resides on individual industries or the micro-level of enterprises, showing a scarcity of studies at the macro level. Regarding the research topic, the primary emphasis lies on qualitative methodologies such as theoretical derivation [20], literature review [21], and case-based qualitative analysis [10], with limited exploration into the underlying mechanisms of impact. Actually, as an emerging type of technological innovation, DI profoundly impacts traditional production factors including labor, capital, and technology, consequently leading to alterations in the efficiency with which resources are allocated [22]. Therefore, revisions in the efficacy of resource allocation resulting from DI could exert a considerable effect on GTFP. On the other hand, the issue of the "Solow paradox" pertaining to emerging technologies has likewise attracted significant academic interest. Gordon [23] argues that the "Solow paradox" persists, given that rapid developments in emerging technologies like artificial intelligence have not resulted in enhanced total factor productivity. Summers [24] highlights the concept of "digital islands," where businesses involved in DI overlook crucial characteristics of digital technology, including information processing, communication, and connectivity. This oversight typically results in less than optimal results in DI, paradoxically leading to reduced business productivity. Brynjolfsson [25] asserts that the innovation stage of emerging technology is characterized by cycles, where significant intangible assets fail to yield immediate economic returns. This leads to a negligible effect on the initial boost in productivity during the R&D phase of digital technologies. Additionally, the measurement of indicators for DI has also stimulated intellectual discourse among numerous scholars. DI possesses the potential to reduce expenses related to data storage and dissemination, going beyond internal mechanisms to incorporate more decentralized entities. Consequently, DI is characterized by uncertain organizational configurations and indistinct demarcations of products [26]. Hence, assessing DI presents challenges, and there is a notable scarcity of large-sample studies. Present methods of evaluating DI primarily depend on investments in R&D spending linked to digital technologies, as well as the input of scientific and technological personnel [27] or analysis of corporate annual reports [28,29].

In summary, a majority of the research has investigated the effects of DI on GTFP from multiple perspectives, but there are still obvious research gaps and limitations. First, regarding the study paradigm, the predominant scholarly perspectives on the role of DI in boosting GTFP are characterized by qualitative analyses, with a limited use of empirical methods involving large samples. Second, previous research primarily concentrates on the individual sector or enterprise-level analysis, with limited quantitative investigations conducted at the macroscopic level. Third, measurement indicators of DI, descriptions within R&D investment data, and company annual reports are often constrained and could be subject to tampering. This issue complicates the precise evaluation of DI levels. Additionally, the reliability of text data may be jeopardized, which poses obstacles in accurately determining the level of DI. Thus, empirical research exploring the effects of DI on GTFP is still relatively scarce.

2.2. The Direct Impact of DI on GTFP

From a theoretical standpoint, DI introduces a new era of advanced information technologies, extensive data resources, and a rapidly growing number of users. These elements bestow notable benefits in developmental dynamics, efficiency, and quality [30]. DI is critically significant in expanding the scope of China's digital economy and increasing its functional efficiency, which in turn supports the enhancement of GTFP.

On one hand, the development of knowledge-intensive industries driven by DI facilitates industrial transformation and upgrading, thereby enhancing resource utilization efficiency and promoting an increase in GTFP. Additionally, knowledge-intensive sectors supported by digital technologies are experiencing rapid growth, contributing fresh dynamism to the development of a newly optimized industrial framework. The application of digital technologies is crucial in driving the emergence of novel business models. These technological applications facilitate data integration, resource circulation, and value sharing, thereby mitigating industrial development costs and environmental pollution. Consequently, these advancements lead to reductions in cost and enhanced efficiency that contribute to an increase in GTFP [31]. Furthermore, the acquisition of knowledge is critical to driving DI. Enabling the movement of skilled professionals in digital technology across different areas can enhance the sharing of digital know-how, thus improving the expertise in digital technologies. The adoption of digitized approaches that include data, information, technology, and expertise, could surmount developmental challenges, thereby substantially enhancing the GTFP [32].

On the other hand, DI predominantly features advanced technologies encompassing big data, artificial intelligence, cloud computing, and blockchain. These interconnected technologies synergize with additional production elements, reorganizing and amalgamating diverse resources throughout the manufacturing process. This instigates a paradigm shift in manufacturing and induces effects of industrial interconnectivity, fostering the structural enhancement of the production sector, thereby mitigating pollution emissions and augmenting GTFP [33]. Specifically, the application of big data technology helps businesses enhance their customer management and forecast market trends. This enables companies to quickly adapt their production capacities, product offerings, and supply chain management to more closely match market demands, while also minimizing inventory risks [34]. As a result, this leads to increased economic advantages. The incorporation of artificial intelligence technology into business processes enables automated and smart management of operations and knowledge. This allows companies to streamline their production processes and improve efficiency, thereby boosting overall productivity [35,36]. Cloud computing reduces the costs related to building and upkeep of IT infrastructure for enterprises, simultaneously improving the effectiveness of cross-regional collaboration regarding information resources. This provides organizations of various sizes within certain areas with greater flexibility, scalability, and financial efficiency [37]. Blockchain technology ensures comprehensive documentation of all phases within an enterprise, including R&D, production, and sales, thereby improving traceability throughout the entire industrial spectrum. Such a system contributes to minimizing the risks of business defaults and boosts productivity [7].

Following the analysis presented, the subsequent hypothesis is proposed.

H1. *DI can effectively enhance GTFP.*

2.3. The Mediating Effect of Resource Allocation Efficiency

On one hand, DI can enhance the efficiency of resource allocation encompassing capital efficiency (CE), labor efficiency (LE), and technical efficiency (TE) [38]. In terms of CE, digital platforms facilitate the improvement of CE within enterprises by amassing and assimilating investments from a wide spectrum of 'long tail' contributors, thus broadening their avenues for funding. This evolving phenomenon aids businesses in the acquisition, recognition, and management of varied financial information, which in turn helps alleviate the discrepancy often found in the allocation of funds by conventional financial entities and eases the challenges of obtaining financial support [39]. Meanwhile, the application of DI technology and the digitization of production factors can optimize traditional procedures and processes, thereby enhancing fund utilization efficiency. This improvement is particularly pronounced within the field of information and communication technologies [40]. Regarding LE, the rise of DI has overcome the inherent constraints of time and space associated with traditional labor patterns, thus providing individuals with a broader spectrum of job opportunities and increased flexibility. Moreover, the enhancement of digital competencies empowers a larger workforce to transition from conventional job roles to more advanced and adaptable positions, thereby facilitating a consequential optimization of working hours allocation [41]. This subsequently fosters an environment conducive for workers to exercise greater flexibility in selecting employment opportunities, ultimately augmenting LE. In terms of TE, the merging and dissemination of informational assets via the internet, big data, and various technological platforms substantially improve TE. This sharing and integration can be achieved through internal corporate learning, cross-industry supply chains, and intra-industry competition, which effectively promote the diffusion and spillover of DI technologies [42]. Such activities contribute to the improved effectiveness of utilizing cutting-edge technologies. Additionally, DI not only broadens the range of innovation and energizes an effective innovation ecosystem but also fortifies mechanisms of innovation driven by demand, thus increasing both the depth and the efficiency of innovative processes [43]. As a result, this can improve the effectiveness of technical factors.

On the other hand, improving the effectiveness of resource distribution can lead to the significant growth of GTFP. Empirical studies have demonstrated that resource misallocation constitutes a significant factor influencing total factor productivity [44]. Considering the theory of industrial structure [45], as more factor resources shift towards industries with higher efficiency, such as knowledge-intensive or technology-intensive sectors, their share and significance continue to rise, thereby optimizing and upgrading the industrial structure. This process results in a decrease in pollution of the environment and an increase in output benefits, ultimately enhancing the GTFP [46]. Furthermore, the prices or rates of return for resources encompassing labor, capital, and technology are contingent upon the effectiveness of factor distribution or the marginal output of those resources. Enabling higher levels of regional DI and improving the efficiency of industrial factors via unrestricted factor mobility can significantly reduce obstacles related to information flow, in turn improving the matching efficiency among market participants. This enhancement is crucial for ultimately increasing GTFP [47].

To sum up, the progress of DI can indirectly boost China's GTFP by improving resource allocation efficiency encompassing CE, LE, and TE.

H2. *DI can promote GTFP by improving CE, LE, and TE.*

3. Measurement Model Setting and Data Description

3.1. Model Design

3.1.1. Directional SBM–GML Index Measurement Model

Considering the characteristics of productivity value-added, energy consumption, and emission pollution, this article draws on the estimation method of Liu [29], which utilizes a non-radial, non-angular slacks-based measure (SBM) assuming variable returns to scale (VRS). The method considers multiple inputs as well as expected and unexpected outputs, and integrates the global Malmquist–Luenberger (GML) productivity index to estimate the GTFP. The main principle of the SBM–GML method is as follows:

Taking the Kth region as the decision-making unit DMU_k, N inputs DMU_k in $x = (x_1, x_2 \ldots\ldots x_n) \in R_N^+$, resulting in M expected outputs $y = (y_1, y_2 \ldots\ldots y_n) \in R_M^+$ and P non-expected outputs $c = (c_1, c_2 \ldots\ldots c_n) \in R_P^+$. The inputs and outputs in the Tth period can be expressed as x_k^t, y_k^t, p_k^t. Oh [48] presented a global production technology framework that highlights how comparable and consistent the production frontier is in order to guarantee the contemporaneity of the reference technology. It is specifically as follows:

$$P^t(x) = \begin{cases} (y^t, c^t) | \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} \lambda_k^t y_{km}^t \geq y_{km}^t, m = 1, \ldots\ldots, M, \\ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} \lambda_k^t x_{kn}^t \leq x_{kn}^t, n = 1, \ldots\ldots, N \\ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} \lambda_k^t c_{kp}^t = c_{kp}^t, p = 1, \ldots\ldots, P \\ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} \lambda_k^t = 1, k = 1, \ldots\ldots, K \end{cases} \quad (1)$$

where λ_k^t represents the weight value of the input and output of the Kth decision unit in the Tth period, and $\sum\limits_{k=1}^{n} \lambda_k^t = 1, \lambda_k^t \geq 0$ represents VRS. It symbolizes constant returns to scale (CRS) in the absence of such a limitation. The global directional SBM model, taking into consideration the presence of non-expected outputs, is founded on this:

$$\vec{S}_k^G = (x_k^t, y_k^t, c_k^t; g^x, g^y, g^c) = \max_{s^x, s^y, s^b} \frac{\frac{1}{N} \sum\limits_{n=1}^{N} \frac{S_n^x}{g_n^x} + \frac{1}{M+P} \left(\sum\limits_{m=1}^{M} \frac{S_m^y}{g_m^y} + \sum\limits_{p=1}^{P} \frac{S_p^c}{g_p^c} \right)}{2}$$

$$s.t. \begin{cases} \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} \lambda_k^t x_{kn}^t + S_n^x = x_{kn}^t, n = 1, \ldots\ldots, N \\ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} \lambda_k^t y_{km}^t - S_m^y = y_{km}^t, m = 1, \ldots\ldots, M \\ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} \lambda_k^t c_{kp}^t + S_p^y = y_{kp}^t, p = 1, \ldots\ldots, P \\ \sum\limits_{k=1}^{K} \lambda_k^t = 1, \lambda_k^t \geq 0, k = 1, \ldots\ldots, K \\ S_n^x \geq 0, S_m^y \geq 0, S_p^c \geq 0 \end{cases} \quad (2)$$

where (g^x, g^y, g^c) shows the directional vectors of changes in inputs, expected outputs, and non-expected outputs; (S_n^x, S_m^y, S_p^c) represents the changes in inputs, expected outputs, and non-expected outputs slack variables. The slack variables in the constraints are all non-negative. When the slack variable exceeds zero, it signifies that the expected output is below the boundary output, while both actual inputs and non-expected outputs surpass the boundary inputs and outputs. Based on the above SBM, the GML index between periods t and t + 1 is constructed as follows:

$$\begin{aligned} GML_t^{t+1} &= \frac{1+\overset{\rightarrow G}{S}_k(x^t,y^t,c^t;g^t)}{1+\overset{\rightarrow G}{S}_k(x^{t+1},y^{t+1},c^{t+1};g^{t+1})} = GTP_t^{t+1} \times GTE_t^{t+1} \\ GTP_t^{t+1} &= \frac{1+S^t(x^t,y^t,c^t;g^t)}{1+S^{t+1}(x^{t+1},y^{t+1},c^{t+1};g^{t+1})} \\ GTE_t^{t+1} &= GSE_t^{t+1} \times GPTE_t^{t+1} = \frac{1+S^G(x^t,y^t,c^t;g^t)}{1+S^t(x^t,y^t,c^{t1};g^1)} \times \frac{1+S^{t+1}(x^{t+1},y^{t+1},c^{t+1};g^{t+1})}{1+S^G(x^{t+1},y^{t+1},c^{t+1};g^{t+1})} \end{aligned} \tag{3}$$

The GML index signifies the variation in GTFP between period t and t + 1, which is analyzable in two main components: the global technical progress (GTP) index and the global technical efficiency (GTE) index. Furthermore, the GTE index can be expanded into the global scale efficiency (GSE) index and the global pure technical efficiency (GPTE) index. For the GML, GTP, GSE, and GPTE indexes, values exceeding 1 denote enhancements in GTFP, technological advancements, boosts in production efficiency due to scale effects, and elevations in production efficiency driven by advancements in management and technology, respectively. Conversely, values falling below 1 for the GML, GTP, GSE, and GPTE indexes imply a decline in GTFP, a setback in technological progress, a diminishing of production efficiency due to scale effects, and a decrease in production efficiency as a consequence of management and technological influences, respectively [49]. The value of 1 indicates no change.

3.1.2. Econometric Model

To investigate the effects of DI on GTFP, this article draws upon relevant literature on GTFP [50,51] and employs a two-way fixed effect model for estimation:

$$GTFP_{i,t} = \partial_0 + \partial_1 DI_{i,t} + \partial_2 X_{i,t} + \omega_i + \mu_t + \varepsilon_{i,t} \tag{4}$$

Among them, X represents control variables, i and t represent the province and time, respectively, ω_i represents the regional individual outcome, μ_t represents the time outcome, and $\varepsilon_{i,t}$ is the disturbance term. The coefficient ∂_0 is a constant term, and ∂_1 is the measure of main concern. Should ∂_1 be positive, this indicates that DI significantly fosters the advancement of GTFP.

3.2. Variable Selection

GTFP. This article utilizes input–output data from 30 Chinese provinces, municipalities, and autonomous areas to determine regional GTFP. The indicators and data necessary for the measurement of GTFP are delineated as follows: energy, capital, and labor are examples of inputs. Labor inputs are quantified by the count of workers employed in the production sectors across each region as the year concludes. Capital inputs are represented by the valuation of fixed assets owned by large enterprises in each region by the fiscal year's end. Energy inputs are represented by the overall amount of energy consumption of production sectors in each region [52]. The outputs encompass both expected and non-expected outputs: Expected outputs are represented by the industrial value added in each region, while non-expected outputs primarily arise from regional emissions of industrial pollutants, including wastewater, exhaust gases, and solid waste [1]. Exhaust gas emissions are represented by industrial sulfur dioxide releases, wastewater emissions are represented by industrial effluent discharges, and solid waste emissions are represented by industrial particulate matter (dust) releases. The GML index means year-on-year growth rate. To ensure comparability, the GTFP for the base year of 2005 is standardized to 1 and then multiplied by the corresponding GML value for each subsequent year, yielding region-specific actual GTFP values. Table 1 describes the measurement indicators of GTFP.

Table 1. Description of the measurement indicators of GTFP.

Indicators Type	Indicators	Definition	Data Sources
Inputs	Capital input	Year-end value of fixed assets for large enterprises	CSY
	Labor input	Year-end employment number in production sector	CLSY
	Energy input	Total energy consumption of the production sector	CESY
Expected outputs	Economic output	Industrial added value	CSY
Unexpected outputs	Exhaust emissions	Industrial sulfur dioxide emissions	CESY
	Wastewater discharge	Industrial effluent discharge volume	
	Solid waste discharge	Industrial particulate matter (dust) emissions	

DI. Given the availability of regional DI data, this article adopts an output-oriented perspective to assess the degree of DI in each region. The examination system for invention patents is more stringent than that of other patents, thereby providing a more effective reflection of the extent of regional DI [53]. This article gauges the level of DI in the region by counting the quantity of invention patents awarded. Considering the distribution with a right skew of digital patent data, we adopt the transformation of logarithms of the patent data after adding 1 for processing purposes.

Control variables. Building upon prior research [34,38,54], this article controls the following factors that may affect the GTFP. The industrial structure (IS) is represented by the proportion of output value of the tertiary industry relative to that of the secondary industry within a given region. The environmental regulation (ER) is characterized by the proportion of finished industrial pollution control investments to the added industrial value within the region. The energy structure (ES) is represented by the ratio of the region's share of the country's overall power consumption. The unemployment level (UL) is represented by the regional unemployment rate. The social consumption (SC) is depicted through the ratio of overall consumer items sold at retail relative to the GDP. Table 2 describes the specific variable definitions.

Table 2. Variable definition.

Variables Type	Variables	Definition	Data Sources
Dependent variable	GTFP	Calculated by the directional SBM–GML model	-
Independent variable	DI	Number of authorized digital economy invention patents	CNRDS
Control variables	IS	Output value of tertiary industry /output value of secondary industry	CSMAR
	ER	Finished investment in industrial pollution control/industrial added value	
	ES	Regional electricity consumption /Total national electricity consumption	
	UL	Regional unemployment rate	
	SC	Total retail sales of consumer goods/GDP	

3.3. Data Sources and Descriptive Statistics

This article selects relevant data from 30 provinces, municipalities, and autonomous regions across China covering the time frame from 2005 to 2021. The input–output data utilized for GTFP estimation are sourced from the China Statistical Yearbook (CSY), China Energy Statistical Yearbook (CESY), China Labor Statistical Yearbook (CLSY), and CSMAR database. We get the digital economy patent data of various provinces and cities from Chinese Research Data Services (CNRDS) Platform Digital Economy Research Database (DERD). Among them, the DI sector determines the industry classification of each patent based on its patent classification number and establishes associations with relevant digital economy patents using the Reference Relationship Table of International Patent Classification and National Economy Industry Classification (2018) as well as the Statistical Classification of Digital Economy and Its Core Industries (2021) issued by the China National Intellectual Property Administration. Additionally, taking into account the standardization of data measurements and the availability of diverse datasets, this article excludes data from Xizang, Hong Kong, Macao, and Taiwan. When there is only a little quantity of missing data, the gaps are filled in using linear interpolation. To mitigate the influence of price-related factors, price data have been adjusted to a constant price series using 2005 as the reference period. In addition, some of the data are logarithmically processed to ensure smoothing of the data. After sorting, this article presents a comprehensive analysis of 510 observations from annual samples at the provincial level. Table 3 demonstrates the descriptive statistics for the key variables.

Table 3. Descriptive statistics.

Variables	N	Mean	SD	Min	Max
GTFP	510	1.001	0.202	0.243	3.224
DI	510	7.377	1.849	1.386	11.77
IS	510	7.580	0.786	5.624	8.864
ER	510	0.034	0.007	0.0121	0.056
ES	510	0.033	0.024	0.003	0.108
UL	510	0.004	0.004	0.0001	0.031
SC	510	0.366	0.064	0.222	0.538

4. Empirical Results

4.1. Benchmark Regression Results

Before conducting the regression analysis, we use the variance inflation factor (VIF) method to evaluate possible multiple correlations between the independent variables. The results indicate that both the average VIF value for the main model and the VIF values for individual explanatory variables are below 5, suggesting the absence of significant multicollinearity among the primary model's explanatory variables. To counteract the issue of estimation inconsistency arising from heteroskedasticity within cross-sectional units, the parameters are estimated using cluster robust standard errors.

The benchmark regression results are shown in Table 4. The fixed effects of year and province are not accounted for in Column (1). The regression coefficient of DI is statistically significant and positive, indicating that areas with greater concentrations of DI exhibit a higher average GTFP. The results in column (2) indicate that, even after adjusting for year fixed effects at the original level, DI remains statistically significant at the 1% confidence level when accounting for cluster standard errors at the provincial level. Column (3) demonstrates that after adjusting for the province and the year fixed effects, the coefficient of DI remains significant. The above results indicate that DI is essential to enhance regional GTFP. Hence, H1 is supported.

Table 4. GTFP and DI return results.

Variables	(1)	(2)	(3)
	GTFP	**GTFP**	**GTFP**
DI	0.017 **	0.043 ***	0.099 ***
	(0.007)	(0.014)	(0.033)
IS	−0.040	−0.179	−0.085
	(0.031)	(0.123)	(0.116)
ER	−6.283 *	−4.259	−0.540
	(3.519)	(3.114)	(2.845)

Table 4. *Cont.*

UL	1.930 *	4.336 *	4.237
	(1.053)	(2.135)	(3.035)
ES	−0.016	−3.144 **	−5.194 ***
	(0.636)	(1.313)	(1.567)
SC	−0.160	−0.408 *	−0.402 **
	(0.138)	(0.207)	(0.159)
FE (year)	No	Yes	Yes
FE (province)	No	No	Yes
N	510	510	510
R^2	0.037	0.123	0.249

Note: *, **, and *** denote significant levels at 10%, 5%, and 1%, respectively; Standard errors at the province level are enclosed in parentheses.

4.2. Robustness and Endogeneity Test

To safeguard the robustness of the estimation outcomes, this study conducts a series of rigorous tests including replacing the measurement indicators of core variables, incorporating additional control variables, integrating multi-dimensional interactive fixed effects, and employing instrumental variable regression. The robustness and endogeneity test findings are displayed in Table 5.

a. Revising the assessment approach of GTFP. The estimation outcomes may be influenced by variations in the measurement methods of GTFP. Therefore, we adopt the SBM–BML methodology as an alternative approach for calculating GTFP. As shown in Column (1), the coefficient of DI is 0.090, which exhibits statistical significance at 5%. The coefficient and its significance remain stable, consistent with the benchmark regression results.

b. Refining the methodology for measuring DI. Given that variations in DI measurement methods may impact estimation results, this research uses the count of utility model patent apps related to the digital economy in each province and city as an alternative indicator for DI. The outcomes are presented in Column (2), where the coefficient of DI is 0.080, demonstrating statistical significance at 5%. Notably, the coefficient and its significance remain robust, aligning consistently with the benchmark regression findings.

c. Incorporating the time-lagged term of GTFP into the analysis. Given the potential presence of temporal sequence correlation in GTFP, which could influence a region's current year GTFP based on previous year figures, this study re-evaluates by incorporating the lagged term of GTFP into the regression analysis. The results are presented in Column (3), where the coefficient of DI is estimated to be 0.103 with a statistical significance. The coefficient and its significance remain robust, consistent with the benchmark regression findings.

d. To further discuss the matter of omitted variables, this article incorporates additional control variables including industrial agglomeration (IA), transportation infrastructure (TI), economic development (ED), and population density (PD). The degree of IA is represented by the employment density within a region, which is quantified as the percentage of people in employment by the area of the administrative district. The level of TI is assessed based on the logarithm of regional road mileage. ED is evaluated using the logarithm of regional per capita GDP, with per capita GDP adjusted for inflation using a price series based on 2005. PD is determined by calculating the ratio between the total population and administrative area. The results are presented in Column (4), where the coefficient of DI is 0.103, demonstrating statistical importance at the 1% level. Importantly, this coefficient remains robust, and this agrees with the benchmark findings.

e. Incorporating the interaction fixed effects of province and year. Provinces with a more developed economy may possess a relatively advanced DIC and enjoy a greater competitive edge in terms of DI. Accordingly, this article incorporates province–year interaction fixed effects to account for time-dependent unobservable attributes at the provincial level. The results are presented in Column (5), where the coefficient of DI is 0.086, demonstrating statistical significance at the 1% level. This coefficient remains robust, aligning with the benchmark results.

Table 5. Robustness and endogeneity tests.

Variables	(1) Change Independent Variable	(2) Change Dependent Variable	(3) Include Lagged Terms	(4) Add Control Variables	(5) Multi-Dimensional Interaction Fixed Effects	(6) Instrumental Variable Regression
DI	0.090 **	0.080 **	0.103 **	0.103 ***	0.086 ***	0.092 *
	(0.038)	(0.034)	(0.039)	(0.036)	(0.024)	(0.059)
IA				0.560		
				(1.716)		
TI				−0.053		
				(0.088)		
ED				−0.005		
				(0.075)		
PD				0.042 *		
				(0.205)		
Province	yes	yes	yes	yes	yes	yes
Year	yes	yes	yes	yes	yes	yes
Control Variables	yes	yes	yes	yes	yes	yes
Province–year	no	no	no	no	yes	no
N	510	510	480	510	510	510
R^2	0.255	0.243	0.282	0.250	-	0.0346
Kleibergen–paap rk LM						6.46 **
Cragg–Donald Wald F						115.03

Note: *, **, and *** denote significant levels at 10%, 5%, and 1%, respectively; Standard errors at the province level are enclosed in parentheses.

f. Instrumental variables regression. Given the positive correlation between a higher level of GTFP and more advanced DIC, as well as potentially stronger systems for safeguarding R&D innovation, this could further facilitate the advancement of DI. Consequently, the benchmark model is potentially vulnerable to issues of endogeneity due to reverse causality, which could lead to biased outcomes in the estimates. Building upon the existing literature [55,56], this study uses postal and telecommunications data as instrumental variables to mitigate endogeneity concerns. The postal and telecommunications data can indicate the initial stage of development in China's postal and telecommunications industry. On one hand, the enhancement of postal and telecommunications infrastructure is advantageous for fostering DI, while previous communication developments within a region can influence local DI progress in diverse manners. In China, landline telephones represented the main method of accessing networks. Therefore, the prevalence of landline telephones during the 1980s can act as a metric indicating the expansion of the postal and telecommunications sector, which exhibits a positive correlation with regional levels of DI. On the other hand, the utilization frequency of landline telephones in regions has witnessed a significant decline in recent years, thereby not directly impacting regional production efficiency and thus satisfying the exclusivity requirement of an instrumental variable. Moreover, given the cross-sectional nature of the aforementioned historical data, we adopt the approach of [57] by incorporating a time series variable that is correlated with it to construct an interaction term, which is subsequently introduced into the fixed effects model. This article utilizes an interaction term, constructed by combining the count of broadband internet connectivity ports from the year prior in each region with the count of landline phones per hundred people in 1984, as an instrumental variable to measure DI. The results are presented in Column (6). The coefficient of DI is remarkably positive, which aligns with the benchmark regression analysis. The Kleibergen–Paap rk LM statistic exhibits statistical significance at the 5% level, while the Cragg–Donald Wald F statistic exceeds the critical value of the Stock–Yogo weak instrument test with a level of significance of 10%, thereby establishing that the instrumental variable meets the relevance criterion. The aforementioned findings indicate that the benchmark results stay robust even after accounting for endogeneity.

5. Further Analysis and Testing

5.1. Impact Mechanism Testing

In previous theoretical analysis, DI can not just possess a direct contribution to GTFP, but also affect GTFP by improving the CE, LE, and TE. Therefore, this research draws on [52,58] to verify the existence of this mechanism. The specific empirical is as follows:

$$Mech_{i,t} = \beta_0 + \beta_1 DI_{i,t} + \beta_2 X_{i,t} + \omega_i + \mu_t + \varepsilon_{i,t} \tag{5}$$

where $Mech_{i,t}$ is the mechanism variable (CE, LE, TE). The focus of Equation (5) is β_1. If β_1 meets the significance criteria, it indicates that DI promotes GTFP by improving the efficiency of resource allocation. The mechanism test results are displayed in Table 6.

Table 6. The results of impact mechanism.

Variables	(1)	(2)	(3)
	CE	**LE**	**TE**
DI	0.088 **	−0.039 **	0.172 ***
	(0.035)	(0.015)	(0.054)
Province	Yes	Yes	Yes
Year	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes
N	510	510	510
R^2	0.853	0.904	0.213

Note: ** and *** denote significant levels at 5%, and 1%, respectively; Standard errors clustered at provincial level are in parentheses.

5.1.1. CE Improvement Mechanism

Following the methodology employed by Xu [59], CE is assessed as the ratio of a gross regional product's added value to the increase in fixed asset investment. This ratio signifies the efficacy of capital factors in generating output, thereby reflecting the economic output increment resulting from each unit of increased capital investment. The aforementioned indicator is a positive metric, wherein higher values are indicative of enhanced CE. The outcomes are shown in Column (1) of Table 6. The coefficient of DI is significantly positive at the 5% level, indicating that DI significantly increases the capital output ratio, meaning that DI effectively enhances CE. A similar conclusion can be found in Zhang et al. [39], which indicate that the improvement in CE brought about by the development of DI provides more diversified and customized investment channels for industrial development, enhances the liquidity and potential return on capital, and thereby yields higher economic benefits and environmental protection, ultimately enhancing the GTFP. The above results imply that DI indirectly increases GTFP by improving CE.

5.1.2. LE Improvement Mechanism

Following the methodology employed by Stuebs and Sun [60], the measurement of LE is the ratio of employed individuals to the growth in gross regional product value. The indicator represents the labor input required for a unit increase in economic output, serving as an inversely proportional measurement of labor factor productivity. That means smaller values of the indicator indicate higher levels of LE. The outcomes are shown in

Column (2) of Table 6. The coefficient of DI exhibits significantly negative correlation between DI and the indicator of LE, demonstrating that DI significantly improves LE. DI can enhance employee flexibility and collaboration efficiency, leading to improvements in the efficiency of production activities, business management, and logistics [42]. This promotes the development of production activities towards higher environmental and economic benefits, thereby enhancing GTFP. In short, the results indicate that DI indirectly increases GTFP by improving LE.

5.1.3. TE Improvement Mechanism

Based on Equation (3), the GTE index can be expanded upon into the global scale efficiency (GSE) index and the global pure technical efficiency (GPTE) index. The GPTE index represents the production efficiency in the region, taking into account factors such as the comprehensive management level and technological enhancement level, within the current environmental conditions [49]. Therefore, we select the GPTE index calculated by the SBM–GML model as the measurement indicator of TE in this article. Considering that GML measures the sequential change, this study assumes a base period GPTE value of 1 for the year 2005 and multiplies it successively with the GPTE values of each subsequent year to obtain comparable actual GPTE values. In Column (3) of Table 6, it is evident that DI has greatly enhanced TE. This result is consistent with Zhao et al. [46], which indicated that adopting advanced DI technologies can transform production methods, optimize product design, and enhance energy efficiency, facilitating the eco-friendliness of production processes and the efficient use of resources, thereby improving GTFP. The above results indicate that DI indirectly increases GTFP by improving TE.

In summary, the aforementioned results demonstrate that DI can enhance CE, LE, and TE, thereby leading to an improvement in the GTFP. Hence, H2 is supported.

5.2. Heterogeneity Analysis

5.2.1. Heterogeneity in the Degree of IPP

According to the existing literature, DI is characterized by its susceptibility to imitation and replication. IPP plays a pivotal role in enabling enterprises to attain legitimate benefits from technological innovation [29,61]. Accordingly, this paper postulates that if the level of intellectual property rights protection is high, enterprises can derive benefits from the exclusivity of digital patent rights and interests. Consequently, they are able to effectively implement DI in practical applications, leading to an enhancement in total factor productivity for enterprises. Therefore, it is expected that in regions with higher levels of IPP, DI will exert a more pronounced impact on the enhancement of GTFP compared to areas with lower degrees of IPP. In accordance with the National Intellectual Property Development Report released by the China National Intellectual Property Administration, this article conducts a comparative analysis between the provincial IPP index and the annual median. Subsequently, based on heterogeneity testing, the regional sample is divided into two groups: strong IPP and weak IPP. The results are in Column (1) and Column (2) of Table 7. Column (1) demonstrates that in regions with strong IPP, the coefficient for DI is significantly positive, whereas in Column (2), the coefficient for DI is not statistically significant in regions with weaker IPP. The empirical p-value of the coefficient difference between these groups is below 0.05, indicating that DI plays a more substantial role in enhancing the GTFP with stronger IPP.

Table 7. Heterogeneity results of IPP and DIC.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
	GTFP	**GTFP**	**GTFP**	**GTFP**
	Strong IPP	**Weak IPP**	**Advanced DIC**	**Outdated DIC**
DI	0.138 ** (0.065)	0.050 (0.040)	0.093 * (0.050)	0.025 (0.048)

Table 7. *Cont.*

Variables	**(1)**	**(2)**	**(3)**	**(4)**
	GTFP	**GTFP**	**GTFP**	**GTFP**
	Strong IPP	**Weak IPP**	**Advanced DIC**	**Outdated DIC**
Inter-group differences	0.088 ** ($p < 0.05$)		0.068 * ($p < 0.1$)	
Province	yes	yes	yes	yes
Year	yes	yes	yes	yes
Control Variables	yes	yes	yes	yes
N	219	225	251	253
R^2	0.385	0.320	0.426	0.323

Note: * and **, denote significant levels at 10% and 5%, respectively; Standard errors at the province level are enclosed in parentheses.

5.2.2. Heterogeneity of DIC

To examine the potential heterogeneity introduced by DIC, this study employs the median value of the ratio between the count of internet broadband access ports and the population size in different regions as an indicator to differentiate levels of DIC across areas. The outcomes are shown in Column (3) and Column (4) of Table 7. Column (3) demonstrates a significantly positive coefficient of DI in regions with advanced DIC development, indicating a noteworthy inverse relationship between DI and GTFP. Column (4) indicates that the coefficient of DI is not statistically significant in regions with outdated DIC development, and the empirical p-value for the difference in coefficients between groups is less than 0.1. The aforementioned observation suggests that the positive impact of DI on GTFP becomes more pronounced in regions with an advanced DIC.

5.2.3. Regional Heterogeneity

The study of regional heterogeneity is crucial for understanding and addressing various geographical, ecological, and socio-economic issues [62]. It helps us to deeply understand the differences and diversity between different regions, and it can provide targeted guidance for policy formulation and practice [63]. To examine the regional disparities in the influence of DI on GTFP, we partitioned the entire sample into eastern, central, western, and northeastern subsets for conducting a grouped regression analysis based on Xie et al. [4]. Table 8 reports the estimation results for regional heterogeneity. The results indicate that, for the eastern and central regions, the coefficient of DI exhibits a statistically significant positive effect at least at the 10% level, while for the western and northeastern regions, the coefficient of DI is not significant. This implies that in comparison to the western and northeastern regions, DI has a bigger impact in driving GTFP growth in the eastern and central regions.

Table 8. Heterogeneity results of region.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
	GTFP	**GTFP**	**GTFP**	**GTFP**
	Eastern	**Central**	**Western**	**Northeastern**
DI	0.046 *	0.161 ***	0.027	0.005
	(0.021)	(0.047)	(0.043)	(0.087)
Province	yes	yes	yes	yes
Year	yes	yes	yes	yes
Control Variables	yes	yes	yes	yes
N	170	102	187	51
R^2	0.277	0.272	0.554	0.622

Note: * and *** denote significant levels at 10% and 1%, respectively; Standard errors at the province level are enclosed in parentheses.

6. Discussion

Based on the aforementioned findings, this study discovered some unexpected discoveries in addition to empirical support for the theoretical framework.

First, this study reveals that DI exerts a positive influence on enhancing GTFP. Previous studies have drawn consistent conclusions regarding the connection between DI and GTFP. Scholars have recognized that the contemporary generation of intelligent information technology and massive data resources embedded in DI have demonstrated evident advantages in terms of developmental dynamics, efficiency, and quality [64]. DI fundamentally drives changes in production modes, enabling regions to generate higher economic benefits with reduced consumption of resources, alongside enhancing GTFP [65]. In other words, it provides digital support for regional development to achieve the decoupling of economic growth from environmental pollution. Specifically, some studies contradict this perspective [66,67], demonstrating that certain activities associated with DI may lead to higher product failure rates and potentially diminish their reliability, consequently exerting economic and environmental pressures. As a result, it is inconclusive about the relationship between DI and GTFP. Our research contributes to a better understanding of the important impact of DI and green sustainable development in the digital era through quantitative methods, echoing the suggestion of [68].

Second, this study provides an in-depth comprehension to understand the indirect effect of DI and GTFP through CE, LE, and TE. The results of this study demonstrate that DI plays a crucial role in enhancing GTFP through CE. This statement is consistent with [69,70], who indicate that DI can optimize the internal capital quality within firms and enhance external financial support, facilitate cross-sectoral capital flow, streamline business processes and control costs, mitigate environmental pollution during capital output, and improve GTFP. The findings of our research reveal that DI positively influences GTFP by increasing LE; several researchers have reached the same discussions [41,71], arguing that DI requires the integration of a highly skilled workforce. This situation forces companies to improve their labor resource composition by elevating the need for more qualified employees and supporting the evolution and advancement of their workforce, ultimately leading to a boost in GTFP. This study finds the mediating function of TE in the relationship between DI and GTFP. Certain research also has illustrated that digital technology serves as a complement to other technologies by restructuring and integrating various resource elements across different modes of production [72,73]. This leads to improvements in production paradigms and industrial linkage effects, thereby promoting the optimization of the sector structure, reducing pollution emissions, and enhancing GTFP. In this research, we have found that previous research conducted limited empirical work on the mediating factors for GTFP in the field of DI; most studies focus on theoretical analysis and qualitative reasoning. Our study offers empirical support for the connections between DI and GTFP, and elucidates the effectiveness of DI as a potent tool for promoting sustainable regional development.

Third, this study reveals that the positive impact of DI on GTFP is specifically significant in regions with higher levels of IPP, advanced DIC, and central and eastern areas. For this finding, several tentative explanations are proposed in this study. Firstly, intellectual property is a fundamental civil right [74], and robust protection of high-level intellectual property can effectively safeguard patent rights for enterprises. This protection encourages greater innovation motivation and facilitates the modification and utilization of patent accomplishments. Therefore, by improving the system of IPP and establishing a stronger structure, the influence of DI on GTFP is significantly amplified. Secondly, activities related to DI are intrinsically linked to the DIC of their specific ecosystems [75]. Moreover, businesses involved in these activities depend on sufficient backing from regional technological environments and infrastructures [76]. Thirdly, the impact of DI on GTFP varies with regional heterogeneity. The research of Liu et al. [62] and Li et al. [63] indicates that the central and eastern regions possess richer resource endowment and a higher concentration of high-quality talents. Additionally, these regions receive greater policy support from the government for DI development, resulting in higher economic returns associated with DI activities. Consequently, the enhancement effect of DI on GTFP becomes more pronounced in these regions. These findings imply that when formulating DI strategies, governments need to consider whether these strategies match with regional circumstances.

7. Conclusions and Policy Recommendations

This research employs the SBM–GML method for GTFP computation based on panel data from 30 Chinese provinces, cities, and autonomous areas from 2005 to 2021. Subsequently, a two-way fixed effects model is used to examine how DI affects GTFP. The empirical evidence supports the theoretical analysis, demonstrating that DI plays a significant role in driving China's GTFP improvement. This conclusion remains valid even after carrying out several robustness tests. Furthermore, the mediating role of CE, LE, and TE in the influence of DI on GTFP is analyzed. According to the analysis of heterogeneity, the promotion and contribution of DI to GTFP is more likely in regions with strong IPP and advanced DIC. Moreover, the central and eastern regions exhibit a greater significance of the digital economy in driving GTFP.

The research verifies the role of DI in promoting GTFP, providing implications for the formulation of policies related to DI in China as well as strategic decisions for sustainable development. There are various policy ramifications that are further proposed as follows:

First, the position of DI should be given priority by the government in promoting GTFP. The study demonstrates that DI can effectively enhance growth in GTFP. The exploration and advancement of digital technologies are crucial for nurturing the digital economy, enabling digital industrialization, and advancing the digitalization of industries. It is essential to escalate the research and development efforts in digital technology to swiftly achieve a leading role in technological innovation. The urgency to continually explore innovative structures and methods for the progression of industries is evident. Enhancing the regulatory policy structure and establishing safeguards at the institutional level are essential steps to support the creation of fresh models and strategies. It is important to amplify the critical function of burgeoning technologies and additional cutting-edge information technologies.

Second, the government should implement policy measures to completely utilize the potential of DI in optimizing resource efficiency, including CE, LE, and TE. Firstly, it is essential to expedite the evolution of digital finance, leveraging the synergistic advantages that emerge from melding digital technology with the financial industry. By accelerating the digitization of finance, we can offer efficient, superior financial services to the real economy, address the fundamental challenges faced by conventional financial systems, and enhance the capacity of digital financial capital to benefit the real economy efficiently. Secondly, it is important to develop a strong framework for incentivizing and protecting talent, while simultaneously improving policies related to the training and recruitment of skilled individuals. Focus ought to be given to capitalizing on the regional strengths in digital economy expansion to enhance the collective labor productivity within the area. Lastly, it is necessary to provide preferential support to companies engaged in R&D within the DI sphere, aiming to accelerate the creation of digital R&D innovation hubs. Such a strategic measure would efficiently direct the influx of capital and the gathering of skilled professionals, ultimately promoting progress in technological effectiveness.

Third, the government should explore the implementation of differentiated DI development strategies. In light of the findings presented in this article, IPP and DIC are the foundation for regions to enhance GTFP through DI. Government departments should bolster the development of IPP mechanisms specific to digital technology, set up appropriate structures for validating and transferring digital patents, protect the lawful rights of enterprises, and cultivate an advantageous setting for DI in the corporate sector. Moreover, government departments should prioritize the development of DIC and reduce investment costs associated with such infrastructure for relevant enterprises, thereby lowering the barriers for enterprises to engage in the research and development of digital technologies and fully harness the positive impact of DI on enhancing GTFP. To promote regional development in western and northeast China, it is crucial to leverage inter-regional cooperation and resource flows, establish digital technology collaboration platforms, exchange knowledge and expertise in digital technology R&D, and enhance technical cooperation and talent training, as well as narrow the developmental disparities between regions.

Despite the fact that the results offer theoretical and empirical experiences for researchers and practitioners in China's sustainable development and digital economy, this study still has a number of shortcomings that will guide further investigation. First, this study quantifies the level of DI through the number of invention patents, without further categorizing them based on technology type or industry attribution. As we all know, the proliferation of digital technologies has exerted an escalating influence on China's economy and environment in recent years. Therefore, it is also an interesting research direction to further discuss the impact of DI activities on GTFP in different industries or technology types. Second, China has introduced a number of legislative actions to promote the development of DI in recent years, and policy evaluation is also a direction that deserves attention [77–79], but is not discussed in this paper. The existing studies have developed some mature research methods for policy evaluation, such as regression discontinuity design [80,81] and difference-in-differences method [82,83]. Thus, evaluating the impact of these policies' implementation on GTFP represents a potential direction for further research.

Author Contributions: Conceptualization, P.L.; Formal analysis, W.R.; Funding acquisition, P.L.; Investigation, W.R.; Methodology, W.R.; Software, W.R.; Supervision, P.L.; Visualization, W.R.; Writing—original draft, W.R.; Writing—review and editing, W.R. and P.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Humanities and Social Sciences Fund of the Ministry of Education of China (Grant 19YJA790057).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Chen, Q.; Wang, Q.; Zhou, D.; Wang, H. Drivers and evolution of low-carbon development in China's transportation industry: An integrated analytical approach. *Energy* **2023**, *262*, 125614. [CrossRef]
2. Chen, S.; Golley, J. Green productivity growth in China's industrial economy. *Energy Econ.* **2014**, *44*, 89–98. [CrossRef]
3. Lin, B.; Chen, Z. Does factor market distortion inhibit the green total factor productivity in China? *J. Clean. Prod.* **2018**, *197*, 25–33. [CrossRef]
4. Xie, R.; Fu, W.; Yao, S.; Zhang, Q. Effects of financial agglomeration on green total factor productivity in Chinese cities: Insights from an empirical spatial Durbin model. *Energy Econ.* **2021**, *101*, 105449. [CrossRef]
5. Xu, C.; Zhu, S.; Yang, B.; Miao, B.; Duan, Y. A review of policy framework research on promoting sustainable transformation of digital innovation. *Sustainability* **2023**, *15*, 7169. [CrossRef]
6. Ciriello, R.; Richter, A.; Schwabe, G. Digital innovation. *Bus. Inf. Syst. Eng.* **2018**, *60*, 563–569. [CrossRef]
7. Goldfarb, A.; Tucker, C. Digital economics. *J. Econ. Lit.* **2019**, *57*, 3–43. [CrossRef]
8. Nambisan, S.; Wright, M.; Feldman, M. The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Res. Policy* **2019**, *48*, 67–72. [CrossRef]
9. Henfridsson, O.; Nandhakumar, J.; Scarbrough, H.; Panourgias, N. Recombination in the open-ended value landscape of digital innovation. *Inf. Organ.* **2018**, *28*, 89–100. [CrossRef]
10. Tu, W.J.; Zhang, L.X.; Sun, D.Y.; Mao, W.Q. Evaluating high-tech industries' technological innovation capability and spatial pattern evolution characteristics: Evidence from China. *J. Innov. Knowl.* **2023**, *8*, 100287. [CrossRef]
11. Huang, X.; Zhang, S.P.; Zhang, J.; Yang, K. Research on the impact of digital economy on regional green technology innovation: Moderating effect of digital talent aggregation. *Environ. Sci. Pollut. Res.* **2023**, *30*, 74409–74425. [CrossRef] [PubMed]
12. Zhang, H.S.; Liu, Q.Q.; Wei, Y.L. Digital product imports and export product quality: Firm-level evidence from China. *China Econ. Rev.* **2023**, *79*, 101981. [CrossRef]
13. Li, J.J.; Zhan, G.H.; Dai, X.; Qi, M.; Liu, B.F. Innovation and optimization logic of grassroots digital governance in China under digital empowerment and digital sustainability. *Sustainability* **2022**, *14*, 16470. [CrossRef]

14. Li, X.; Wu, T.; Zhang, H.J.; Yang, D.Y. Digital technology adoption and sustainable development performance of strategic emerging industries: The mediating role of digital technology capability and the moderating role of digital strategy. *J. Organ. End User Comput.* **2023**, *34*, 315645. [CrossRef]
15. Svahn, F.; Mathiassen, L.; Lindgren, R. Embracing digital innovation in incumbent firms: How volvo cars managed competing concerns. *MIS Q.* **2017**, *41*, 239–253. [CrossRef]
16. Ciarli, T.; Kenney, M.; Massini, S.; Piscitello, L. Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Res. Policy* **2021**, *50*, 104289. [CrossRef]
17. Gong, Q.; Wang, X.; Tang, X. How can the development of digital economy empower green transformation and upgrading of the manufacturing industry?—A quasi-natural experiment based on the national big data comprehensive pilot zone in China. *Sustainability* **2023**, *15*, 8577. [CrossRef]
18. Yuan, S.; Pan, X.F. Inherent mechanism of digital technology application empowered corporate green innovation: Based on resource allocation perspective. *J. Environ. Manag.* **2023**, *345*, 118841. [CrossRef]
19. Zhong, S.; Li, A.Z.; Wu, J. How does digital finance affect environmental total factor productivity: A comprehensive analysis based on econometric model. *Environ. Dev.* **2022**, *44*, 100759. [CrossRef]
20. Acemoglu, D.; Restrepo, P. Automation and new tasks: How technology displaces and reinstates labor. *J. Econ. Perspect.* **2019**, *33*, 3–30. [CrossRef]
21. Kohli, R.; Melville, N.P. Digital innovation: A review and synthesis. *Inf. Syst. J.* **2019**, *29*, 200–223. [CrossRef]
22. Acemoglu, D.; Restrepo, P. The race between man and machine: Implications of technology for growth, factor shares, and employment. *Am. Econ. Rev.* **2018**, *108*, 1488–1542. [CrossRef]
23. Gordon, R.J. *The Rise and Fall of American Growth*; Princeton University Press: Woodstock, UK, 2016.
24. Summers, L.H. U.S. economic prospects: Secular stagnation, hysteresis, and the zero lower bound. *Bus. Econ.* **2014**, *49*, 65–73. [CrossRef]
25. Brynjolfsson, E.; Collis, A.; Diewert, W.E.; Eggers, F.; Fox, K.J. GDP-B: Accounting for the value of new and free goods in the digital economy. *SSRN Electron. J.* **2019**, *w25695*. [CrossRef]
26. Firk, S.; Gehrke, Y.; Hanelt, A.; Wolff, M. Top management team characteristics and digital innovation: Exploring digital knowledge and TMT interfaces. *Long Range Plan.* **2021**, *55*, 102166. [CrossRef]
27. Chen, D.; Jin, Y.; Dong, Z. Policy uncertainty, political connection and firms' innovation efficiency. *Nankai Bus. Rev.* **2016**, *4*, 27–35.
28. Braunerhjelm, P.; Ding, D.; Thulin, P. Labour market mobility, knowledge diffusion and innovation. *Eur. Econ. Rev.* **2020**, *123*, 103386. [CrossRef]
29. Liu, Y.; Dong, J.; Mei, L.; Shen, R. Digital innovation and performance of manufacturing firms: An affordance perspective. *Technovation* **2023**, *119*, 102458. [CrossRef]
30. Brynjolfsson, E.; Collis, A. How Should We Measure the Digital Economy? *Harv. Bus. Rev.* **2019**, *97*, 140–148.
31. Turcan, V.; Gribincea, A.; Birca, I. Digital economy-A premise for economic development in the 20th century. *Econ. Sociol. Theor. Sci. J.* **2014**, *2*, 109–115.
32. Tumbas, S.; Berente, N.; Brocke, J. Digital innovation and institutional entrepreneurship: Chief digital officer perspectives of their emerging role. *J. Inf. Technol.* **2018**, *33*, 188–202. [CrossRef]
33. Zhang, W.Q.; Zhao, J.L. Digital transformation, environmental disclosure, and environmental performance: An examination based on listed companies in heavy-pollution industries in China. *Int. Rev. Econ. Financ.* **2023**, *87*, 505–518. [CrossRef]
34. Gao, Q.; Cheng, C.M.; Sun, G.L. Big data application, factor allocation, and green innovation in Chinese manufacturing enterprises. *Technol. Forecast. Soc. Chang.* **2023**, *192*, 122567. [CrossRef]
35. Bukht, R.; Heeks, R. Defining, conceptualising and measuring the digital economy. *Dev. Inform. Work. Pap.* **2017**, *68*, 703–740. [CrossRef]
36. Han, F.; Mao, X. Artificial intelligence empowers enterprise innovation: Evidence from China's industrial enterprises. *Appl. Econ.* **2023**, 1–16. [CrossRef]
37. El-Haddadeh, R. Digital innovation dynamics influence on organisational adoption: The case of cloud computing services. *Inf. Syst. Front.* **2020**, *22*, 985–999. [CrossRef]
38. Lyu, Y.W.; Wang, W.Q.; Wu, Y.; Zhang, J.N. How does digital economy affect green total factor productivity? Evidence from China. *Sci. Total Environ.* **2023**, *857*, 159428. [CrossRef]
39. Zhang, P.; Wang, Y.R.; Wang, R.Y.; Wang, T.W. Digital finance and corporate innovation: Evidence from China. *Appl. Econ.* **2023**, *56*, 615–638. [CrossRef]
40. Dewan, S.; Kraemer, K.L. Information technology and productivity: Evidence from country-level data. *Manag. Sci.* **2000**, *46*, 548–562. [CrossRef]
41. Gao, Y.; Zhang, M.; Zheng, J. Accounting and determinants analysis of China's provincial total factor productivity considering carbon emissions. *China Econ. Rev.* **2021**, *65*, 101576. [CrossRef]
42. Teece, D.J. Profiting from Innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Res. Policy* **2018**, *47*, 1367–1387. [CrossRef]
43. Boudreau, K.J.; Lacetera, N.; Lakhani, K.R. Incentives and problem uncertainty in innovation contests: An empirical analysis. *Manag. Sci.* **2011**, *57*, 843–863. [CrossRef]

44. Wu, L.; Zhang, Z. Impact and threshold effect of internet technology upgrade on forestry green total factor productivity: Evidence from China. *J. Clean. Prod.* **2020**, *271*, 122657. [CrossRef]
45. Chenery, H.; Robinson, S.; Syrquin, M. *Industrialization and Growth: A Comparative Study*, Oxford University Press: New York, NY, USA, 1986.
46. Zhao, Y.; Song, Z.Y.; Chen, J.; Dai, W. The mediating effect of urbanisation on digital technology policy and economic development: Evidence from China. *J. Innov. Knowl.* **2023**, *8*, 100318. [CrossRef]
47. Jin, L.Q.; Dai, J.Y.; Jiang, W.J.; Cao, K.R. Digital finance and misallocation of resources among firms: Evidence from China. *N. Am. J. Econ. Financ.* **2023**, *66*, 101911. [CrossRef]
48. Oh, D.H. A global malmquist-Luenberger productivity index. *J. Product. Anal.* **2010**, *34*, 1345–1355. [CrossRef]
49. Li, Y.; Ren, X. The dynamic mechanism, operation path and development countermeasures of digital economy innovation from the perspective of science and technology. *Guizhou Soc. Sci.* **2020**, *12*, 113–120.
50. Lee, C.C.; Lee, C.C. How does green finance affect green total factor productivity? Evidence from China. *Energy Econ.* **2022**, *107*, 105863. [CrossRef]
51. Shen, X.B.; Lin, B.Q. Green growth, carbon intensity regulation, and green total factor productivity in China. *Energy J.* **2023**, *43*, 169–193. [CrossRef]
52. Zhu, Q.; Xu, C.; Chen, Q.; Wu, L. Oil price distortion and its impact on green economic efficiency in China's transportation: A spatial effect perspective. *Renew. Sustain. Energy Rev.* **2024**, *191*, 114148. [CrossRef]
53. He, Z.L.; Tong, T.W.; Zhang, Y.; He, W. Constructing a Chinese patent database of listed firms in China: Descriptions, lessons, and insights. *J. Econ. Manag. Strategy* **2018**, *27*, 579–606. [CrossRef]
54. Zhang, J.X.; Lu, G.Y.; Skitmore, M.; Ballesteros-Pérez, P. A critical review of the current research mainstreams and the influencing factors of green total factor productivity. *Environ. Sci. Pollut. Res.* **2021**, *28*, 35392–35405. [CrossRef] [PubMed]
55. Amiti, M.; Konings, J. Trade liberalization, intermediate inputs, and productivity: Evidence from indonesia. *Am. Econ. Rev.* **2007**, *97*, 1611–1638. [CrossRef]
56. Brandt, L.; Biesebroeck, J.V.; Zhang, Y.F. Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *J. Dev. Econ.* **2012**, *97*, 339–351. [CrossRef]
57. Nunn, N.; Qian, N.U.S. Food aid and civil conflict. *Am. Econ. Rev.* **2014**, *104*, 1630–1666. [CrossRef]
58. Lin, K. The impact of intellectual property protection on business performance of high-tech enterprises: The mediating effect of political-business relations. *Financ. Res. Lett.* **2023**, *54*, 103718. [CrossRef]
59. Xu, Y.; Zhao, X.; Zhou, X.; Yuan, L. Financial structure Fand capital allocation efficiency: An empirical analysis of China from 2005–2018. *Appl. Econ.* **2021**, *53*, 3347–3358. [CrossRef]
60. Stuebs, M.T.; Sun, L. Business reputation and labor efficiency, productivity and cost. *J. Bus. Ethics* **2009**, *96*, 265–283. [CrossRef]
61. Chen, W.; Wu, Y. Does intellectual property protection stimulate digital economy development? *J. Appl. Econ.* **2022**, *25*, 723–730. [CrossRef]
62. Liu, X.H.; Yang, J.J.; Xu, C.Z.; Li, X.C.; Zhu, Q.Y. Environmental regulation efficiency analysis by considering regional heterogeneity. *Resour. Policy* **2023**, *83*, 103735. [CrossRef]
63. Li, Y.Y.; Liu, W.J. Spatial effects of environmental regulation on high-quality economic development: From the perspective of industrial upgrading. *Front. Public Health* **2023**, *11*, 1099887. [CrossRef]
64. Tsou, H.T.; Chen, J.S. How does digital technology usage benefit firm performance? Digital transformation strategy and organisational innovation as mediators. *Technol. Anal. Strateg. Manag.* **2021**, *35*, 1114–1127. [CrossRef]
65. Lyu, Y.; Xiao, X.; Zhang, J.N. Does the digital economy enhance green total factor productivity in China? The evidence from a national big data comprehensive pilot zone. *Struct. Chang. Econ. Dyn.* **2024**, *69*, 183–196. [CrossRef]
66. Oláh, J.; Aburumman, N.; Popp, J.; Khan, M.A.; Haddad, H.; Kitukutha, N. Impact of industry 4.0 on environmental sustainability. *Sustainability* **2020**, *12*, 4674. [CrossRef]
67. Sun, X.M.; Xiao, S.Y.; Ren, X.H.; Xu, B. Time-varying impact of information and communication technology on carbon emissions. *Energy Econ.* **2023**, *118*, 106492. [CrossRef]
68. Feng, Z.; Cheng, S.N.; Qu, G.H.; Cui, Y.L.; Ye, J.M. Research on theoretical mechanism and promotion path of digital economy driving China's green development under "Double Carbon" background. *Int. J. Environ. Res. Public Health* **2023**, *20*, 437. [CrossRef] [PubMed]
69. Chen, S.Q.; Zhang, H. Does digital finance promote manufacturing servitization: Micro evidence from China. *Int. Rev. Econ. Financ.* **2021**, *76*, 856–869. [CrossRef]
70. Fuster, A.; Plosser, M.; Schnabl, P.; Vickery, J. The role of technology in mortgage lending. *Rev. Financ. Stud.* **2019**, *32*, 1854–1899. [CrossRef]
71. Dou, B.; Guo, S.L.; Chang, X.C.; Wang, Y. Corporate digital transformation and labor structure upgrading. *Int. Rev. Financ. Anal.* **2024**, *90*, 102904. [CrossRef]
72. Jiang, Z.S.; Xu, C.H. Disrupting the technology innovation efficiency of manufacturing enterprises through digital technology promotion: An evidence of 5G technology construction in China. *IEEE Trans. Eng. Manag.* **2023**, *71*, 6918–6928. [CrossRef]
73. Li, Y.; Dai, J.; Cui, L. The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model. *Int. J. Prod. Econ.* **2020**, *229*, 107777. [CrossRef]

74. Zheng, P.P.; Li, Z.; Zhuang, Z.Y. The impact of judicial protection of intellectual property on digital innovation: Evidence from China. *Financ. Res. Lett.* **2023**, *58*, 104257. [CrossRef]
75. Sun, J.J.; Zhai, C.C.; Dong, X.Q.; Li, C.M.; Wang, Z.Y.; Li, D.D.; Sun, Y.P. How does digital infrastructure break the resource curse of cities? Evidence from a quasi-natural experiment in China. *Resour. Policy* **2023**, *86*, 104302. [CrossRef]
76. Jia, X.F.; Xie, B.J.; Wang, X.A. The impact of network infrastructure on enterprise digital transformation—A quasi-natural experiment from the "broadband China" Strategy. *Appl. Econ.* **2023**, *56*, 1363–1380. [CrossRef]
77. Zhang, Q.; Zheng, Z.Q.; Wan, Z.; Zheng, S.Y. Does emission control area policy reduce sulfur dioxides concentration in Shanghai? *Transp. Res. Part D-Transp. Environ.* **2020**, *81*, 102289. [CrossRef]
78. Tang, L.; Cao, C.; Lien, D.; Liu, X.O. The effects of anti-corruption campaign on research grant reimbursement: Regression discontinuity evidence from China. *Sci. Eng. Ethics* **2020**, *26*, 3415–3436. [CrossRef] [PubMed]
79. Yin, L.; Wang, D.; Li, Y.Y. Effectiveness of tax policies in corporate restructuring: Evidence from China. *Emerg. Mark. Financ. Trade* **2022**, *58*, 2942–2956. [CrossRef]
80. Tuvaandorj, P. Regression discontinuity designs, white noise models, and minimax. *J. Econom.* **2020**, *218*, 587–608. [CrossRef]
81. Zhou, W.; Rao, W.Y.; Lu, S. Market stability analysis after the circuit breaker for the CSI 300 energy index. *Financ. Res. Lett.* **2020**, *34*, 101348. [CrossRef]
82. Baker, A.C.; Larcker, D.F.; Wang, C.C.Y. How much should we trust staggered difference-in-differences estimates? *J. Financ. Econ.* **2022**, *144*, 370–395. [CrossRef]
83. Yu, H.W.; Liao, L.Q.; Qu, S.Y.; Fang, D.B.; Luo, L.F.; Xiong, G.Q. Environmental regulation and corporate tax avoidance:A quasi-natural experiments study based on China's new environmental protection law. *J. Environ. Manag.* **2021**, *296*, 113160. [CrossRef] [PubMed]