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Research article

Can the digital economy improve green total factor productivity? An empirical study based on Chinese urban data

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Abstract: With the new generation of technological revolution, the digital economy has progressively become a key driver of global economic development. In this context, how to promote green economic growth and improve green total factor productivity (GTFP) with the help of the digital economy is an important issue that urgently needs empirical research. We adopted the panel data of 278 Chinese prefecture-level cities from 2011 to 2020 to test whether the digital economy improves the GTFP through the Gaussian Mixed Model (GMM) dynamic panel model. The moderating effect model has been used to explore the impact mechanism from the perspectives of industrial structure upgrade and environmental regulation. In addition, a grouping regression was applied to the sample cities to test the heterogeneous impact of the digital economy on the GTFP. Based upon the empirical findings, this work has the following conclusions. First, the digital economy plays a significant role in improving the GTFP. Second, an industrial structure upgrade has a positive moderating effect on the ability of the digital economy to enhance the GTFP. The environmental regulation, in contrast, has a negative moderating effect. Third, the digital economy exerts heterogeneous impacts on the GTFP across regions, but not at the city level.

Keywords: green total factor productivity; digital economy; industrial structure upgrading; environmental regulation

1. Introduction

1.1. Background and research motivation

The digital economy is a powerful engine for high-quality economic development. Over the past few years, digital technologies like the Internet, cloud computing, big data, the Internet of Things, blockchain and artificial intelligence (AI) have continuously accelerated innovation. With digital information as core production factors and digital technology as the critical engine, the digital economy has been widely integrated with various economic and social development fields. It plays an increasingly prominent role in promoting consumption, adjusting the industrial structure, stimulating innovation, increasing employment and expanding investment. It is becoming a key element in restructuring factor resources, changing competition patterns and reshaping economic structure worldwide. The period of the "14th five-year plan" is a critical period for China to transform and upgrade its industries and replace old growth engines with new ones. Breaking the traditional development pattern of high inputs, high pollution and high emissions, as well as fostering green economy, is a pressing demand for China's high-quality development. Meanwhile, the booming digital economy has injected a strong impetus into high-quality economic development, brought new opportunities for China's sustainable economic growth and provided an essential path for green development. First of all, the digital economy can mitigate the negative impact of the "three-phase superposition" turning into "threefold pressure". In essence, the "threefold pressure" furthers the "three-phase superposition" pressure. Despite the impact of the COVID-19 epidemic, China was already in a critical period of optimizing the economic structure, transforming the development mode and changing the growth engine, even before the outbreak. Over the past few years, China's economy has experienced sustained pressure in three aspects: economic stability, economic structure transformation and long-term economic growth. In the context of replacing old engines with new ones, the innovation features of the digital economy have become increasingly prominent, transforming the Chinese economic development from the previous factor-driven and investment-driven model to the innovative technology-driven and green total factor productivity (GTFP)-driven model. Second, the digital economy can bring into full play to the superiority of digital information, improve the driving factors, accelerate the breeding of new factors of production such as technology, talents, knowledge, information and data; penetrate all walks of life; and derive a large number of new products, new formats and new business models. Especially, at the onset of the COVID-19 epidemic outbreak, the industrial chain of many countries contracted and the volume of international trade declined to varying degrees. However, the epidemic has also caused a transformation of people's living and working ways, facilitated society's digital transformation and promoted the rapid development of the digital economy industry. Therefore, the high-quality economic development eagerly requires the orientation of the digital economy in the post-COVID-19 era.

Green development, or eco-development, is a universal type of high-quality development. The digital economy has a positive externality in terms of green development. The GTFP is an essential indicator of green development. During the last 40 years of reform and opening-up, China has accomplished remarkable achievements in its rapid economic development. However, behind the rapid economic growth are serious resource waste and environmental pollution problems that cannot be ignored. According to the 2022 global Environmental Performance Index report jointly released by Yale University, Columbia University and the World Economic Forum, China scored 28.4 points in this assessment, ranking 160 out of 180 countries (regions) participating in the evaluation. To some extent, the report provided inspiration and reference for China to improve the environment and promote green development. China has been active in implementing green development and promoting the green transformation of the economy in recent years. Industrial development has gradually shifted from a decentralized and extensive high-energy consumption model to an intensive, efficient, green and low-carbon model. The focus is on improving the GTFP. Thus, we should further study the factors driving the improvement of the GTFP, which is of paramount importance for the promotion of high-quality economic development in contemporary China.

The research on the relationship between the digital economy and GTFP can better guide the economic transformation and upgrade in China. This is currently a hot issue of concern at the national policy level in China. This paper presents the panel data for a sample of 278 Chinese prefecture-level cities from 2011 to 2020, as well as shows that the digital economy can significantly improve GTFP through the use of a GMM dynamic panel model. Then, we present a moderating effect model to show that the advanced industrial structure has a positive moderating effect on the digital economy that helps to improve GTFP, while environmental regulation has a negative moderating effect. The function of digital economy development in improving GTFP is greater in non-central cities rather than central cities. Nowadays, China is in a new stage of promoting high-quality economic development. It is urgent to clarify the impact of digital economy development on GTFP and the mechanism of impact to help improve GTFP with the power of digital economy. Our findings are positive for China's search for pathway support for green development.

1.2. Literature review and contribution

1.2.1. Definition and evolution of the digital economy

The concept of the digital economy is constantly enriched with its development. Since Tapscott first put forward the term "digital economy" in his book "Digital Economy: Promise and Peril in the Age of Networked Intelligence" in 1999 [1], the digital economy is growing rapidly worldwide. In the past two decades, the digital economy has run through three stages: the information economy, the Internet economy and the new economy. At different stages, the digital economy development has different priorities, so there is no unified standard for defining the digital economy. Initially, the development of the digital economy was closely related to informatization, which laid the foundation for the digital economy development [2]. Based on information and communication technology (ICT), the digital economy can realize the digitalization of transactions, exchanges and cooperation, encourage enterprises to innovate [3], gradually promote the digitalization and intelligent upgrading of various industries and improve the total factor productivity (TFP), thus promoting the development and progress of economic society. With the further development of information technology, the digital economy takes data as a new driving force and the Internet as a key platform for development, giving birth to a new economic form and driving profound changes in the ways of production, life and governance. Especially, after the popularization of the mobile Internet, information dissemination has been dramatically strengthened, data-driven assets have been better allocated responding to rapid changes in market behavior and platform economies have been formed based on market organization and matching supply and demand [4,5]. The inherent green attributes of the digital economy, such as lower marginal cost [6], lower transaction cost and data creation [7], have become more prominent with the development of informatization and the Internet. What is more, the innovative consolidation of digital technology and the traditional manufacturing and service industry enables the re-engineering of the production service process and accelerates the establishment of new business forms and models, covering platform economy, which can greatly promote green economy development.

Relevant research at present is mainly concerned with the impact of the digital economy on high-quality development. For enterprises, a digital economy accelerates their digital transformation, enables enterprise management reform and becomes a strong driving engine for improving the production efficiency of manufacturing enterprises [8]. That greatly strengthens the supply and demand interaction and exerts power from the demand side to the supply side [9]. In terms of industries, the digital economy can optimize the industrial structure and provide a targeted path for high-quality economic development. Digital technology should be applied to various production fields, reorganize production factors, reconstruct production links, realize the production optimization based on the Internet of things and provide new services and business models in the value chain. Thus, new value-added and the value creation of traditional industries can be realized [10]. At the macroeconomic level, a digital economy can enhance the resource allocation efficiency and TFP and boost high-quality economic development [11]. As a new key factor with high technical and information value, data can collaborate with traditional factors, such as technology, capital and labor, thus playing a role in promoting productivity, innovation and economic growth [12]. Different from traditional factors of production, the information value in the digital economy era is characterized by increasing marginal revenue [13], which has the effects of amplification, superposition and multiplication on economic growth.

The index selection and measurement of the digital economy are still in the exploration phase internationally, and there needs to be a consensus on a unified and recognized system. Currently, the measurement methods for the digital economy can be broadly sorted into three categories: the measurement of the added value, the compilation of relevant indexes and the construction of satellite accounts. In terms of value-added measurement and research, the Bureau of Economic Analysis of the USA's Department of Commerce classifies the digital economy into three categories: infrastructure, e-commerce and other toll-based digital services, while the Chinese Academy of Information and Communications mainly measures the digital economy scale from the aspects of industrial digitalization and digital industrialization. As for the research on the compilation of relevant indexes, many relevant institutions mainly adopt index evaluation methods to set and weight specific indicators in different dimensions to acquire the relative development of the digital economy or some specific fields. Regarding satellite account construction, academia has mainly carried out research on the construction of ICT satellite accounts and digital economy satellite accounts. The three methods of measuring the digital economy each have their own emphasis and are applicable to different situations, but they also have limitations and need to reflect the development of the digital economy comprehensively, systematically and accurately.

1.2.2. GTFP

TFP has been a research focus for a long time, but, now, facing the pressure of economic transformation and upgrade, the GTFP has gradually attracted extensive attention from the government, the public and academia. TFP describes the growth degree of "desirable outputs" driven by innovation or management, such as technological progress and the improvement of allocation efficiency, excluding tangible factors such as labor and capital. It has long been widely used to measure economic growth and development quality [14]. Based on the TFP, the GTFP adds "undesirable outputs" such as energy and resource inputs and pollution emissions. It considers environmental issues in the economic development process, and it is more compatible with the new concept of green development in the current era.

The measurement method of GTFP is the starting point for studying green development. Pittman [15] used the DEA method to incorporate undesirable outputs into the measurement framework of TFP for the first time to estimate the GTFP. Chung et al. [16] employed the DEA and the Malmquist-Luenberger (ML) methods to make the results more consistent with the green concept. Later, Tone [17] made relevant improvements and proposed a more general slacks-based measure (SBM) model on the basis of non-radial and non-angular slack variables, which effectively reduced the calculation error. In order to overcome the shortcomings of the ML index, such as infeasibility and the lack of circularity, Oh [18] proposed the global ML (GML) index on the basis of the ML index. Since then, some scholars have started to effectively combine the two and calculate GTFP with the help of the GML index based on the SBM directional distance function.

With the deepening of research, exploring the path to improve GTFP has become the focus of current research. Environmental regulation, foreign direct investment (FDI) and fiscal decentralization are considered to be important factors affecting GTFP, but no unanimous conclusions have been reached in the existing studies, and different scholars hold different views. First, environmental regulation is considered to be either negative or positive for GTFP. Traditional neoclassical economics schools hold that environmental regulation can increase the pollution control cost of enterprises and has an "offsetting effect" on productive investment and innovation activities, exerting a negative impact on enterprises' improvement of GTFP. Scholars who hold a positive view believe that rational environmental regulations can encourage companies to develop green products, partially or even completely offset the cost increase caused by environmental regulations and improve enterprise productivity [19]. Second, debate exists over the effect of FDI. Developing countries, at the early stage of economic development, have received FDI and took on the industrial transfer and the pollution transfer from developed countries, becoming "pollution paradise". Relative to high-growth countries, low-growth countries can more easily become pollution havens for other countries in which the exports of environmental products are not conducive to China's green development [20]. However, Farouq et al. found that FDI had a remarkable positive influence on the environment in their study on the correlation between financial globalization uncertainty, economic growth, renewable energy and environmental degradation in nine sub-Saharan African economies [21]. Third, opposite views are held in terms of the impact of fiscal decentralization on the GTFP. Li et al. included the ecological environment in GTFP and found that GTFP was motivated by technical efficiency, while fiscal decentralization weakened the improvement in the green production efficiency [22]. On the other hand, some scholars conducted research on the basis of the intensity of fiscal decentralization, and they believed that reasonable fiscal decentralization could improve the GTFP, while a fiscal decentralization that is too strong would become a hindrance to improving the GTFP [23].

With the continuous improvement of science and technology and the enhancement of public awareness of environmental protection, the driving forces for improving GTFP are becoming increasingly diversified. First, technological innovation has become important driving forces to promote green development [24]. Finance further promotes TFP improvement through technological progress and capital allocation. Scholars have found that green finance can significantly improve green productivity and GTFP. The implementation of green credit policies [25], the improvement of fintech [26] and the digital economy development can improve the GTFP [27]. In addition, scholars have also proved that China's specific green policies, such as the carbon emission trading system [28] and smart city construction [29], are significantly positively correlated with GTFP. It can be seen that existing studies have analyzed the influential factors of the GTFP from diverse perspectives, providing rich governing experience and effective policy implications for regional green development.

1.2.3. Correlation between digital economy and GTFP

Current research indicates that there is a remarkable positive relationship between the digital economy and the GTFP, but further research on the influence mechanism is needed. At present, most relevant literature mainly studies at the national, provincial, industrial and regional levels, with little focus on smaller scales, which comprises cities and enterprises. The existing research results have shown a remarkable relationship between the digital economy and the GTFP. At the same time, a significant spatial correlation between the GTFP and the digital economy has also been found; that is, the vigorous development of the digital economy can not improve only the regional GTFP, but also the GTFP in neighborhood regions due to the spatial spillover effect [30]. Meng and Zhao took the embedded position of the global value chain as the threshold variable to find that, when the embedded position is low, there is a positive but insignificant relationship between the digital economy and GTFP; when the threshold is exceeded, the digital economy can significantly promote GTFP [31]. Due to the different economic foundations and natural endowments of different regions, obvious regional differences exist in terms of improving the GTFP via the digital economy. Taking China as an example, existing studies have proved that the development of the digital economy in central and eastern China can greatly improve local cities' GTFP, while the digital economy development in the western region has minimal ability to improve the local GTFP level [32]. The digital dividend released by eastern cities, major urban agglomeration cities and major cities can improve GTFP and promote urban green development more effectively [33]. There are relatively few studies on the mechanism of digital economy impact on GTFP. The main findings are that the digital economy can enhance the GTFP by instituting an industrial structure upgrade, capital allocation distortion, enhancing the green technology innovation capability and optimizing the embeddedness of the global value chain.

In addition, a lot of relevant research focuses on the correlation between the digital economy or a certain aspect of the digital economy and the green economy. For example, Ranta et al. [34] summarized the development experiences of four companies and found that digital technology can promote the flow and value creation in different businesses of different enterprises in different industries, catalyzing various business models of a circular economy. Wen et al. [35] proved that digital technology can significantly improve corporate environmental performance through technical and structural effects. Ballestar et al. [36] held that the application of digital technology has a long-term TFP promotion effect and labor substitution effect by performing an empirical study on the manufacturing industry.

Although there has been a lot of valuable research on the digital economy and the GTFP, the following two aspects still need to be improved. Firstly, the research on the digital economy is mainly qualitative, as quantitative studies are fewer and mainly at the national and provincial levels, with little studies at the urban level. Therefore, the existing research needs to fully reflect the different development levels of different cities in the same province. Second, the green value in the digital economy is rarely discussed. Most existing research focuses on how the digital economy can promote high-quality economic development through innovative development, green development, open development, coordinated development and shared development. The green value behind the digital economy needs to be deeply explored, as the GTFP is rarely studied through the green development characteristics of the digital economy. Currently, China is in a new phase of promoting high-quality economic development, so it is urgent to clarify the impact of digital economy development on GTFP, as well as the impact mechanism, so as to improve GTFP with the help of the digital economy and promote green development.

Therefore, this paper makes some marginal contributions to existing research from the following three aspects. 1) Unlike most of the existing relevant literature, which centers around the correlation between the digital economy and the GTFP from the macro-perspective, this work examines China's digital economy and the GTFP at the city level (taking 278 Chinese cities from 2011 to 2020 as samples). 2) This paper presents an indicator system that can be used to estimate the development level of China's urban digital economy from the perspectives of digital industries, digital innovation, digital users and digital platforms. Besides, the SBM-GML model has been adopted to measure the GTFP with a comprehensive consideration of undesirable outputs. 3) By introducing two moderating variables, i.e., industrial structure upgrade and environmental regulation, the mechanism of impact of the digital economy on the GTFP is explored.

2. Theoretical analysis and hypothesis

2.1. Promotional effect of the digital economy on GTFP

With the development of the new generation of the information technology revolution, the digital economy is becoming a new engine of economic and social development. The ecological modernization theory also holds that information technology can fundamentally improve the resource utilization efficiency in industrialization, promoting industrial civilization to ecological civilization.

The theoretical logic of the digital economy promoting the GTFP is mainly embodied in two aspects: industrial digitalization and digital industrialization. Firstly, the digital economy can promote GTFP through industrial digitalization. Since the digital economy takes data as a new production factor, through its intense penetration, the digital economy combines with agriculture, industry and the service industry to promote the digitalization of traditional industries, making full use of digital advantages to boost the factor allocation efficiency of traditional industries and eliminate unnecessary energy consumption in the production process. Meanwhile, the digital economy reshapes individual lifestyles, production, business models, industrial structures, and energy consumption and efficiency [37], which is conducive to cultivating new business forms and models, creating new values, driving all industries to realize intensive and efficient economic growth mode, and thus accelerating the GTFP growth. Secondly, the digital economy can improve GTFP via digital industrialization, including the digital product manufacturing industry, the digital product service industry, the digital technology application industry and the digital factor driving industry, providing digital technology, services, products, infrastructure and solutions for industrial digitalization. The digital economy can promote the GTFP by integrating digital technologies [38]. Taking the production mode as an example, digital technologies, like the Internet and 5G, can accomplish the information interaction between people and machines, provide the manufacturing industry with a green intelligent closed-loop channel, allow enterprises to realize the optimal control of machines in the production process and enhance the resource utilization efficiency [39]. On the other hand, enterprises can make use of the openness and sharing of digital platforms, which can not only promptly respond to market supply and demand changes and effectively bring down the information cost in the production process, but they can also reduce the resources waste caused by information asymmetry in energy utilization [40]. Therefore, this paper proposes the following research hypothesis: **H1: Digital economy development can improve GTFP.**

2.2. Heterogeneous effects of the digital economy on GTFP

China has a vast territory, and different areas have different resource endowments. Especially, after the reform and opening-up, the Chinese government has had different policy preferences for different regions and cities, leading to great differences in the levels of economic development, informatization development and human resources in various regions. Therefore, the digital economy development level in different regions also varies [41]; thus, the promotional effects of the digital economy on green total factor productivity also differ. Meanwhile, in the same region, heterogeneity exists in the development level of the digital economy between central and non-central cities [42]. The central city has a "siphoning effect" on various production factors of surrounding cities; thus, advanced technology, human resources and capital flow into the central city preferentially, further improving the digital economy of the central city. Therefore, we propose the following research hypothesis: **H2: The impact of the digital economy on the GTFP is heterogeneous in different regions and cities at different developing levels.**

2.3. Mechanism by which the digital economy improves the GTFP

The mechanism of the impact of the digital economy on GTFP is complex. Whether the digital economy can exert its due role in GTFP will be influenced and hindered by other factors. The industrial structure and environmental regulation are widely believed to alter the green benefits of the digital economy, so this work mainly explores the mechanism of the impact of the digital economy on GTFP from the two aspects of industrial structure and environmental regulation.

The industrial structure serves as an important connection among the environment, resources and economic development. An industrial structure upgrade enhances the promotional effect of the digital economy on the GTFP through the effect of resource allocation. The Petty-Clark theorem, which is a representative of the traditional school of the industrial structure, holds that, with economic development, the production factors, such as the labor force, will flow to high-efficiency sectors, and that these factors follow a development trend of first transferring from the primary industry to the secondary industry, and then to the tertiary industry. Therefore, industrial structure optimization will speed up the flow of factors, reset production factors and help the digital economy to connect all aspects of production and circulation. Further, the optimization of the industrial structure enables the rapid development of the digital industry itself, creating a more efficient new economic model and reducing the dependence on resources via integration with traditional industries. On the one hand, the optimization of industrial structure promotes the digitalization, rationalization and green economy development [43]; on the other hand, with the advanced industrial structure, the digital economy can better integrate traditional industries as well as elevate the intensive development of the industry. Empirical studies have proved that the application of big data analysis to the production process can improve the efficiency of resource utilization, reduce carbon emissions and reduce environmental pollution, thus promoting sustainable economic development [44]. The application of digital technology also greatly improves the productivity and value of the manufacturing of the middle section in the industrial chain, narrowing the value gap between the manufacturing and the R&D link as well as the marketing & service link. All links in the industrial chain constitute an interests community on the digital platform. The competitive relationship gradually shifts to a new competitive and cooperative relationship, which will upgrade the industrial value chain. In anticipation, it can help the digital economy to improve GTFP [45].

At present, there are few academic papers discussing the moderating role of environmental regulations in the correlation between the digital economy and GTFP, but relative research on the relationship between environmental regulation and GTFP is rich. The relationship between the two can be divided into promotional, inhibitory non-linear and inconsequential. The effect of environmental regulations on the relationship between the two varies in accordance with the differences in region, regulation type, industry type and stage. The Chinese government has, for a long time, played a crucial part in China's economic activities [46]. During the development of the digital economy, the Chinese government has been indirectly stimulating and guiding it through environmental regulation. Environmental regulation imposes mandatory requirements on production and living activities through different policy tools to achieve the purpose of environmental protection and green development. Enterprises are a significant carrier of the development of the digital economy, and their green innovation not only reflects corporate social responsibility, but it also promotes the development of digital technology [47]. Environmental regulations are applied to enterprises by means of collecting emission fees from non-compliant enterprises, granting subsidies to green and clean enterprises and ordering highly polluting enterprises to close down and rectify. First, environmental regulation has an "offsetting effect" on the productive investment and innovation activities of enterprises. The direct influence of environmental regulations on most enterprises is primarily reflected in the cost, and the impact on small enterprises will be greater than that on large enterprises. The pollution control costs paid by small enterprises to meet the environmental protection standards increase their production costs and occupy their production resources. Although environmental pollution is reduced, the improvement of GTFP is also inhibited [48,49]. Therefore, in the short term, environmental regulations can put pressure on firms to allocate resources and emission fees can crowd out firms' innovation funds, which adversely affects the further development of the digital economy. However, reasonable environmental regulations can motivate companies to carry out innovation activities and develop green innovative products [50], which may partially or entirely offset the cost increase caused by environmental regulation, or even generate net income and improve enterprise productivity [51]. Further, in terms of corporate environmental responsibility (CER), the impact of economic policy uncertainty has a less negative impact on the common stock returns of high-CER enterprises as compared with low-CER enterprises [52]. Since China is currently under the tremendous pressure of contractions in demand, supply shocks and weak expectations, the authors hold that environmental regulation has a negative moderating function in the digital economy's ability to improve GTFP in most Chinese cities. Therefore, we propose the following research hypotheses:

H3a: An industrial structure upgrade can strengthen the promotional effect of the digital economy on GTFP;

H3b: Environmental regulations inhibit the ability of the digital economy to improve GTFP.

3. Research design

3.1. Model specification

To verify H1, we constructed the following econometric model to reflect the impact of the digital economy on GTFP:

$$GTFP_{it} = \alpha_0 + \alpha_1 lnDEI_{it} + \alpha_2 Fina_{it} + \alpha_3 Hum_{it} + \alpha_4 Fdi_{it} + \alpha_5 Urban_{it} + \alpha_6 Gov_{it} + \alpha_7 Tran_{it} + \mu_{it} + \varepsilon_{it}, \quad (1)$$

where i represents a city, t stands for time (year) and $GTFP_{it}$ is the explained variable GTFP; $lnDEI_{it}$ is the core explanatory variable, I..e, the digital economy index; $Fina_{it}$ represents financial support; Hum_{it} stands for human capital; Fdi_{it} represents the degree of opening-up; $Urban_{it}$ is the level of urbanization; Gov_{it} represents the government intervention; $Tran_{it}$ stands for the level of infrastructure; α_0 is a constant term; μ_{it} is the unobserved regional effect; ε_{it} is the random error term.

Considering that GTFP has the feature of continuity in time, its growth and change process is a dynamic adjustment process; therefore, the one-period lag GTFP is added to Eq (1) for analysis, and the dynamic panel model is adopted. We construct the following dynamic panel model equation:

$$GTFP_{it} = \alpha_0 + \alpha_1 GTFP_{it-1} + \alpha_2 lnDEI_{it} + \alpha_3 Fina_{it} + \alpha_4 Hum_{it} + \alpha_5 Fdi_{it} + \alpha_6 Urban_{it} + \alpha_7 Gov_{it} + \alpha_8 Tran_{it} + \mu_{it} + \varepsilon_{it}, \quad (2)$$

In Eq (2), $GTFP_{it-1}$ is the one-period lag GTFP, and the meanings of other symbolic variables are the same as those in Eq (1). The GMM method mainly consists of the differential GMM (DIF-GMM) and the system GMM (SYS-GMM). The DIF-GMM has the defect of weak instruments, while the SYS-GMM can not only overcome the model bias caused by the traditional least square estimation method and fixed effects, but it can also solve the potential problem of weak instruments in the model. Based on the above considerations, the SYS-GMM is used to estimate the equation.

3.2. Indicator description

3.2.1. Measurement of GTFP

GTFP is the explained variable in this research. A production possibility set containing desirable and undesirable outputs is constructed, and the GML index of non-radial SBM directional distance is used to estimate the GTFP of 278 Chinese cities from 2011 to 2020, assuming constant returns to scale.

Each city is regarded as a production decision unit, and a production possibility set containing two kinds of outputs is constructed. Suppose that each city uses N inputs $x = x_1,\ldots,x_n \in R_N^+$, produces M desirable outputs $y = y_1,\ldots,y_m \notin R_M^+$ and produces I undesirable outputs $b =,\ldots,b_I \in R_I^+$.The input-output of a city $k(k = 1, \ldots, K)$ at a time $t(t = 1, \ldots, T)$ is (x^{kt}, y^{kt}, b^{kt}). The form of the constructed global production possibility set is as follows:

$$P^t(x^t) = \left\{ \begin{array}{c} (y^t, b^{t,}) \colon \sum_{k=1}^{K} Z_k^t\, y_{km}^t \geq y_{km}^t, \forall m; \sum_{k=1}^{K} Z_{ki}^t\, y_{ki}^t = b_{ki}^t, \sum_{k=1}^{K} Z_k^t\, y_{kn}^t \leq x_{kn}^t, \\ \forall n; \sum_{k=1}^{K} Z_k^t = 1; Z_k^t \geq 0\, , k = 1, \ldots, K \end{array} \right\}, \tag{3}$$

where Z_k^t represents the weight of each section; the weight sum is 1 and the weight constraint is positive, indicating that the return to scale is constant. The directional distance of SBM is as follows:

$$\overrightarrow{S_V^G}\left(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b\right) = \max_{s^x, s^y, s^b} \frac{\frac{1}{N} \sum_{n=1}^{N} \frac{S_n^x}{g_n^x} + \frac{1}{M+I}\left(\sum_{m=1}^{M} \frac{s_m^y}{g_m^y} + \sum_{i=1}^{I} \frac{s_i^b}{g_i^b}\right)}{2},$$

$$s.t. \sum_{k=1}^{K} Z_k^t\, x_{kn}^t + s_n^x = x_{k'n}^t, \forall n;$$

$$\sum_{k=1}^{K} Z_k^t\, y_{km}^t - s_m^y = y_{k'm}^t, \forall m;$$

$$\sum_{k=1}^{K} Z_k^t\, b_{ki}^t + s_i^b = b_{k'i}^t, \forall i;$$

$$\sum_{k=1}^{K} Z_k^t = 1; Z_k^t \geq 0, \forall k; s_n^x \geq 0, \forall n; s_m^y \geq 0, \forall m; s_i^b \geq 0, \forall i, \tag{4}$$

where $\left(x^{t,k'}, y^{t,k'}, b^{t,k'}\right)$ represents the input-output vector of city k', (g^x, g^y, g^b) represents the direction vector of the input-output and s_n^x, s_m^y, s_i^b is the slack vector of the input-output.

On the basis of the SBM directional distance function, combined with the GML index, we can calculate the GTFP, which can be expressed as

$$GTFP = \frac{1 + S_v^G(x^t, y^t, b^t; g)}{1 + S_v^G(x^{t+1}, y^{t+1}, b^{t+1}; g)}, \tag{5}$$

Specific measurement indicators are mainly divided into the input side and the output side, as presented in Table 1.

The input side mainly consists of three indicators. The first indicator is the labor input, measured by the year-end number of employees. The second indicator is the energy input. Traditionally, the consumption of coal or oil is used as the indicator for measuring GTFP. Considering the data availability at the city level in China and the comprehensiveness of statistics, we used urban electricity consumption as the indicator [53]. The third is capital input. The measurement indicator is the capital stock. The perpetual inventory method of Zhang et al. was used to calculate the urban fixed capital stock [54]. The calculation formula is $K_t = K_{t-1}(1 + \delta_t) + I_t$, where t represents a certain year; K represents the capital stock; K_t represents the capital stock of a certain year, and K_{t-1} represents the capital stock of the previous year; I_t stands for the investment in fixed assets in a certain year, and δ_t represents the depreciation rate of the same year. In this study, the fixed value is 9.6%. In parallel, the initial capital stock is measured by dividing the actual total investment in fixed assets in 2003 by 10%.

Table 1. Measurement indicators of the urban GTFP development level in China.

Level I indicators	Level II indicators	Level III indicators
Output indicators	Desirable output	Urban real GDP
	Undesirable output	Total sewage discharge
		Industrial soot emissions
		Industrial sulfur dioxide emissions
Input indicators	Capital input	Capital stock
	Energy input	Total electricity consumption
	Labor input	The year-end number of employees

The output side includes positive desirable output and negative undesirable output. The real Gross Domestic Product (GDP) of each city (10,000 yuan) is used to represent the desirable output. The total amount of urban sewage discharge, industrial soot emissions and industrial sulfur dioxide emissions were selected to reflect the undesirable output. Considering that it is difficult to apply single emission datasets to measure the undesirable output comprehensively, we adopted the entropy method to build a synthetic index of pollution discharge with the above three indicators.

3.2.2. Digital economy measurement

The digital economy index is the key explanatory variable of this model. By referring to the relevant research findings of Ma and Li [55], we comprehensively evaluated the urban digital economy development level from four different perspectives: digital industries, digital innovations, digital users and digital platforms; then, we calculated the weights of indicators at all levels by using the grey-target entropy weight method, finally forming the digital economy index. The specific digital economy indicators are in Table 2.

The grey-target entropy weight method was formed by combining the grey-target decision-making method and the entropy weight method. First, we set a grey target without a standard model and found the bullseye in the grey target; then, we determined the weight of the bullseye's coefficient by introducing the entropy weight method to avoid the single weighting problem in the conventional grey target theory, making the index weight more objective and the digital economic index of each city more persuasive. The specific calculation steps of this method are presented below.

The first step is to establish the urban digital economy influence space, that is, to determine the evaluation objects and indicators. The evaluation objects in this model are 278 prefecture-level cities in China, and the evaluation indicators are those shown in Table 2.

The second step is to establish the urban digital economy indicator sequence. That is, the data sequence of the evaluated object and the selected evaluation indicator is obtained and arranged in chronological order $(t_1, t_{2,} \dots t_n)$. For example, sorting the original data of the urban digital economy $x_{ij}(t|k)$ to form an indicator sequence from 2011 to 2020.

Step 3 is to establish the standard model of the urban digital economy indicator sequence. The indicators to measure the urban digital economy are all positive ones, and the greater the expectation, the better. So, the indicators in this study have maximum polarity. Therefore, the maximum value of each indicator sequence was selected as the standard sequence, that is, the maximum value of each indicator sequence was taken as the bullseye. See Eq (6) for details.

$$x_{0j} = max_{1\le i\le m} max_{t_1\le t_k\le t_N}\{x_{ij}(t_k)\}, \tag{6}$$

Fourth, the indicator sequence of each city is converted into a grey target. The indicator sequence in Step 2 is compared with the standard mode sequence in Step 3 to obtain the polarity-converted mode sequence, as shown in Eq (7).

$$T\left(x_{ij}(t_k)\right) = \frac{min\{x_{ij}(t_k), x_{0j}\}}{max\{x_{ij}(t_k), x_{0j}\}}, \tag{7}$$

The fifth step is to establish the grey relation diverse information space. That is, the diverse information between the corresponding elements of the grey-target converted mode sequence and the standard mode sequence is calculated, denoted as $\Delta_{ij}(t_k)$, as shown in Eq (8).

$$\Delta_{ij}(t_k) = \left|T(x_{0j}) - T\left(x_{ij}(t_k)\right)\right| = \left|1 - T\left(x_{ij}(t_k)\right)\right|, \tag{8}$$

The sixth step is to calculate the bullseye coefficient of each city. That is, the bullseye coefficient of each city can be calculated by combining the diverse information measured in the fifth step with the resolution coefficient ρ, as shown in Eq (9). It is generally believed that, when $\rho = 0.5$, the resolution effect and stability are better [56]. Therefore, we adopted $\rho = 0.5$.

$$\gamma\left(\mathrm{x_{0j}}(t_k), \mathrm{x_{ij}}(t_k)\right) = \frac{\Delta_{min} + \rho\Delta_{max}}{\Delta_{0i}(t_k) + \rho\Delta_{max}}, \tag{9}$$

Seventh, we calculate the bullseye of each city. The entropy approach is employed to measure the indicator weights at all levels, which is used as the weight of the bullseye coefficient of different indicators for each city, denoted by ω_j; this replaces the weighting method in the conventional grey target decision-making model. Finally, by weighting the bullseye coefficient of each indicator of a city, the bullseye degree of each city is finally formed to estimate the city's digital economy development level.

$$\gamma(\mathrm{x_0}, \mathrm{x_i})(t_k) = \sum_{j=1}^{n} \omega_j \gamma\left(\mathrm{x_{0j}}(t_k), \mathrm{x_{ij}}(t_k)\right), \tag{10}$$

In Eqs (6)–(10), i represents the city; j is the evaluation indicator in the indicator system of the urban digital economy and t_k stands for the year. Through the above steps, the weights of indicators at all levels of the urban digital economy index are finally calculated as presented in Table 2.

Table 2. Indicator system of the development level of the urban digital economy.

Level I indicator	Level II indicators	Level III indicators	Weight
Development level of the urban digital economy	Digital industries	Number of employers in information transmission, computer services and software industries	10.19%
		Total retail sales of social consumer goods	3.59%
		Market value of listed digital economy enterprises	18.85%
	Digital innovations	Number of patent applications	2.94%
		Number of patents authorized	4.63%
		R&D funds	4.58%
	Digital users	Mobile phone penetration rate	11.37%
		Internet penetration rate	9.76%
		Total telecommunications services per capita	9.67%
	Digital platforms	Number of listed digital economy enterprises	14.00%
		Policy support for digital finance	4.03%
		The Internet comprehensive development index	6.38%

The results in Table 2 show that, among all of the level 3 indicators in the indicator system, the market value of listed digital economy enterprises has the largest weight, i.e., 18.85%, whereas the weight of the number of patent applications is the smallest, i.e., 2.94%.

3.2.3. Measurement of moderating variables

1) Measurement of the industrial structure upgrade

The evolutional direction of the three-industry structure is that the proportion of the primary industry continues to decline, the proportion of the secondary industry increases first and then decreases and the proportion of the tertiary industry continues to grow. However, in many empirical studies, the industrial structure is simplified into the relative proportion of the secondary industry and the tertiary industry, or the relative proportion of agriculture and non-agriculture. Such a pair-to-pair comparison makes it easy to ignore an industry and cannot reflect the improvement degree of the industrial structure. We followed Fu [57] to adopt the three-dimensional vector angle of the spatial analytic geometry to calculate the industrial structure upgrade. The proportion of each industry in the regional GDP of the three industries is taken as a component of the spatial vector so as to constitute a set of three-dimensional vectors: $X_0 = x_{1,0}, x_{2,0}, x_{3,0}$. Then, the angle between the vector X_0 and the standard vectors $X_1(1,0,0), X_2(0,1,0), X_3(0,0,1)$, i.e., the industrial structure vectors arranged from low to high, can be calculated respectively. The advantage of this method is that it can integrate the three industries into a spatial coordinate system; a change of the proportion of any industrial sector will induce changes in the other two sectors, which can reflect a dynamic change of the industrial structure. The angle θ_j between the three-dimensional industry vector and the standard vectors is calculated with the following formula:

$$\theta_j = arcos\left[\frac{\sum_{i=1}^{3}\left(x_{i,j} \cdot x_{i,0}\right)}{\sum_{i=1}^{3}(x_{i,j}^2)^{\frac{1}{2}} \cdot \sum_{i=1}^{3}(x_{i,0}^2)^{\frac{1}{2}}}\right], \tag{11}$$

Thus, the calculation formula for the industrial structure upgrade can be expressed as follows:

$$His = \sum_{k=1}^{3}\sum_{j=1}^{k}\theta_j = 3\theta_1 + 2\theta_2 + \theta_3. \tag{12}$$

2) Measurement of environmental regulation

Environmental regulation is a major way for the Chinese government to promote green economic development. The government regulates through direct and indirect means, such as directly promulgating rules and regulations or indirectly regulating pollution emission enterprises by charging fees, establishing emission rights and implementing a carbon emission trading system.

At present, the environmental regulation intensity is mainly measured indirectly by means of pollution cost control, pollution emission or comprehensive measurement combined with the two methods. In this work, China's urban environmental regulation index was obtained by examining and summarizing the annual work reports of the Chinese government. First of all, we selected keywords like "green development", "new energy", "environmental protection", "haze", "haze control", "pollution", "pollution control", "energy consumption", "emission reduction", "pollution discharge", "ecological environment", "ecological damage", "ecological protection", "water ecology", "low carbon", "carbon dioxide", "sulfur dioxide", "PM10", "PM2.5", "chemical oxygen demand", "COD", "scattered pollution", "discharge", "air", "water environment", "water safety", "water quality", "clear water", "black odor", "sewage", "waste gas", "waste residue", "environmental violation", "environmental case", "environmental crime", "environmental treatment", "environmental punishment", "environmental quality", "coal combustion", "blue sky", "greening", "dust", "tail gas" and "VOCs" related to environmental laws and regulations. Then, all sentences in the local government reports that contain those keywords were taken as "environment-related sentences". Finally, the environmental regulation index was calculated [58].

$$\begin{aligned} &The\ environmental\ regulation\ index \\ &= \frac{the\ total\ number\ of\ words\ in\ the\ \text{“}environment-related\ sentences\text{”}}{the\ total\ number\ of\ words\ in\ the\ work\ report} \end{aligned}$$

3.2.4. Selection of control variables

GTFP is affected by various factors. Based on the existing studies, the following variables were chosen as the control variables in this model. 1) Financial development level (fina), represented by the ratio of the year-end balance of deposits and loans of financial institutions to the GDP of the whole city. 2) Human capital level (hum). It is calculated with the ratio of the number of people with general college or above degrees in the city to the city's permanent resident population. 3) Opening-up level (fdi). It is calculated by using the ratio of the actual amount of foreign capital utilized in the current year (converted by the average exchange rate of RMB in the current year) to the GDP of the whole city. 4) Urbanization level (urban), which is depicted as the ratio of the population of the whole city to the administrative land area. 5) Government intervention (gov), which is represented by the ratio of the fiscal expenditure of a city's government to the city's GDP. 6) Transportation (tran). It is expressed by using the ratio of urban road area to the population of the whole city.

3.3. Data source and description

The data used in this research are the panel data of 278 Chinese cities from 2011 to 2020. The data were mainly taken from Chinese urban statistical yearbooks, Chinese urban construction statistical yearbooks, statistical yearbooks of provinces and cities, statistical bulletins and government work reports of each city, the China Research Database Services database, and the Economy Prediction

System database. This study deals with the samples in the following aspects. First, cities with serious data missing were excluded. Second, a linear method was employed to supplement the missing data, and the method of cumulative probability distribution has been used to deal with the relevant outliers. Finally, the descriptive statistics of all variables are presented in Table 3. There are basically no outliers for the main variable; also, the deviations of the mean and maximum values of some control variables are slightly larger but satisfy the basic requirements for the empirical evidence.

Table 3. Descriptive statistics.

Variable	(1) N	(2) mean	(3) sd	(4) min	(5) max
gtfp	2780	1.001	0.0481	0.511	1.897
lndei	2780	4.615	0.0424	4.605	5.548
fina	2780	2.469	1.169	0.588	12.51
hum	2780	1.783	2.020	0.00516	12.76
fdi	2780	0.0188	0.0272	0	0.775
urban	2780	0.0483	0.0579	0.000567	0.883
gov	2780	0.199	0.0978	0.013186	0.916
tran	2780	4.722	4.072	0.248	53.89

4. Empirical results

4.1. Analysis on benchmark regression results

This section discusses the dynamic panel model, as expressed in Eq (2), which can reflect the dynamic characteristics of the GTFP. To further eliminate interference from heteroscedastic factors, we also used robust modified Z-statistics in the regression analysis. The Hansen test results and the AR (2) results reported in Table 4 show that the SYS-GMM is effective. Therefore, the instrument variables set in the model are effective, and endogenous problems can be controlled to a certain extent.

As shown in Table 4 of the regression results, the digital economy affects the GTFP significantly and the regression coefficients are all positive, indicating that the core explanatory variable digital economy can greatly promote GTFP. In other words, the digital economy can not only improve production efficiency and promote economic growth, but it also plays a part in low-carbon environmental protection and pollution reduction. It can be a new engine for economic growth in harmony between humanity and nature. From the perspective of control variables, the human capital coefficient is significant and positive at the 1% level, indicating that, where the human capital level is high, there are more knowledgeable talents and the increase of human capital will crowd out the energy input, changing the technical level to improve efficiency and reduce pollution emissions. What's more, human capital can help to enhance people's environmental awareness and thus improve the urban environment. The urbanization level coefficient is positive and significant at the 1% level, showing that the improvement of urbanization level also has a positive promotional effect on GTFP. The urbanization level improves urban production efficiency through the agglomeration of positive externalities of economic production activities and innovation compensation effect. If the population is dispersed and the agglomeration is reduced, the positive effect on GTFP will be offset [59]. The government intervention coefficient is negative and significant at the 10% level, showing that the higher the degree of government intervention, the more suppressive the effect on GTFP. This is because government intervention will distort the leading role of the market in resource allocation, resulting in resource mismatch and low production efficiency.

Table 4. Regression results for evaluating digital economy influence on GTFP.

Variable	SYS-GMM gtfp	SYS-GMM gtfp
L.gtfp	-0.144**	-0.145
	(0.064)	(0.106)
lndei	0.087***	0.064***
	(0.025)	(0.012)
fina		-0.000
		(0.000)
hum		0.001***
		(0.000)
fdi		-0.045
		(0.046)
urban		0.030***
		(0.011)
gov		-0.016*
		(0.009)
tran		0.000
		(0.000)
Constant	0.743***	0.852***
	(0.110)	(0.109)
Individual effect	YES	YES
Time effect	YES	YES
Control variable	NO	YES
AR1	-2.959	-2.436
	(0.00309)	(0.0149)
AR2	-0.116	-0.103
	(0.908)	(0.918)
Hansen	3.180	0.563
	(0.204)	(0.905)
N	2502	2502

Note: *, ** and *** represent the significance levels of 10%, 5% and 1%, respectively; the values in the brackets of AR2 and Hansen tests are P values; the values in other brackets are robust Z-statistics.

It should be noted that the one-period lag GTFP was found to be negative, which is significant when no control variables are added, indicating that the growth of GTFP was in a fluctuating state. In other words, the faster the growth rate of a green economy in the previous period, the lower the growth rate during the current period, while the growth rate of the green economy in the next period will increase [60]. This is similar to the characteristics of China's environmental regulation, which is "relaxing this year and tightening the next year". Therefore, the negative coefficient may be due to discontinuing environmental regulations. The following subsection will further analyze the ability of environmental regulation to influence the digital economy and improve the GTFP.

4.2. Robustness test

To guarantee the reliability of the results of this work, four different methods were adopted to test the robustness of the benchmark regression results, as presented in Table 5.

Table 5. Robustness test results.

Variable	(1) gtfp	(2) gtfp	(3) gtfp	(4) gtfp
L.gtfp	-0.148**	-0.137**	-0.141***	
	(0.065)	(0.067)	(0.053)	
newdei	0.065***			
	(0.010)			
lndei		0.178***	0.210***	0.060***
		(0.047)	(0.050)	(0.020)
Constant	0.000	0.000	0.177	0.723***
	(0.000)	(0.000)	(0.243)	(0.110)
Individual effect	YES	YES	YES	NO
Time effect	YES	YES	YES	NO
Control variable	YES	YES	YES	YES
Number of code	278	274	278	278
AR1	-2.511	-2.468	-5.858	
AR2	-0.163	-0.127	0.222	
Hansen	2.243	1.989	4.796	
R-squared				0.012
wald				25.90
N	2502	2466	2502	2780

Note: *, ** and *** represent the significance levels of 10%, 5% and 1%, respectively; the values in the brackets of AR2 and Hansen tests are P values; the value in other brackets are robust Z-statistics.

4.2.1. Changing the indicators of the explanatory variable

The digital economy index used in this model was constructed by using indicators focusing on the four aspects of digital industries, digital innovations, digital users and digital platforms, reflecting the multiple impacts of digital economy on economic life. By considering the robustness of regression, we referred to the idea of Zhao et al. to use the entropy weight method to calculate the digital economy development level from the aspects of Internet development and digital financial inclusion [42]. The regression results are reported in Column (1) of Table 5. Clearly, the digital economy development can still significantly contribute to the GTFP's improvement. The research findings of this work are robust.

4.2.2. Eliminating the influence of municipalities

Considering that municipalities directly under the central government are provincial administrative units in China, and they are significantly superior to other ordinary prefecture-level cities in terms of economy, politics, population, science and technology; a big difference may exist between the digital economy development level in municipalities and that in other prefecture-level cities. Therefore, samples from municipalities directly under the central government were excluded to eliminate the impact of such special administrative status on the results; and, an empirical test was conducted again to ensure the reliability of the regression conclusions. The regression results are presented in Column (2) of Table 5. After removing the samples of municipalities, the regression results of the digital economy on GTFP were still positive and significant, showing that the research conclusion is robust.

4.2.3. Removing the impact of extreme values

Considering that the results of empirical regression will be affected by extreme values and outliers, we applied winsorizing and trimming to the 1% of regression samples with the highest and lowest levels of GTFP and digital economy. Column (3) of Table 5 displays the regression results. We can see that the digital economy still promotes urban GTFP significantly. Thus, the research conclusion is robust.

4.2.4. Changing the estimation method

In Column (4) of Table 5, the estimation method was replaced; that is, the panel-corrected standard error approach was adopted to solve the estimation error induced by the inter-group heteroscedasticity and intra-group auto-correlation. The results are still significant, as they show that the digital economy significantly improves GTFP; so, the research conclusion is proven to be robust.

4.3. Mechanism analysis

Table 6. Moderating effect test results.

Variable	DIF-GMM gtfp	SYS-GMM gtfp	DIF-GMM gtfp	SYS-GMM gtfp
L.gtfp	-0.119***	-0.095***	-0.168**	-0.100**
	(0.040)	(0.033)	(0.065)	(0.050)
lndei	0.221***	0.236***	0.255***	2.738**
	(0.028)	(0.010)	(0.014)	(1.324)
lndei*ins	0.241***	0.216***		
	(0.074)	(0.051)		
ins	-1.087***	-0.991***		
	(0.337)	(0.233)		
lndei*envir			-0.055***	-0.399**
			(0.009)	(0.202)
envir			0.253***	1.841**
			(0.042)	(0.933)
Constant	0.000	0.000	0.000	-11.547*
	(0.000)	(0.000)	(0.000)	(6.089)
Individual effect	YES	YES	YES	YES
Time effect	YES	YES	YES	YES
Control variable	YES	YES	YES	YES
Number of codes	278	278	278	278
AR1	-2.436	-2.959	-2.705	-2.768
AR2	0.682	1.053	-0.604	-0.434
N	2502	2502	2502	2502

Note: *, ** and *** represent the significance levels of 10%, 5% and 1%, respectively; the values in the brackets of the AR2 test are P values; the values in other brackets are robust Z-statistics.

The previous sub-section has analyzed the direct influence of the digital economy on GTFP. However, theoretically speaking, it is not a simple and straightforward process regarding the digital economy in promoting the GTFP, and this promotion needs to be realized through some path. Thus the specific mechanism by which the digital economy affects the GTFP needs to be analyzed. Based on research hypotheses, we respectively tested the moderating effects of industrial structure upgrade and environmental regulation to explore the aforementioned mechanism. The results can be found in Table 6.

4.3.1. Analysis of the moderating effect of industrial structure upgrade

1) Model setting

In order to further study whether the impact of the digital economy on the GTFP is affected by an upgrade of the industrial structure, based on H2a, we added the industrial structure upgrade variable and its interaction with the digital economy variable on the basis of Model (2) to evaluate the possible effect of how an industrial structure upgrade can impact the digital economy's influence GTFP. The model set is shown in Eqs (13) and (14).

$$GTFP_{it} = \alpha_0 + \alpha_1 GTFP_{it-1} + \alpha_2 lnDEI_{it} + \beta ins_{it} + \alpha_3 Fina_{it} + \alpha_4 Hum_{it} + \alpha_5 Fdit_{it} + \alpha_6 Urban_{it} + \alpha_7 Gov_{it} + \alpha_8 Tran_{it} + \mu_{it} + \varepsilon_{it}, \tag{13}$$

$$GTFP_{it} = \alpha_0 + \alpha_1 GTFP_{it-1} + \alpha_2 lnDEI_{it} + \beta ins_{it} + \gamma \times lnDEI_{it} \times ins_{it} + \alpha_3 Fina_{it} + \alpha_4 Hum_{it} + \alpha_5 Fdit_{it} + \alpha_6 Urban_{it} + \alpha_7 Gov_{it} + \alpha_8 Tran_{it} + \mu_{it} + \varepsilon_{it}, \tag{14}$$

2) Analysis of the empirical results

The final empirical results of Model (13) are displayed in Columns (1) and (2) of Table 6, where the DIF-GMM and the SYS-GMM were used, respectively. Clearly, the regression coefficients for the GTFP and the interaction term for the digital economy and the industrial structure upgrade were significant at the 1% significance level; and, the signs of the regression coefficients were positive, indicating that an industrial structure upgrade exerts an obvious and positive effect on the digital economy's ability to improve the GTFP. That is to say, the higher the industrial structure upgrade degree, the more the digital economy is able to improve the GTFP. It should be additionally noted that, when the main effect is consistent with the coefficient of the cross-product term, the positive or negative coefficient of the moderating variable does not affect the explanation. Moderating variables will act as a part of the control variable. Therefore, the negative coefficient of industrial structural advancement in the empirical results did not affect the ability of industrial advancement to increase GTFP in the digital economy.

The digital economy accelerates its involvement in various fields of society through digital technology, driving the digitalization of industry; this improves the efficiency and utilization of resource allocation and reduces the waste of production resources and pollution emissions. In addition, the development of the digital economy itself provides conditions for the upgrade of the industrial structure. In the era the of the digital economy, the sharing of information decreases the cost of information asymmetry between enterprises and consumers, making the allocation of technology, human resources and capital more efficient. For example, under the new economic model, the digital economy has provided consumers with more consumption possibilities with the accurate analysis of big data, providing consumers with more accurate products and services. Meanwhile, the digital economy also urges enterprises to continue product innovation, improve product added value, extend the value chain and promote the industrial structure upgrade so as to better meet consumer demand and win the market. An upgrade of the industrial structure improves the efficiency in the process of resource allocation, which further reduces the ecological damage in the process of economic development and improves GTFP.

4.3.2. Analysis of the moderating effect of environmental regulations

1) Model settings

The one-period lag GTFP was found to be significantly negative from the regression results for the digital economy and the GTFP. In order to further explore the reasons for the large fluctuation of GTFP in the study period, based on H2b, we added the environmental regulation variable and its interaction with the digital economy variable based on Model (2) to evaluate the possible effect of environmental regulation on the mechanism by which the digital economy improves GTFP. The model settings are shown in Eqs (15) and (16).

$$GTFP_{it} = \alpha_0 + \alpha_1 GTFP_{it-1} + \alpha_2 lnDEI_{it} + \beta envir_{it} + \alpha_3 Fina_{it} + \alpha_4 Hum_{it} + \alpha_5 Fdit_{it} + \alpha_6 Urban_{it} + \alpha_7 Gov_{it} + \alpha_8 Tran_{it} + \mu_{it} + \varepsilon_{it}, \tag{15}$$

$$GTFP_{it} = \alpha_0 + \alpha_1 GTFP_{it-1} + \alpha_2 lnDEI_{it} + \beta envir_{it} + \gamma \times lnDEI_{it} \times envir_{it} + \alpha_3 Fina_{it} + \alpha_4 Hum_{it} + \alpha_5 Fdit_{it} + \alpha_6 Urban_{it} + \alpha_7 Gov_{it} + \alpha_8 Tran_{it} + \mu_{it} + \varepsilon_{it}, \tag{16}$$

2) Empirical results analysis

Columns (3) and (4) of Table 6 presented the final empirical results of Model (16), where the DIF-GMM and the SYS-GMM were respectively applied. The regression coefficients for the GTFP and the interaction between the digital economy and environmental regulation are significant at levels of 1% and 5%, respectively, but the regression coefficient signs are negative, indicating that environmental regulations have a significant negative effect on the ability of the digital economy to improve the GTFP. That is to say, the more stringent the environmental regulations, the less effective the digital economy will be in raising GTFP.

Environmental regulation mainly reduces the intensity of pollution discharge through governmental administrative orders. Currently, its impact on the economy tends to be the “compliance cost” effect, which will increase the cost of enterprise pollution discharge and governance and consume production resources; thus, it is not conducive to the improvement of the GTFP at the present stage. That is to say, China is now experiencing a painful period of economic restructuring, and economic development and environmental improvement cannot be achieved simultaneously. However, under the long-term implementation of environmental protection policies, enterprises with high productivity will adopt higher technology levels to adapt to new environmental regulations, such as improving the technology of the production process so as to save pollution reduction costs and improve GTFP. Moreover, because GTFP contains the characteristics of green technology progress, it can offset the cost of enterprise pollution control while reducing the intensity of pollution emissions, ultimately achieving a win-win situation of economic development and environmental governance improvement.

4.4. Analysis on heterogeneity

Due to differences in natural and geographical conditions, resource endowments and economic foundation, great differences exist in the levels of economic and social development among various regions in China, and the phenomenon of unbalanced and inadequate development exists. To further explore the heterogeneous impact of the digital economy in terms of its ability to improve the GTFP, we investigated the mechanism by which the digital economy promotes urban GTFP from two aspects: regional heterogeneity and city-hierarchy heterogeneity. Table 7 presents the results.

Table 7. Heterogeneity test results.

Variable	(1) Eastern China gtfp	(2) Central China gtfp	(3) Western China gtfp	(4) Central City gtfp	(5) Non-central city gtfp
L.gtfp	0.004	-0.113*	0.066	-0.349***	-0.089
	(0.034)	(0.065)	(0.059)	(0.043)	(0.072)
lndei	0.048***	0.265**	0.535	0.065***	0.163***
	(0.006)	(0.105)	(0.371)	(0.017)	(0.057)
Constant	0.773***	-0.109	-1.529	1.099***	0.342
	(0.032)	(0.459)	(1.688)	(0.083)	(0.278)
Individual effect	YES	YES	YES	YES	YES
Time effect	YES	YES	YES	YES	YES
Control variable	YES	YES	YES	YES	YES
AR1	-1.651	-2.572	-1.924	-1.655	-2.218
	(0.0987)	(0.0101)	(0.0543)	(0.0979)	(0.0266)
AR2	1.417	-0.374	0.943	-1.069	-0.526
	(0.157)	(0.708)	(0.346)	(0.285)	(0.599)
Hansen	6.042	5.026	1.230	1.810	0.897
	(0.418)	(0.170)	(0.706)	(0.613)	(0.826)
N	900	891	711	315	2187

Note: *, ** and *** represent the significance levels of 10%, 5% and 1%, respectively; the values in the brackets of AR2 and Hansen tests are P values; the values in other brackets are robust Z-statistics.

4.4.1. Regional heterogeneity

In terms of regional heterogeneity, we performed a grouping regression of Chinese cities according to the division of eastern China, Central China and western China, with reference to the China Statistical Yearbook. Guangdong Province, Fujian Province, Zhejiang Province, Jiangsu Province, Shandong Province, Shanghai Municipality, Beijing Municipality, Tianjin Municipality, Hebei Province, Liaoning Province and Hainan Province are all eastern regions, with 99 cities selected. The central region comprises Hubei Province, Hunan Province, Henan Province, Anhui Province, Jiangxi Province, Shanxi Province, Jilin Province and Heilongjiang Province, and 100 cities were selected. In the western region, 79 cities were selected from Xinjiang Uygur Autonomous Region, Qinghai Province, Gansu Province, Ningxia Hui Autonomous Region, Yunnan Province, Guizhou Province, Sichuan Province, Shaanxi Province, Chongqing Municipality, Guangxi Zhuang Autonomous Region and Inner Mongolia Autonomous Region. The regression results are presented in Columns (1)–(3) of Table 7, which show that the digital economy can significantly improve the GTFP in eastern and central cities, but, for the cities in eastern China with relatively higher levels of digital economy development, the promotional effect was stronger and the regression result was more significant, while those of the western region were not significant. That is to say, the development of the digital economy in western China has little to do in the GTFP improvement.

Distinct heterogeneity exists between eastern and western China in terms of the improvement of the GTFP by the digital economy; the possible reasons are presented below. First of all, as the carrier of the digital economy, the digital industries in the central and eastern China are stronger than those in western China in terms of scientific and technological innovation capacity, and the digital technology application level is also higher than that in western China. Second, in terms of industrial digitalization, the central and eastern regions enjoy more dividends of the digital economy than the western region due to the earlier development of the digital economy and higher industrial intensity. However, the western region has a relatively weak economic foundation, and the "digital divide" may lead to an increasingly obvious difference between the western China and the central and eastern China.

4.4.2. City-hierarchy heterogeneity

Since great differences exist in resource endowment, there are different business attractiveness levels of cities, innovation capabilities and development stages of Chinese cities at different levels; thus, the impact of the digital economy on the GTFP must be heterogeneous in terms of the city hierarchy [61]. Based on the method of Zhao et al., we also divided municipalities, sub-provincial cities and provincial capitals into the group of central cities, and other cities into the group of peripheral cities [42]. According to the results in Columns (4) and (5) of Table 7, the influence of the digital economy on the GTFP in central cities and non-central cities has passed the 1% significance level, indicating that the digital economy has a positive promotional effect on GTFP improvement for both central cities and non-central cities. The empirical results indicate that the digital economy plays a more prominent role in improving the GTFP of non-central cities. When the digital economy level increases by 1%, the GTFP of central cities will increase by 0.017%, while that of non-central cities can increase by 0.057%, more than that of the central cities.

Compared to central cities, the digital economy development level in non-central cities is lower and the digital economy foundation is relatively weak, so the development space is broader. At present, they are in a period of rapid growth. Therefore, the digital economy has a larger marginal role in improving the production efficiency, promoting the industrial structure upgrade and improving the ecological environment in non-central cities. The digital economy in non-central cities can play a greater role in promoting GTFP.

5. Conclusions and policy implications

On the basis of the panel data of 278 cities at the prefecture level and above in China from 2011 to 2020, we established a GMM dynamic panel model to test the digital economy's impact on the GTFP; we then studied the mechanism by which the digital economy affects the GTFP, as well as the heterogeneity caused by the development imbalance in different regions of China. Following conclusions have been drawn.

First, at the urban level, the digital economy development will significantly improve the GTFP and turn into a significant power source to accelerate the high-quality development of economy. This conclusion was still valid after a series of robustness tests.

Second, an industrial structure upgrade plays a positive moderating role in the mechanism by which the digital economy improves the GTFP.

Third, the growth of GTFP is volatile, and it is related to the negative moderating effect of environmental regulations on the improvement of GTFP in the digital economy.

Fourth, among different regions of China, heterogeneity exists in the effects of the digital economy on green total factor productivity. This heterogeneity is caused by imbalances in China's long-term development process, which has led to different economic foundations in different regions. At the city-level, the digital economy is not heterogeneous for GTFP. The digital economy significantly increases GTFP in both central and non-central cities. Even the function of the digital economy in non-central cities in improving the GTFP is greater than that in central cities. This is because the digital economy in non-central cities has been in a rapid growth stage in the past 10 years, so its marginal role is greater than that of central cities.

On the basis of the research findings, we put forward the following policy implications. Firstly, it is necessary for the government to focus on promoting the R&D and the application of key digital technologies such as cloud computing, big data and artificial intelligence. The digital infrastructure conditions in all regions, especially those in western China, should be upgraded and improved to fully release the dividends of the development of the digital economy so that the positive role of the digital economy in technological progress and efficiency improvement can be optimized to improve the GTFP [62]. Second, the government should constantly optimize the urban industrial structure by developing new digital industries. With the help of digital technology, the digital economy can improve the productivity of traditional industries and reduce pollution emissions. Moreover, governments at all levels should coordinate the contradictory relations and formulate reasonable environmental regulations. The governments should take into account the negative effects of environmental regulations so as to avoid the loss of production efficiency caused by the of environmental governance effects. Finally, an overall strategic reflection must be established to promote the coordinated development of the digital economy among cities [63]. The central and eastern China cities need to focus more on the digital economy and combine it with the industrial structure to promote economic transformation and upgrade. Western cities can still take full advantage of the productivity gains from scale expansion. For central and non-central cities, they should continue to maximize the green function of the digital economy and continue to explore new dynamics of economic growth while pursuing development.

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Conflict of interest

The authors declare that there is no conflict of interest.

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