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The Impact of the Digital Economy on the Urban Total-Factor Energy Efficiency: Evidence from 275 Cities in China

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Abstract: The widespread application of new-generation information technology, such as big data and artificial intelligence, has promoted the development of economic and technological transformation and the deep integration of digital and real economies. The digital economy is an essential force of China in the new era and it is promoting China's economic development in a high-quality way. In this study, we theoretically describe the mechanism of the digital economy that affects total-factor energy efficiency and empirically analyze the impact of digital economy development on total-factor energy efficiency using data from 275 cities at the prefecture level and above in China from 2011 to 2019. We found that the digital economy has significantly improved total-factor energy efficiency. We used instrumental variable estimation and the replacement of explanatory variables to test the robustness of our results, finding that our conclusions were valid. Technological innovation, industrial structure optimization, and resource misallocation improvement are the channels through which the digital economy affects total-factor energy efficiency. Resource misallocation at the city level as the intermediary variable was this paper's research gap. Further research showed that the improvement effect of the total-factor energy efficiency in eastern regions and megacities was more evident under the influence of the digital economy. All regions in China should combine their resource endowments to further release the dividends of the digital economy, enabling it to best promote total-factor energy efficiency. The relevant departments of the government should also stimulate market demand and promote the deep integration and balanced development of the digital economy and energy industry in low-energy-efficiency cities.

Keywords: digital economy; total-factor energy efficiency; industrial structure; resource misallocation

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1. Introduction

As an essential input factor of production and life, energy is a significant driving force for economic development (Tang and He, 2021) [1]. However, energy promotes economic growth, and brings severe environmental problems. Energy consumption generates many atmospheric pollutants, such as carbon dioxide and particulate matter, leading to ecology and public health problems, such as climate change, environmental pollution, and unfavorable external health factors (Hosseini-Fashami et al., 2019) [2]. The share of coal consumption in China's energy consumption structure has consistently remained above 60%, while low-carbon environmental protection of new energy accounts for a relatively low share (Yu, 2021) [3]. China's coal resources have advantages in terms of reserves and prices; therefore, the coal-based energy structure will not change long-term (Yu and Shen, 2020) [4]. Because China is the world's largest energy-consumer and carbon-emitter, low energy efficiency has become an essential obstacle to China's sustainable development (Liu et al., 2020) [5]. China's coal-dominated energy structure will be difficult to change in the short-term. Therefore, improving total-factor energy efficiency will be an effective way to eliminate the contradiction between green development and economic growth. At this stage, China is committed to the green transformation of its development mode, and reducing energy intensity and improving energy efficiency have become the top priority. <<Made in China 2025>> also proposes to optimize the energy structure and lead the green development of society. Therefore, the deep integration of energy development and the digital revolution has become the trend nowadays and an essential support for ensuring national energy security in the new era.

The extensive use of new-generation information technologies such as artificial intelligence, cloud computing, and big data has brought a new economic development model to the "digital economy". The digital economy is a production system with digital knowledge and information as its core and a series of financial behaviors that use information and communication technology to improve efficiency and optimize the economic structure with modern information networks as a carrier (OECD, 2014) [6]. China's digital economy has significantly developed in recent years, and it has gradually integrated enterprise production, government governance, and even residents in every field of life. Both the economy and society are undergoing profound changes. According to the White Paper on the Development of China's Digital Economy 2021, the scale of China's digital economy reached CYN 39.2 trillion in 2020, accounting for 38.6% of its GDP. The growth rate was more than three times the nominal GDP growth rate in the same period. Economic growth and development are inseparable from the promotion of the digital economy. As a significant force in new emerging technologies, formats, and models, can the digital economy improve urban total-factor energy efficiency? If so, what is its internal mechanism? What are the differences between different regions and city sizes regarding the influence of the digital economy on total-factor energy efficiency? According to China's "Fourteenth Five Year Plan", we should promote the energy revolution, accelerate the construction of the digital economy, and deepen the integration of digital technologies with the real economy. At the same time, we should enable the transformation and upgrading of traditional industries and encourage the digital transformation of enterprises. The 2022 work report of the Chinese government also stated that the overall layout of Chinese digital construction should be strengthened to promote the digital transformation of industries while cultivating the data element market and promoting the development of the digital economy. In this context, discussing these issues is conducive to enriching digital economy research and has important practical significance for improving ecological environment quality and even high-quality economic development.

In summary, the influence of the digital economy on the total-factor energy efficiency of cities at the metropolitan level has rarely been discussed. Against increasingly severe constraints on resources and the environment, improving energy efficiency is particularly important for high-quality economic development. Accordingly, we analyzed the digital economy's impact on urban total-factor energy efficiency from the theoretical and empirical perspectives in this study. First, we investigated the effect of the digital economy on energy efficiency at the micro-urban level relative to the national or provincial level. In previous studies on energy efficiency at the city level, carbon dioxide emissions were not included in the energy efficiency measurements; as an essential aspect of energy consumption, carbon dioxide emissions need to be better considered to reflect the total-factor energy efficiency situation of cities. Second, in previous research on the digital economy, mechanism analysis was mainly conducted from the perspective of technological innovation or industrial structure optimization. In addition to these mechanisms, we also theoretically considered and empirically tested the mechanism of capital and labor misallocation improvement in this study. Third, we explored the heterogeneity of the influence of the digital economy on total-factor energy efficiency from the perspective of different regions and city sizes.

2. Literature Review

Scholars have closely studied the rapid development of the digital economy. Previous research on the digital economy can be summarized as follows.

(1) First, the digital economy has been measured. The digital economy has overturned the traditional business model and is a new business model (Kim et al., 2014) [7]. Xu and Zhang (2020) [8] measured the scale of the digital economy in four aspects: digitally enabled infrastructure, digital media, digital transactions, and digital economy trading products. Chinoracky and Corejova (2021) [9] constructed a digital economy scale evaluation system from the three first-level economic, labor force, and technical capacity indexes. In addition, they used entropy to measure the size of the digital economy in 19 European countries, including Belgium, from 2008 to 2018.

(2) Second, the impact of the digital economy has been considered. ① Economic growth or high-quality economic development: Zhao Tao et al. (2020) [10] empirically tested the effect of the digital economy on high-quality urban development, and their results showed that the digital economy has significantly promoted high-quality development. Jiao and Sun (2021) [11] empirically tested how urban economic growth was affected by the digital economy through the instrumental variable method, difference-in-difference method, and spatial metrology using Chinese cities' data. They found that the digital economy has significantly promoted economic growth. ② Total-factor productivity or technological innovation: Yang and Jiang (2021) [12] measured the development level of the provincial digital economy in China from 2004 to 2017 using the principal component analysis method. They empirically tested the impact of the digital economy on total-factor productivity. Their results showed that the digital economy has significantly increased the total-factor production rate. Li et al. (2022) [13] empirically tested the impact of the digital economy on enterprise innovation using the data of A-share listed companies in China. Their results showed that the digital economy had promoted enterprise innovation. ③ Transformation and upgrading of industrial structure: Su et al. (2021) [14] empirically tested the impact of the digital economy on the optimization of industrial systems using provincial-level data in China. Their results showed that upgrading the industrial structure was inseparable from vigorously promoting the digital economy. Zhou et al. (2022) [15] showed that the digital economy enables the global value chain of Chinese manufacturing. ④ Green development: Li Tao and Sha Weihua (2022) [16] used China's provincial-level data, Tobit, and GMM empirical regression to test the mechanism and channel of energy efficiency under the influence of the digital economy. Their results showed that the digital economy promoted the efficiency of all elements in the region and that market trade was the main transmission channel of real estate. The research of Li and Wang (2022) [17] showed that the digital economy and carbon emissions were in an inverted U-shaped relationship, first increasing carbon emissions and then reducing carbon emissions. Chen's (2022) [18] research on Chinese cities showed that the digital economy had promoted clean energy development. The digital economy has not only improved the capital accumulation rate (Acemoglu and Restrepo, 2020) [19] but also improved the allocation efficiency of capital and labor (Hjort and Pouslen, 2019) [20], and achieved green and sustainable development.

3. Mechanism and Research Hypothesis

3.1. Digital Economy Improves Total-Factor Energy Efficiency by Promoting Technological Innovation

The ICT (information and communication technology) industry in the digital economy is highly knowledge-intensive with rich innovation resources. Internal innovation activities are frequent, which makes it easy to produce digital innovation results (Zhang et al., 2020) [21]. First, the extensive use of digital technology in production directly affects total-factor energy efficiency. With the application of digital technology, production equipment is gradually becoming intelligent. Multi-functional production equipment can achieve real-time communication and cooperation, which is conducive to coordinating production lines and improving product quality and efficiency (Gao et al., 2022) [22]. An efficient and intelligent production mode has been formed, which has promoted the optimization of production processes and improved production efficiency, thus enhancing the energy efficiency of all factors. Secondly, the digital economy affects all elements of energy efficiency by promoting the efficient integration of innovative resources and technology diffusion. The digital economy can integrate resources across regions. It uses online innovation platforms or innovation entities to realize the reorganization of innovation resources across areas under the influence of the multiple effects of network links (Li et al., 2022) [23]. The capital, talent, technology, and other innovation elements in different fields are effectively integrated under the multiplier effect of the network link point (Zhang et al., 2022) [24], thereby promoting innovation activities. In addition, the spread of new technologies among industries has been accelerated under artificial intelligence, the Internet of Things, big data, cloud computing and other technologies (Zhang, 2021) [25]. Under the digital economy model, it is more convenient for all innovation subjects to obtain information and knowledge. The digital economy is also conducive to sharing innovative technologies and expertise among enterprises, and promotes the spread of new technologies and knowledge. It will undoubtedly help promote technological innovation and enhance total energy efficiency. Therefore, we propose the following assumption in this paper:

Hypothesis 1 (H1). *The development of the digital economy has contributed to an increase in technological innovation, which has improved total-factor energy efficiency.*

3.2. Digital Economy Improves Total-Factor Energy Efficiency by Promoting Industrial Structure Optimization

The upgrading of an industrial structure is a complex process. Traditional factor resources have been transferred from industries with low allocation efficiencies to technology-intensive industries with high allocation efficiencies. New factor resources also flow to technology-intensive industries with higher resource efficiencies. It has led to an increasing share of technology-intensive industries (Qin et al., 2017) [26]. First, the digital economy promotes the optimization of the industrial structure by accelerating the transformation and upgrading of traditional industries. With the integration of the digital economy, traditional industries have gradually transformed into digital industries (Zhu et al., 2022) [27]. The digital economy takes information and data as its main production factors.

In the integration process of traditional industries, the digital economy has promoted the intelligent and digital transformation of enterprises and gradually transformed the conventional labor-intensive and capital-intensive sectors into data-intensive and technology-intensive industries (Zhang et al., 2022) [24]. It has also improved production efficiency, increased the number of industries with high production efficiencies, promoted industries to the middle and high-end levels, and optimized industrial structure. Secondly, the digital economy encourages the optimization of the industrial structure by promoting the integration and development of related industries. The digital economy can rely on its high innovation, high permeability, and strong diffusion characteristics to encourage the integration of associated industries and upstream and downstream industries (Ma and Ning, 2020) [28]. The integrated development of enterprises has promoted the continuous upgrading of the industrial structure. For example, the integrated development of the manufacturing industry and producer services enables the transformation and upgrading of the manufacturing industry and the development of producer services, thus promoting the upgrading of the industrial structure. The productive service industry is knowledge- and technology-intensive; therefore, it is more likely to exert a knowledge spillover effect (Ali et al., 2021) [29]. It is conducive to embedding advanced production technology into the production and manufacturing links and promoting production extension of production to the high value-added end. In this integration process, producer services will also be further developed, increasing knowledge- and technology-intensive industries and promoting the optimization and upgrading of the industrial structure. The upgrading of the industrial structure also means that the industry is moving in a clean and green direction

(Zhu et al., 2019) [30]. The clean and green development of the entire industrial system will undoubtedly improve the energy efficiency of all factors. Therefore, we propose the following assumption in this paper:

Hypothesis 2 (H2). *The digital economy has promoted the optimization and upgrading of the industrial structure, thereby improving total-factor energy efficiency.*

3.3. Digital Economy Improves Total-Factor Energy Efficiency by Improving Resource Misallocation

The digital economy is centered on information technology. In the traditional production process, knowledge and data can be introduced into the digital economy as essential production factors. The asymmetric contradictions of capital, labor and other flow elements can also be effectively solved (Qian et al., 2022) [31]. The digital economy can reduce the costs of search, transaction, matching, and replication by alleviating information asymmetry and reducing transaction barriers. It can also break the market boundary, make it more convenient for resources to flow in a larger space, and optimize resource allocation (Goldfarb and Tucker, 2019) [32]. With the development of the internet, elements in different areas can be quickly and efficiently connected and reorganized according to different needs, thus accelerating the integration of resources across regions (Wu et al., 2021) [33]. Therefore, the opacity of capital and the labor market can be more effectively improved with the development of the digital economy, and capital and labor factors can be effectively allocated through more channels. With the development of the digital economy, the cross-regional flow of various elements has been accelerated, and the allocation efficiency of capital and labor factors has been improved. In addition, the broad application of the internet, big data, and other technologies as part of the rapid flow of information in the market increases the transparency and competitiveness of the market (Li et al., 2022) [23]. The effect of the survival of the fittest brought about by market competition has also eliminated some inefficient enterprises and released their production resources for transfer to efficient enterprises (Wang et al., 2014) [34]. This process has also promoted the optimal allocation of capital and labor elements. The higher the allocation efficiency of capital, labor, and other factors, the higher the green total-factor energy efficiency (Hao et al., 2020) [35]. Therefore, we propose the following assumption in this paper:

Hypothesis 3 (H3). *The development of the digital economy has improved the misallocation between capital and labor resource allocation efficiency, consequently enhancing total-factor energy efficiency.*

4. Methodology and Materials

4.1. Econometric Model Setting

The purpose of this paper was to discuss the impact of the digital economy (de) on total-factor energy efficiency (eff). Therefore, we took the digital economy as the core explanatory variable, and total-factor energy efficiency as the explained variable. Then, we conducted a benchmark regression analysis based on panel data from 275 cities in China from 2011 to 2019. Moreover, to minimize the estimation deviation caused by omitting other variables, six control variables were added to the benchmark model to build the model (1) (refer to Tang and He (2021) [1], Yu (2018) [36], Wang and Cao (2019) [37]): the agglomeration of productive services ($sagglo$), human capital (H), expenditure on science and technology (rd), foreign direct investment (fdi), foreign trade ($open$), and infrastructure ($infra$). We treated these as the control variables and logarithmically processed the non-proportionate variables. The following benchmark regression models were established:

$$\ln eff_{it} = \alpha_0 + \alpha_1 \ln de_{it} + \alpha_2 \ln sagglo_{it} + \alpha_3 H_{it} + \alpha_4 rd_{it} + \alpha_5 \ln fdi_{it} + \alpha_6 \ln open_{it} + \alpha_7 \ln infra + \varepsilon_{it} \tag{1}$$

where total-factor energy efficiency (eff) is the energy efficiency considering the interaction of various input factors, the digital economy (de) is a new economic form that uses the new generation of digital technologies, such as cloud computing and the internet as the carrier, takes data as the new production factor, and promotes the high-quality economic development through the acceleration and improvement of the essential environment of the digital economy. The productive service industry refers to the service industry that provides guaranteed services to maintain the continuity of the industrial production process and improve production efficiency. The spatial organization formed by the concentrated development of producer services in a specific geographical space is called producer services agglomeration ($saggl o$). Human capital (H) is the capital embodied in workers, such as the knowledge and skills, cultural and technical level, and the health status of workers. Scientific and technological expenditures (rd) refer to the expenses of the state for the development and promotion of various scientific research undertakings. Foreign direct investment (FDI) (fdi) refers to the direct investment in China by foreign enterprises, economic organizations or individuals (including overseas Chinese, compatriots in Hong Kong, Macao and Taiwan, and Chinese enterprises registered overseas) in cash, physical goods, technology, etc., following relevant Chinese policies and regulations. Foreign trade ($open$) refers to the exchange of goods, services and technology between a country (region) and other countries (region). Infrastructure ($infra$) refers to the material engineering facilities that provide public services for social production and residents' lives. A public service system is used to ensure the regular progress of social and economic activities of a country or region. i and t denote the city and year, respectively; α denotes the parameter to be estimated, and ε determines the random disturbance.

Based on the above theoretical mechanism, we believe that the digital economy can promote total-factor energy efficiency through technological innovation, optimize the industrial structure, and improve resource allocation. To verify the mediating effect of improving resource misallocation and other factors on the influence of the digital economy on total-factor energy efficiency, we referred to the practice of Yang Jiang (2021) [12] and used technological innovation, industrial structure and resource misallocation as intermediary variables to establish the following mediating effect experimental model:

$$\ln M_{it} = \beta_0 + \beta_1 \ln de_{it} + \beta_2 Conrol_{it} + \varphi_{it} \quad (2)$$

where M is the intermediate variable. Technological innovation refers to achieving business growth, improving quality and achieving cost-effectiveness by changing the form of technology. Industrial structure refers to the five-dimensional spatial relationship among the industry's production factors, industries, time, space and levels within the industry. In this paper, resource misallocation includes capital misallocation and labor misallocation. Capital misallocation is the misallocation between capital investment and capital return. Labor misallocation refers to the failure to achieve Pareto optimal labor allocation due to insufficient labor flow. $control$ is the control variable; i and t represent the city and year, respectively; and β describes the parameter and random disturbance terms to be estimated.

4.2. Variable Measurement and Data Description

In this paper, we selected data from 275 cities at the prefecture level and above in China from 2011 to 2019 (Tibet, Hong Kong, Macao and Taiwan were eliminated) for empirical analysis. This data was collected from the "China City Statistical Yearbook", "China Regional Economic Statistical Yearbook", "Peking University 2011–2019 Digital Inclusive Financial index", "China Statistical Yearbook", "China Research Data Service Platform" (CNDRS), statistical yearbooks of various provinces and cities, and the Bulletin of Urban National Economic and Social Statistics. Carbon emission data were taken from county-level carbon dioxide emissions measured by Chen et al. (2020) [38]. Through the comprehensive analysis of the city data, the carbon emissions from 2018 to 2019 were predicted using the double exponential smoothing method.

(1) The explained variable of total-factor energy efficiency (eff):

Total-factor energy efficiency refers to energy efficiency considering the interaction of various input factors. Only by effectively improving total-factor energy efficiency can we achieve the goal of "double carbon" (specifically, carbon peak and carbon neutral). In economic growth, the input of capital, labor and other factors remains unchanged, excluding the input of energy factors, according to the best production practices. Total-factor energy efficiency refers to the calculation method of total-factor productivity in economics that takes energy as an input to investigate economic output. It is a comprehensive index for evaluating energy efficiency. It is a dimensionless variable. This paper mainly examined the relationship between the digital economy and total-factor energy efficiency. Table 1 shows the measurement index of total-factor energy efficiency.

Table 1. Measurement index of total-factor energy efficiency.

Index	Index Structure	Variable	Unit
Input	Labor force	Number of employees in urban units	Ten thousand people
	Capital stock	The capital stock of each city	CNY 10,000
	Energy consumption	Industrial power consumption	Kwh
Output	Expected output	Real GDP	CNY 100 Million
	Unexpected output	Industrial sulfur dioxide emissions	10,000 tons
		CO_2 emissions	10,000 tons

Many conventional DEA models ignore the influence of slack factors on efficiency. To solve this problem, Tone (2001) [39] established a non-radial and angle-free model of the SBM direction distance function. Since there is no limit on the number of inputs and outputs, the SBM model can effectively solve and evaluate a situation in which there are multiple indices of inputs and outputs by avoiding the efficiency difference of radial and angular selection. To solve efficiency evaluation problems involving unexpected outputs, Tone (2002) [40] proposed an improved SBM model containing unexpected outputs based on DEA. This paper used this model for reference and used MaxDEA8.22 software to measure total-factor energy efficiency. The input index included labor force, capital stock, and energy consumption. The output index selected the actual GDP as the expected output and the industrial sulfur dioxide emissions and carbon dioxide emissions as the unexpected output.

The first input index was labor input, i.e., the number of employees in urban units. The second input index was capital stock, and we used the perpetual inventory method to estimate the capital stock of each city. The specific formula is as follows: $K_t = I_t/P_t + (1-\delta)K_{t-1}$. Here, K_t is the capital stock of the current period, K_{t-1} is the capital stock of the previous period, I_t is the nominal fixed-asset investment amount of the current period, P is the fixed-asset investment price index of each province and city with the base period of 2003, and δ is the depreciation rate.

Zhang Jun et al. (2004) [41] recorded a capital stock value of 9.6% using the following calculation formula of the capital stock with the base period of 2003: $K_0 = I_0/(g+\delta)$. Here, g is the annual average growth rate of the actual fixed-asset investment in each city from 2003 to 2019 and I_0 is the real fixed-asset investment in 2003. According to Yu's (2018) [32] study, the third input index was energy consumption, which can be expressed in terms of industrial electricity consumption.

The output index was as follows. First was the real GDP, which was used as the expected output. We considered 2003 as the base period and utilized a provincial GDP deflator to deflate the corresponding urban GDP. The second was sulfur and carbon dioxide, China's leading polluting gases emitted by fossil energy. Fossil fuel combustion is a significant source of carbon dioxide. The average consumption of coal, coke, gasoline, diesel, and fuel oil accounts for more than 80% of China's total energy consumption (Wang and Cao, 2019) [33]. Based on the research of Wang and Cao (2019) [33], we took carbon dioxide and industrial sulfur dioxide emissions as unexpected outputs in this paper.

(2) The core explanatory variables of the digital economy (*de*): The development of the digital economy is inseparable from the support of computers and communication

equipment, as well as the support of telecommunications services and digital finance. This means that various factors must be comprehensively considered in the analysis. To measure the development degree of the digital economy, we referred to the research results of Zhou et al. (2020) [8], Huang et al. (2019) [42] and Huang et al. (2023) [43]. At the city level, from the perspective of data availability, we measured the development degree of China's digital economy from two perspectives: network development and digital finance. We considered five leading indices: internet penetration rate, mobile phone penetration rate, relevant practitioners, the output value of network-related industries, and digital financial development status. More details are shown in Table 2. Ultimately, we used principal component analysis to measure China's digital economy development index.

Table 2. Comprehensive evaluation index system of the urban digital economy.

Level I Index	Secondary Index	Proxy Variable	Index Attribute
Digital economy	Internet penetration rate	Number of internet users per 100 people	Positive
	Mobile phone penetration	Number of mobile phone users per 100 people	Positive
	Internet-related practitioners	The proportion of employees in the computer and software industry in total employees	Positive
	The output of internet-related industries	Per capita telecom service volume	Positive
	Development of digital finance	China digital inclusive financial index	Positive

(3) Control variables: Regarding the agglomeration of producer services, following the research of Cheng (2016) [44], we used the location entropy index to measure the concentration level of producer services in various regions. For the classification of productive service industries, we referred to the research of Han and Yang (2020) [45]. In this paper, we merged 11 sectors: transportation, warehousing, postal services, information transmission, computer services and software, wholesale and retail, finance, leasing and commercial services, scientific research and technology services, environmental governance, and public facilities management to represent productive services. Human capital is mainly reflected in the number of middle school, college, and university students and their proportion in the total urban population. The government expenditure on science and technology ratio represents the spending on science and technology. Foreign direct investment (FDI) is described as the utilization of foreign direct investment in cities. Foreign trade is expressed in terms of total imports and exports. Both foreign direct investment and foreign exchange were converted into constant prices in 2003 using the provincial consumer price index. Infrastructure is expressed in terms of urban per capita road area.

(4) Intermediary variables: The technical innovation level (PT) is expressed by the number of city patents granted. Industrial structure optimization (S) is represented by the ratio of the output value of the tertiary industry to that of the secondary sector. For the measurement of resource misallocation, we referred to the research of Bai and Liu (2018) [46]. In this paper, we used capital and labor misallocation coefficients to express capital and labor misallocation. The calculation formulae of capital and labor distortion coefficients are, respectively:

$$distk = \frac{MP_K}{r} - 1 = \beta_{Ki}\frac{p_i y_i}{rK_i} - 1; \quad (3)$$

$$distl = \frac{MP_L}{w} - 1 = \beta_{Li}\frac{p_i y_i}{wL_i} - 1 \quad (4)$$

where $P_i y_i$ is the actual gross regional product of city i; K_i is the capital stock; L_i represents the employees of urban units; r is the capital price expressed by the interest rate level (referring to the work of Hsieh and Klenow (2009) [47], we set the interest rate level to 10%); W represents the labor price, which is expressed by the average wage of urban workers and was converted into the constant price in 2003 with the provincial consumer price index; MP_k and MP_L are the marginal outputs of capital and labor, respectively; and β_{Ki} and β_{Li} are the elasticity of capital output and labor output, respectively. The elasticity of the factor output of each city was determined based on the practice of Bai and Liu (2018) [46]. In this paper, we used the least squares dummy variable method (LSDV) for estimation. The descriptive statistics of each variable are shown in Table 3.

Table 3. The statistical description of variables.

Variable	Mean	Standard Deviation	Minimum	Maximum
eff	0.5249	0.2464	0.1768	3.3233
de	3.3546	1.4414	1.0582	14.8790
$sagglo$	0.8119	0.3805	0.2433	13.6159
H (%)	6.9710	2.9526	1.1442	20.6260
rd (%)	1.6659	1.6763	0.0598	20.6835
fdi (CYN million)	443,920.9000	1,050,251.9074	1.0000	14,673,946
$open$ (CYN million)	6,931,495.5884	24,885,776.2211	17.1790	253,919,824.6207
$infra$ (m^2/person)	13.1976	8.9107	0.5000	108.3700

5. Empirical Test and Result Analysis

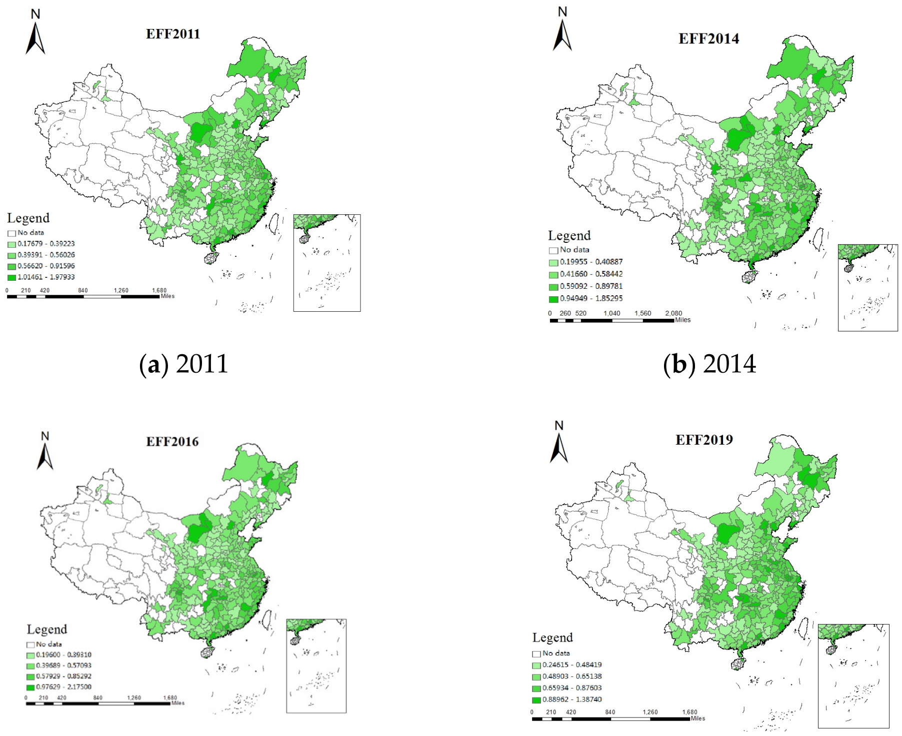
5.1. Measurement Results of Total-Factor Energy Efficiency

According to the calculation results, the total-factor energy efficiency of the top 10 cities from 2011, 2014, 2016 and 2019 is shown in Table 4. The total-factor energy efficiency value is greater than 1, indicating that the total-factor energy efficiency of the city is in the optimal state. The total-factor energy efficiency value is less than 1, meaning that the city's total-factor energy efficiency still needs to be improved. The top 5 cities in 2011 were Suihua city, Sanya city, Shenzhen city, Ordos city and Maoming city. Beijing city, Ordos city and Shenzhen city have consistently been ranked in the top ten, indicating that the total-factor energy efficiency of these three cities is relatively high. It suggests that the local government and relevant departments have implemented policies on environmental pollution control very well. The total-factor energy efficiency of Changsha city, Sanya city and Suihua city is also relatively stable. It shows that the local government and relevant departments have stable control over energy emissions. The top 5 cities in total-factor energy efficiency in 2019 were Shenzhen city (1.39), Beijing city (1.32), Sanya city (1.31), Changsha city (1.11) and Changzhou city (1.05). It shows that these five cities have a high understanding of energy conservation and emission reduction, and implement the policies in place. There are also some cities with a relatively backward level of total-factor energy efficiencies, such as Yinchuan city (0.32), Baiyin city (0.32), Guyuan city (0.31), Xining city (0.28) and Tongchuan city (0.25). It may be affected by local resource endowments and economic policies.

This paper uses ArcGIS10.8 (Environmental Systems Research Institute (Esri), Redlands, CA, USA) to draw the spatial distribution of total-factor energy efficiency of cities in 2011, 2014, 2016 and 2019, as shown in Figure 1. The darker the color in the map, the higher the total-factor energy efficiency; The lighter the color, the lower the total-factor energy efficiency. The blank part in the map indicates that no relevant data have been obtained in this paper. Therefore, this paper does not study the total-factor energy efficiency level in this area.

Table 4. Total-factor energy efficiency level of each city from 2011, 2014, 2016 and 2019.

Ranking	City	2011	City	2014	City	2016	City	2019
1	Suihua	1.98	Shenzhen	1.85	Suihua	2.17	Shenzhen	1.39
2	Sanya	1.95	Suihua	1.75	Changsha	1.55	Beijing	1.32
3	Shenzhen	1.89	Ordos	1.70	Ordos	1.53	Sanya	1.31
4	Ordos	1.80	Changsha	1.60	Shenzhen	1.53	Changsha	1.11
5	Maoming	1.34	Sanya	1.21	Huaihua	1.30	Changzhou	1.05
6	Dongguan	1.25	Beijing	1.21	Zigong	1.24	Ordos	1.05
7	Ziyang	1.24	Ziyang	1.18	Beijing	1.22	Zhoushan	1.04
8	Foshan	1.21	Guangzhou	1.17	Guangzhou	1.08	Zigong	1.03
9	Beijing	1.20	Dingxi	1.16	Baotou	1.08	Zhenjiang	1.03
10	Huaihua	1.18	Shangluo	1.14	Sanming	1.03	Langfang	1.03
11	Ningde	1.13	Maoming	1.11	Changde	1.02	Sanming	1.02
12	Dingxi	1.12	Shanwei	1.07	Neijiang	1.02	Maoming	1.02
13	Changsha	1.09	Dalian	1.07	Hohhot	1.00	Haikou	1.02
14	Chaozhou	1.07	Baotou	1.05	Wuxi	1.00	Foshan	1.00
15	Dalian	1.03	Changde	1.04	Maoming	0.98	Qingdao	1.00
16	Suzhou	1.03	Ningde	1.02	Dalian	0.85	Guangzhou	1.00
17	Guangzhou	1.01	Shangrao	1.02	Shanghai	0.84	Wuxi	1.00
18	Changde	0.92	Neijiang	1.00	Harbin	0.84	Xuzhou	1.00
19	Neijiang	0.89	Changzhou	1.00	Mudanjiang	0.83	Dalian	0.99
20	Wuxi	0.89	Zigong	0.96	Lishui	0.80	Shanghai	0.98



(**a**) 2011 (**b**) 2014

(**c**) 2016 (**d**) 2019

Figure 1. Spatial distribution of annual total-factor energy efficiency in different cities from 2011, 2014, 2016, and 2019.

5.2. Estimation Results of the Full Sample

Table 5 shows estimations of the digital economy's effect on total-factor energy efficiency. Hausman's test results showed that the fixed-effect model was more appropriate than the random-effect model; therefore, we chose a fixed-effect (fixed city) model for further estimations. Column (1) represents estimates without the addition of any control variables. According to the results in column (1), the regression coefficient of digital economy development on the total-factor energy efficiency of each element was 0.2131, and the significance test was 1%. These results show that the development of the digital economy has a significant positive correlation with total-factor energy efficiency. Column (2) represents the evaluation results after introducing a control variable. The results of column (2) show that there was still a significant positive relationship between digital economy development and total-factor energy efficiency. It shows that the digital economy has significantly improved the energy efficiency of all elements (Jiang et al., 2022) [48].

Table 5. Estimation results of the full sample.

Explanatory Variable	(1)	(2)
$\ln de$	0.2131 *** (10.89)	0.1807 *** (9.07)
$\ln saggl o$		0.0974 *** (3.80)
H		0.0179 *** (3.59)
rd		0.0114 *** (2.61)
$\ln fdi$		0.0093 ** (2.34)
$\ln open$		0.0213 ** (2.43)
$\ln infra$		0.0747 *** (4.86)
cons	−0.9675 *** (−42.79)	−1.6256 *** (−12.80)
R^2	0.0512	0.0834
Hausman test	11.65 [0.0006]	45.83 [0.0000]
Estimation method	FE	FE
Number of samples	2475	2475

Note: The values in brackets are t-statistics; ** and *** are significant at the 5% and 1% levels, respectively. The t-statistic values are in round brackets, and the concomitant probabilities are in middle brackets.

Regarding control variables, producer service agglomeration significantly promotes total-factor energy efficiency. Productive services are knowledge-intensive and technology-intensive. The spatial aggregation of producer services encourages the diffusion of new knowledge and technologies while vigorously fostering technological innovation and improving all elements of energy utilization. Human capital was found to have a significant impact on total-factor energy efficiency. Enhancing human capital's capacity can promote workers' technological progress, thereby promoting improvements in labor productivity. Investment in science and technology was shown to have significantly improved energy efficiency. Our results showed that increasing investment in science and technology would help promote technological progress and, consequently, energy utilization. Both foreign direct investment and foreign trade have improved energy efficiency, showing that the open development of the economy is conducive to the spillover of advanced technology and improvements in the energy utilization efficiency of domestic enterprises. The estimated coefficient of infrastructure was found to be significantly positive, indicating that infrastructure improvements are conducive to reducing the transport costs of factors and speeding up the flow of resources, thus enabling the optimization of resource allocation, promotion of technological progress, and improvements in energy efficiency.

5.3. Robustness Test

In this section, we primarily consider the impact of the development of the digital economy on urban total-factor energy efficiency, including the possible endogenous problems caused by replacing core variables and rejecting samples.

5.3.1. Robustness Test of Substitution Variables and Sample Removal

To explore the digital economy's impact on improvements in the total-factor energy efficiency of cities, we used alternative core explanatory variables and the rejection of samples to conduct empirical analysis. Referring to the work of Jiang and Sun (2020) [49], we used the "Internet +" digital economy index to evaluate the fixed-effect model with substitute variables in the "China Internet + Index Report" (2015–2019) released by the Tencent Research Institute in 2015–2019. Since the 2019 report does not list the "Internet +" index of all cities, the "Internet +" index in 2019 was estimated by multiplying the "Internet +" index in 2018 by the average annual growth rate from 2015 to 2018. The economic development level gap between different regions in China was found to be pronounced. This conclusion may be affected by the economic particularity of municipalities directly under the Central Government; therefore, data from Beijing, Shanghai, Tianjin, and Chongqing were excluded for regression. Table 4 reports the robustness test results of substitution variables and sample removal. Column (1) of Table 4 represents the estimated results of replacing the core explanatory variables, and column (2) of Table 6 represents the estimated results excluding Beijing and other municipalities directly under the Central Government. It can be seen in Table 6 that the estimated coefficients and significance of the digital economy ($\ln de$) were consistent with the results in Table 6 (Zhao et al., 2022) [50], indicating that the regression results in this paper were robust.

Table 6. Robustness test results: substitution variables and sample removal.

Explanatory Variable	(1)	(2)
$\ln de$	0.0675 *** (12.39)	0.1784 *** (8.92)
$\ln sagglo$	0.0478 (1.07)	0.0939 *** (8.92)
H	0.0195 ** (2.14)	0.1784 *** (3.65)
rd	0.0074 (1.07)	0.0116 *** (2.62)
$\ln fdi$	0.0041 (0.80)	0.0096 ** (2.39)
$\ln open$	0.0224 (1.38)	0.0211 ** (2.40)
$\ln infra$	0.0394 (1.56)	0.0736 *** (4.78)
cons	−1.2604 *** (−5.20)	−1.6219 *** (−12.81)
R^2	0.1996	0.0826
Estimation method	FE	FE
Number of samples	1375	2439

Note: The values in brackets are t-statistic values; ** and *** are significant at the 5% and 1% levels, respectively.

5.3.2. Endogeneity Test

If a model has endogenous problems, its estimation results will be biased. The digital economy and total-factor energy efficiency have specific two-way impacts. Digital technology is the basis for the development of the digital economy because the level of technology is the main driving force for the development of the digital economy. The total-factor energy efficiency also reflects the level of digital technology. Endogenous problems arise because of a causal relationship between the explanatory and explained variables, though the explanatory variable is related to random disturbances. Referring to the research of Li and Wang (2022) [17], we used the spherical distance between Hangzhou and various cities in 1984 and the number of post offices per million people at the city level in 1984 as instrumental variables of the digital economy. Since the instrumental variable comprised cross-sectional data, the instrumental variable was multiplied by the annual dummy variable. In addition, regarding the empirical research of Yang and Jiang (2021) [12], we used the primary and secondary lag of digital economy development as instrumental variables and conducted an empirical analysis of them. Table 7 presents the results of the two-step least squares (2SLS) estimation of the instrumental variables described above. Column (1) of Table 7 represents estimations of the number of post offices per million people in 1984, the intersection of spherical distances from Hangzhou to various cities, and annual dummy variables as instrumental variables.

Table 7. Robustness test results: two-stage least squares method (2SLS).

Explanatory Variable	**(1)**	**(2)**
$\ln de$	0.2786 *** (5.98)	0.3302 *** (5.25)
$\ln sagglo$	0.0817 *** (3.61)	0.0261 (0.70)
H	−0.0223 *** (−5.99)	0.0158 ** (2.10)
rd	0.0066 (1.49)	0.0141 *** (3.74)
$\ln fdi$	0.0289 *** (8.29)	0.0099 ** (1.97)
$\ln open$	0.0299 *** (5.09)	0.0267 ** (2.34)
$\ln infra$	−0.0280 (−1.46)	0.0497 ** (2.12)
R^2	0.2178	0.0558
Kleibergen–Paap rk LM	780.601 [0.0000]	142.82 [0.0000]
Kleibergen–Paap rk Wald F	73.251 {11.37}	149.37 {19.93}
Estimation method	2SLS	2SLS

Note: ** and *** are significant at the 5% and 1% levels, respectively. The t-statistic values are in round brackets, the concomitant probabilities are in square brackets, and the Stock–Yogo test thresholds are in the braces.

The development level of the digital economy represented by column (2) of Table 7 was found to lag behind the estimated results of the first- and second-stage instrumental variables. Table 7 shows that the KPrk LM statistic was significant at 1%, indicating that the model had sufficient instrumental variable identification. The KPrk Wald F statistic was more than the critical value of the Stock–Yogo weak recognition test at 10%; therefore, weak instrumental variables could be excluded. This result also demonstrated the rationality and effectiveness of the instrumental variables. After excluding possible endogenous problems, the estimated coefficient of the digital economy was still significantly positive. These results showed that the digital economy's development could improve a city's total-factor energy efficiency, which is valid and consistent with the previous econometric regression results.

5.3.3. Mechanism Test

Our regression results showed that the development of the digital economy has dramatically promoted improvements in total-factor energy efficiency, but its transmission path needs further research. The results of the mechanical tests carried out according to model (2) are shown in Table 8. The estimated effects of "technological innovation, " "industrial structure optimization, " "capital misallocation", and "labor misallocation" are listed in columns (1), (2), (3), and (4), respectively, of Table 8. The results in column (1) show that the digital economy's estimated coefficient (ln*de*) was obviously positive at the level of 1%, showing that the development of the digital economy promotes technological innovation. This result also verified theoretical Hypothesis 1: the development of the digital economy has contributed to an increase in technological innovation, which has improved total-factor energy efficiency. According to the estimation results in column (2), the development of the digital economy has significantly promoted the optimization of the industrial structure, which also validates theoretical Hypothesis 2: the digital economy has boosted the optimization and upgrading of the industrial structure, thereby improving total-factor energy efficiency.

Table 8. Test results of the mechanism of the digital economy affecting total-factor energy efficiency.

Explanatory Variable	(1)	(2)	(3)	(4)
$\ln de$	1.2426 ***	0.5886 ***	−0.2507 **	−0.1084 ***
	(22.89)	(19.82)	(−2.41)	(−3.16)
$\ln sagglo$	−0.2806 ***	0.0144	0.0222	0.1165 ***
	(−4.02)	(0.38)	(0.17)	(2.65)
H	−0.0341 **	0.0015	0.0073	0.0334 ***
	(−2.50)	(0.20)	(0.28)	(3.89)
rd	0.0899 ***	0.0172 ***	−0.0356	−0.0228 ***
	(7.47)	(2.62)	(−1.54)	(−3.00)
$\ln fdi$	−0.0204 *	−0.0496 ***	−0.0306	0.0074
	(−1.87)	(−8.31)	(−1.46)	(1.07)
$\ln open$	0.2518 ***	0.0178	−0.0361	0.0042
	(10.52)	(1.36)	(−0.79)	(0.28)
$\ln infra$	0.4751 ***	0.1517 ***	−0.1439 *	−0.0867 ***
	(11.34)	(6.62)	(−1.79)	(−3.28)
cons	1.4983 ***	0.2352	0.3825	0.8864 ***
	(4.33)	(1.24)	(0.58)	(4.06)
R^2	0.3478	0.2276	0.0086	0.0273
Estimation method	FE	FE	FE	FE
Number of samples	2475	2475	2475	2475

Note: The t-statistics values are in parentheses; *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

According to columns (3) and (4), the estimated coefficients of capital misallocation and labor misallocation in the digital economy showed significantly negative values between 5% and 1%, indicating that the development of the digital economy can effectively promote capital misallocation and labor misallocation. As the development of the digital economy was shown to break the traditional factor market and promote the cross-regional flow of factors, these results also validate theoretical Hypothesis 3: the development of the digital economy has improved the misallocation between capital and labor resource allocation efficiency, which has consequently enhanced total-factor energy efficiency.

6. Further Analysis

6.1. Analysis Based on Eastern, Western, and Central China

There are differences between China's regions, which are influenced by location, history, economy, and other factors. There are obvious spatial imbalances in the development level of China's digital economy and its total-factor energy efficiency. In different regions, the impact of the digital economy on total-factor energy efficiency also produces different results. In this study, we divided the sample into three areas—eastern, central, and western—and used the fixed-effect model for regression analysis (Ren et al., 2021) [51]. Table 9 reports the results of the regional heterogeneity test. Table 9 shows that the estimated coefficient of the digital economy ($\ln de$) was significantly positive in all regions. The results showed that with the development of the digital economy, the total-factor energy efficiency in each region improved. In China, the effect of the digital economy on total-factor energy efficiency was found to be significantly higher in the eastern region than in the central and western regions. The eastern region has a better foundation for economic and industrial development than the western and central regions. The digital infrastructure in the eastern region is perfect because its digital economy developed earlier; therefore, the pace of digital industrial development has been faster, and the level of its digital economy is higher. Additionally, the transformation of traditional industries has been more powerful. The integration of digital technology and traditional industries has been better, and the dividends of the digital economy have been better released.

Table 9. Results of regional heterogeneity test.

Explanatory Variable	Eastern	Central	Western
$\ln de$	0.3388 *** (9.03)	0.1886 *** (6.34)	0.0895 ** (2.46)
$\ln saggl o$	0.3927 *** (8.62)	−0.0414 (−1.02)	0.0031 (0.07)
H	0.0278 *** (3.19)	0.0163 ** (2.09)	0.0091 (0.99)
rd	0.0046 (0.79)	0.0042 (0.60)	0.0312 *** (2.86)
$\ln fdi$	0.0591 *** (7.09)	−0.0198 ** (−2.44)	0.0033 (0.57)
$\ln open$	0.0086 (0.32)	0.0149 (1.14)	0.0312 ** (2.26)
$\ln infra$	0.0280 (0.94)	0.1108 *** (5.05)	0.0529 * (1.81)
cons	−2.0576 *** (−5.07)	−1.3382 *** (−6.92)	−1.5627 *** (−8.62)
R^2	0.2466	0.1172	0.0498
Estimation method	FE	FE	FE
Number of samples	873	864	738

Note: The values in brackets are t-statistic values; *, **, and *** are significant at 10%, 5%, and 1%, respectively.

6.2. Analysis Based on Different City Sizes

The scale of major cities in China is enormous, and there are not enough human resources to support the development of its digital economy. The greater the population, the greater the abundance of labor resources. The development of the digital economy is inseparable from the vast population. To further study the relationship between the digital economy and total-factor energy efficiency, according to the Notice on Adjusting the Standards for City Size Division issued by the State Council, we divided cities into four categories according to the year-end population of municipal districts: megacities (with a population of more than 5 million), large cities (with a population from 1 million to 5 million), medium-sized cities (from 500,000 to 1 million), and small cities (with a population of 500,000 and below). Heterogeneity was estimated for different city sizes, as shown in Table 10. The research results showed that in small towns in China, the estimated coefficient of the digital economy did not pass the significance test. In other areas, the digital economy was found to contribute to improvements in total-factor energy efficiency significantly. Because megacities are either eastern seaboard cities or the capitals of other regions, the effect of the digital economy on total-factor energy efficiency is ranked as follows: mega cities > large cities > medium-sized cities. Therefore, based on geographical location, transportation infrastructure, and economic development in technological innovation and human resources, megacities have the most obvious development advantages, followed by superpowers. Therefore, large and megacities have relatively high degrees of digital economy development, and relatively large digital economic benefits.

6.3. Discussion

In this article, we mainly studied the impact of the digital economy on urban total-factor energy efficiency, selecting 275 cities in China as our research object. Our results demonstrate that the digital economy has significantly promoted improvements in total-factor energy efficiency in three aspects: improving technological innovation, optimizing the industrial structure, and improving resource misallocation.

Table 10. Test results of urban size heterogeneity.

Explanatory Variable	Megacities	Large Cities	Medium-Sized Cities	Small Cities
$\ln de$	0.3576 ***	0.2065 ***	0.1652 ***	0.1006
	(3.18)	(8.01)	(4.72)	(1.47)
$\ln sagglo$	0.3148 **	0.1203 ***	−0.0351	0.4112 ***
	(2.49)	(3.85)	(−0.80)	(3.44)
H	−0.0309 *	0.0322 ***	−0.0003	0.0204
	(−1.76)	(5.04)	(−0.03)	(1.37)
rd	−0.0076	0.0104 **	0.0054	0.0542
	(−0.61)	(1.98)	(0.65)	(1.26)
$\ln fdi$	0.0688 **	0.0049	0.0153 **	0.0099
	(2.09)	(0.78)	(2.10)	(1.09)
$\ln open$	0.2083 ***	0.0552 ***	−0.0140	0.0306
	(2.71)	(4.08)	(−0.94)	(1.36)
$\ln infra$	0.3447 ***	0.0619 ***	0.1137 ***	0.0003
	(2.81)	(2.91)	(4.61)	(0.01)
cons	−6.1626 ***	−2.1363 ***	−1.2192 ***	−1.4491 ***
	(−4.70)	(−10.61)	(−5.98)	(−5.02)
R^2	0.3757	0.1453	0.0743	0.0654
Estimation method	FE	FE	FE	FE
Number of samples	144	1269	756	306

Note: The values in brackets are t-statistic values; *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

First, unlike previous studies, we not only theoretically analyzed but also empirically tested capital and labor misallocation. In research on the influencing factors of the digital economy, most mechanisms have been theoretically expounded from the aspects of technological innovation and industrial structure. In this paper, we also discussed the mechanism of capital and labor misallocation, which is a beneficial extension of the existing theoretical mechanism. In theory, the digital economy is conducive to the cross-regional flow of resources. Convenient access to information promotes market competition and improves resource misallocation. However, empirical research on enhancing the misallocation between capital and labor in the digital economy has been relatively rare. Based on the measurement of urban capital and labor misallocation, we empirically tested the impact of the digital economy on total-factor energy efficiency by improving capital and labor misallocation. Not only is it a marginal contribution of this paper, but it has also enriched the study of the digital economy. In addition, our research provides a reference for other scholars.

The measurement of total-factor energy efficiency is another highlight of this paper. Many previous studies also used the super efficiency model (SBM) to measure the total-factor energy efficiency; however, those studies were limited by urban carbon emission data, and carbon emissions were often not included in their expected output. China is one of the world's largest carbon emitters, and carbon dioxide is the primary emission of energy consumption. Therefore, carbon dioxide emissions can better reflect a location's total-factor energy efficiency. In the literature, carbon dioxide has rarely been considered when measuring total-factor energy efficiency. In measuring total-factor energy efficiency at the urban level, we took industrial sulfur dioxide and carbon dioxide emissions as unexpected outputs. Standard fossil fuels include coal, oil and natural gas. During the combustion of fossil fuels, various exhaust gases are produced, and the gases that form acid rain are sulfur dioxide and nitrogen dioxide. The carbon in fuel is converted into carbon dioxide. It enters the atmosphere, increasing the atmospheric concentration of carbon dioxide and results in the intensification of the greenhouse effect. Therefore, considering carbon dioxide emissions is not just a marginal contribution of this paper, but it has also enriched research on energy efficiency measurements and provided a reference for other scholars.

Third, different perspectives were considered in our empirical analysis of the effect of the digital economy on total-factor energy efficiency. We analyzed our subject in terms of the eastern and central regions of China, and the urban scale. Previous studies have only conducted empirical tests and analyses of China's eastern, central and western regions or the urban scale alone. We conducted a heterogeneity test of our results from the eastern, central and western regions. We also conducted empirical analysis from the four perspectives of megacities, large cities, medium-sized cities and small cities. Therefore, our research provides a comprehensive and detailed overview of the impact of the digital economy on total-factor energy efficiency.

Fourth, our research areas differed from most previous studies, which focused on the research of digital economies or total-factor energy at the provincial level. This paper was more microscopically focused on 275 cities in China from 2011 to 2019. As an essential unit of the high-quality development of China's economy, improvements in urban total-factor energy efficiency directly affect China's high-quality development. Moreover, our urban-level conclusions and relevant policy recommendations can provide a useful reference for national policy formulation.

7. Conclusions, Policy Recommendations and Research Prospects

7.1. Conclusions

In this paper, we used the panel data of 275 cities at the prefecture level and above in China from 2011 to 2019 and used a fixed-effect model to conduct an empirical study on the impact of the digital economy on total-factor energy efficiency. The specific conclusions are as follows.

When no control variable was introduced, the regression coefficient of digital economic development to total-factor energy efficiency was 0.2131, which passed the significance test of 1%; when the control variables (productive service industry agglomeration, human capital, science and technology expenditure, infrastructure, foreign direct investment, and foreign trade) were introduced, the digital economy still significantly improved urban total-factor energy efficiency. After replacing the core explanatory variables and excluding the Beijing, Shanghai, Tianjin and Chongqing data, the regression results were robust. After considering the potential endogenous problems, the estimated coefficient of the digital economy was still significantly positive. The correctness of the conclusion was proven again.

In the mechanism analysis, the estimated coefficient of the digital economy was found to be significantly positive, indicating that the digital economy has promoted technological innovation, optimized the industrial structure, improved the misallocation between capital and labor, and improved the efficiency of urban total-factor energy efficiency.

At the regional level, the estimated coefficients of the digital economy for the eastern, central and western regions were significantly positive, indicating again that the digital economy has improved the total-factor energy efficiency. We also found that the role of the digital economy in promoting total-factor energy efficiency was in the following order: the eastern, central, and western regions.

From the perspective of city size, the digital economy was found to have improved the total-factor energy efficiency of megacities, large cities, and medium-sized cities, and this effect was the largest among megacities. However, the impact on small towns was not clear.

7.2. Policy Recommendations

Based on our conclusions, we propose the following policy recommendations.

First, the digital economy has played a significant role in improving the energy efficiency of all factors. However, it is still necessary to further release the dividends of the digital economy to achieve more substantial development in the energy efficiency of various elements. To develop the digital economy, we must strengthen 5G, the Internet of Things, and big data (Li et al., 2022) [23]. The government should also increase investment in technological innovation, establish digital technology development funds and start-up funds, and invest them in vital technical fields such as artificial intelligence. The government should also promote the leapfrogging of digital infrastructure, the mutual integration and penetration of digital technologies such as artificial intelligence and big data, the development of the digital industry, and digital transformation.

Second, the government should consider technological innovation, industrial structure optimization, and resource allocation optimization so that the digital economy can maximize the energy efficiency of all factors and strengthen scientific and technological innovation. It is also necessary to encourage enterprises to actively carry out technological innovation. All localities should actively promote the optimization of their industrial structure according to their respective strengths and advantages. Regions with good economic foundations and complete industrial development should vigorously develop high-end modern service industries and promote the upgrading of their industrial structure; in areas with poor industrial foundations, the "two and three" and "two-three" development strategies should be simultaneously adopted in the course of the "integration of two industrializations", and industrial enterprises should be gradually pushed to the middle and high ends. The transformation and upgrading of the industrial structure should be realized. Furthermore, institutional barriers should be broken down, the integrated development of regional markets should be strengthened, and the free circulation of factors between different regions should be promoted. It is also necessary to continuously improve the market mechanism, be market-oriented, effectively promote the allocation of capital and labor, and optimize the allocation of resources.

Third, the government should fully use its power to accelerate the development of the digital economy in the eastern region, megacities, and large cities; broaden the field of the digital industry in the primary, core, and high-end fields; and promote the in-depth development of the digital economy through the combination of digital technology and industry. Radiation and the driving effect can be better exerted by truly achieving the cross-regional division of labor and cooperation. The government should also strengthen support for the central and western regions and small and medium-sized towns. It is necessary to enhance the construction and attractiveness of the digital infrastructure in cities and towns, as well as introduce excellent talents and companies to accelerate the development of the digital industry. It is also necessary to vigorously develop the digital resources of large cities in the eastern region and use them in the small and medium-sized cities of the western and central regions by relying on digital technology and establishing a regional cooperation network to promote the development of the digital economy.

7.3. Research Prospects

Due to the slow updating of the data of the relevant indices, especially data at the city level, the data used in this paper were limited to 2011–2019. Therefore, there is room for the further expansion of research on the digital economy and urban total-factor energy efficiency. The research object of this paper was 275 cities, and future research could use more city-level data. We will continue to pay attention to the latest official data published by the China Bureau of Statistics and relevant departments, and learn new techniques and methods for analyzing relevant data. In our following study, relevant data (especially regarding indices related to the digital economy) will be further updated. Because of the rapid development of the current digital economy, the updated data will be of better reference value and significance for studying this topic.

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