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Exploring the Impact of the Digital Economy on Carbon Emission Efficiency Under Factor Misallocation Constraints: New Insights From China

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The digital economy has introduced far-reaching innovations in the fields of government governance, enterprise production, and social operation. How to motivate the economic development mode towards a low-carbon and greenway transformation through the digital economy is a major issue concerning the Chinese government. However, there is scarce evidence to interpret the role mechanism of the digital economy on carbon emission efficiency from the factor misallocation scenario. Taking a database from 30 provincial-level administrative regions for the period from 2011 to 2019 in China as an example, the paper examines the effect of the digital economy on carbon emission efficiency, as well as explores its role mechanism deeply in terms of factor misallocation (capital misallocation and labor misallocation). The results suggest that there is a significant potential for the digital economy to contribute to carbon emission efficiency, as well as this finding, is valid when considering both the endogeneity issue and a series of robustness checks. Also, the digital economy can significantly contribute to carbon efficiency in both southern and northern regions, but more strongly in the northern region. Besides, the digital economy can inhibit the factor misallocation (labor misallocation and capital misallocation) level which ultimately improves carbon emission efficiency. Finally, as a digital economy, it can positively impact carbon efficiency in the long run by mitigating factor misallocation (labor misallocation and capital misallocation).

Keywords: digital economy, factor misallocation, carbon emission efficiency, regional heterogeneity, economic development

1 INTRODUCTION

Global warming has already emerged as an extremely serious impediment to low-carbon development, and how effectively controlling and reducing greenhouse gas emissions (GHG), mainly carbon dioxide, has proven to be a major issue in front of mankind. As China's industrialization and urbanization continuously advance, the rapid economic growth and social productivity continue to rise, while energy consumption emits enormous amounts of carbon dioxide (Wang et al., 2019; Wang et al., 2020a). Excessive GHG emissions which result in increasingly frequent extreme and severe weather phenomena also have an adverse impact on production, economic development, and physical and mental health, and consequently, the resulting ecological concerns are already inflicting incalculable economic losses (Deng et al., 2019; Jia et al., 2022; Li Z. et al., 2021). As evidenced by data published by the International Energy Agency (IEA), China's carbon emissions surged dramatically since the 21st century, with its total carbon emissions surging from 8.83 billion tons to 9.9 billion tons over the past decade, rendering it the world's largest carbon emitter[1]. In response to the increasingly challenging climate environment, the Chinese government has successively enacted several policies to shoulder its share of responsibility in the developing process (Yang et al., 2022; Ren et al., 2021). China, for example, has made clear that it will contribute more autonomously by aiming for "peak carbon emissions by 2030 and carbon neutrality by 2060" (Hao et al., 2021; Fang et al., 2022; Xin et al., 2022). Nevertheless, as China strives to fulfill its carbon emission reduction goals, the most immediate dilemma is the need to optimize the ecosystem by boosting carbon emission efficiency while guaranteeing stable and healthy economic development (Meng et al., 2021). Carbon emission efficiency is considered as one of the parameters to evaluate low carbon economy level, which is essentially a production technology efficiency considering carbon emission that can reflect the resource utilization efficiency of production activities as well as the carbon utilization capacity (Shi et al., 2022). Therefore, an in-depth discussion on carbon emission efficiency not only helps analyze the scope for carbon emission reduction improvement in each area, but also contributes to the early achievement of the double carbon goal.

Since the double carbon goal is proposed, how to strengthen carbon emission efficiency has become a hot topic for scholars, and scholars have conducted investigations on carbon emission efficiency-related issues from various fields. As a newly emerging economic phenomenon, the digital economy has been continuously elevating the digitalization, networking, and intelligentization of the economy and society through digital industrialization and industrial digitization, effectively driving economic development (Li J. et al., 2021). Meanwhile, the digital economy reacts directly to the huge changes in the internal endowment and external environment of the economy under its high penetration, scale effect, and network effect. The White Paper on the Development of China's Digital Economy covers the Chinese digital economy scale from RMB 9.5 trillion in 2011 to RMB 39.2 trillion in 2020, as well as the share of GDP accounted for by the digital economy at 38.6% in 2020, with a 9.7% growth rate, significantly faster than the nominal GDP growth rate in the same period[2]. Consequently, the digital economy has experienced rapid growth with continuous attention from academia (Wang et al., 2021a). Among them, the impact of the digital economy on carbon emission efficiency is one of the key points of academic interest. Some scholars consider that the digital economy can directly or indirectly influence the carbon emissions generated by energy activities and thus the carbon emission efficiency through its wide application in the chain of energy production, consumption, transmission, operation, management, measurement, and trading. Other scholars believe that the e-commerce industry, big data industry, communication and Internet industry in the digital economy, as environmentally-friendly industries, can crush highly energy-consuming and high-emission industries through the crowding-out effect and optimize the industrial structure, which in turn affects carbon emission efficiency.

Moreover, lagging factor market reform is a critical factor in China's slow marketization process, which is largely reflected in the excessive intervention of local governments in factor trading activities (Yang et al., 2021a). Such excessive intervention can distort factor prices and consequently trigger factor misallocation (Wang et al., 2020c; Wang et al., 2021b; Wu et al., 2022). The Chinese government, suggests that the proliferation and transmission of resource allocation distortions have brought about economic and structural problems. However, market-based factor allocation is the fundamental way to drive high-quality economic development. Simultaneously, the spread of digital infrastructure and digital technology has a huge impact on economic development. Regarding the allocation of resources, the digital economy can alleviate information asymmetry, which is an essential factor affecting the flow and allocation of labor and capital. However, few existing studies seek to quantify the impact of the digital economy on carbon emission efficiency by considering factor misallocation. So, what is the impact of the evolving digital economy on carbon emission efficiency, and how does this impact differ from a regional heterogeneity perspective? What is the role of the impact of the digital economy on carbon efficiency in factor misallocation scenarios? Responses to the above questions are not only informative and instructive for realizing a green and low-carbon economic transition by raising carbon emission efficiency, but also serve as policy guidance for emerging economies with similar development to China. Therefore, this paper incorporates factor misallocation into the research framework of the impact of the digital economy on carbon emission efficiency, systematically discusses the role mechanism and heterogeneity of the digital economy on carbon emission efficiency under factor misallocation, and quantifies the dynamic effect of the digital economy and factor misallocation on carbon emission efficiency. This study aims to provide a scientific basis and theoretical reference for improving the construction of the digital economy, reducing factor misallocation, and facilitating the steady improvement of carbon emission efficiency through rigorous empirical analysis.

This paper primarily supplements the current research in the following dimensions. First, because of its high penetration, the digital economy is highly integrated with other industries, so the results of directly measuring the value-added to the digital economy or using the satellite account method may underestimate the scale of the digital economy. Comparatively, utilizing the input-output method of national accounting to evaluate the value-added to the digital economy may be nearer to the real value. Therefore, this paper adopts the input-output method to estimate the digital economy to develop the existing content of the research on measuring the digital economy.

[1]See more detail: https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2021-full-report.pdf.

[2]See more detail: http://m.caict.ac.cn/yjcg/202007/P020200703318256637020.pdf.

Second, this paper examines the role mechanism of the digital economy in influencing carbon emission efficiency according to the current literature, and then investigates the nexus that emerges between the digital economy and carbon emission efficiency with the help of an econometric model, as well as demonstrating the heterogeneity of the relationship between the two based on geographical location, which is conducive to the development of related theories. Thirdly, the intrinsic mechanism of interaction between the digital economy and carbon emission efficiency is further fully dissected from the factor misallocation perspective, which is empirically inspected by constructing a mediating effect on the basis of measuring the degree of resource misallocation. Finally, in conjunction with the findings of the study, this paper gives specific policy implications for the better role of the digital economy in factor allocation improvement and carbon emission efficiency enhancement, and policy rationale for digital economy development following specific local conditions.

2 LITERATURE REVIEW

Judging from the available studies, those highly linked to the digital economy, factor misallocation, and carbon emission efficiency can be largely categorized as three categories as follows. The first category is concerned with the discussion of the digital economy measurement and its economic and social effects (Li Y. et al., 2021). Digital technologies, such as cloud computing, the Internet of Things, as well as artificial intelligence, have been continuously integrated with public administration, logistics, transportation, and traditional manufacturing industries in recent years, empowering traditional industries with a digital economy to achieve high-quality economic development has become a topical issue (Corbett, 2018). Since its birth, the concept of the digital economy has gone through roughly the stages of an information economy, internet economy, and digital economy (Mesenbourg, 2001; Ma et al., 2022). As the digital economy develops and evolves, scholars have gradually widened the differences in their understanding of the digital economy (Bowman, 1996; Moulton, 2000; Turcan and Juho, 2014). As a result, there are also significant differences in the measurement methods of the digital economy. The current calculation of the digital economy can be categorized in four ways, which are national economic accounting methods, studying the value-added of the digital economy, measuring satellite account construction, and indexing (Acevedo Ruiz and Pena-Lopez, 2017; Jolliff and Nicholson, 2019; Ojanperä et al., 2019). Li J. et al. (2021), for example, measure the digital economy in terms of the Internet dimension using the entropy value method. Li Y. et al. (2021) take "Digital Inclusive Finance Index of China Peking University" as benchmark indicators to construct the digital economy index. Although scholars are yet to develop a unified concept of the digital economy, they have affirmed its positive effects on economic and social development. Labaye and Remes (2015) demonstrate that digital technologies have significantly contributed to China's economic growth. Goldfarb and Tucker (2019) argue that the digital economy is a manifestation of the marketization of a new generation of digital technologies, which have natural advantages in reducing data-processing costs, transaction costs, and optimizing resource allocation. Ghasemaghaei and Calic (2019) describe the digital economy in terms of data that can improve the quality and efficiency of traditional factors such as labor and capital, which in turn can contribute to economic growth.

The second category is the research associated with carbon emissions. In line with the increasing prominence of climate issues, scholars have conducted increasingly profound investigations on carbon emissions, mainly concentrating on two dimensions of carbon emission level measurement and influence factor exploration (Xu et al., 2014). Ran et al. (2015) and Tang et al. (2020), for example, investigate carbon emissions in the Yellow River basin and the Yangtze River basin, respectively. Zheng et al. (2022) use multi-source data to investigate carbon emissions from energy consumption in Beijing as well as formulate a novel framework to calculate carbon emissions from houses and urban facilities. Cheng et al. (2018) account for the total factor carbon emission efficiency of the industrial sector separately by provincial administrative regions, and carbon emission efficiency has a significant growth trend. Shi et al. (2017) examine the factors influencing carbon emissions in the building industry, which shows that the energy intensity are the largest positive and negative roles on carbon emissions increase in the building industry, respectively. Zhou et al. (2020) analyze that regarding the association with industrial structure upgrading and carbon emission efficiency from a coupling perspective, discovering that a significant dynamic asymmetry is observed between carbon emission efficiency and industrial structure upgrading in most regions. Fang et al. (2022) utilizes the ICPP emission inventory method to estimate carbon emissions in eight industries in China and predicts that it is highly improbable that agriculture, building, manufacturing and transportation emissions will peak in 2030, while emissions from power and mining could peak in 2030.

The third category is the research associated with resource misallocation. It is an extremely crucial issue in economics research and one of the most critical issues via economic development in the world economy, thus, it has been a hot issue in the scientific community. A typical study on resource misallocation is Hsieh and Klenow's (2009) computational index of resource misallocation and productivity gap estimation model, which measures such factors as labor and capital that are not optimally allocated and the resulting efficiency deficit. Additionally, Banerjee and Moll (2010) demonstrate that reallocating factors under conditions where the marginal output of all firms' factors are all equivalent can still contribute to higher output. A study by Ljungwall and Tingvall (2015) highlights the insufficient R&D spending in China owing to the presence of more severe factor market distortions, causing a lag in innovation capacity. Examining 30 provincial administrative regions in China, Brandt et al. (2013) report that total factor productivity losses in China primarily originate from the misallocation of capital among provinces and the public and non-public sectors. Dollar and

Wei (2007), using a study of more than 12,000 Chinese firms, suggest that improvement in capital distortion can increase GDP by 5% with constant inputs. Li and Du (2021) examine the micro-firm level to reveal that, in Chinese firms, internet development can contribute to energy efficiency by mitigating resource misallocation, resulting in energy savings. Yang et al. (2022) identify a significant spatial distribution heterogeneity of energy misallocation in China, which is strongly linked to the degree of energy internet development. Wu et al. (2022) assert that the distortions of capital distortions and output distortions to total factor productivity in the thermal power industry are more significant in hydropower plants in hydro-rich regions.

An overview of the existing studies suggests that the study on the role influence of the digital economy on carbon emission efficiency is just in its initial stage, especially few reports investigating the role mechanism of the digital economy on carbon emission efficiency from the consideration of factor misallocation. On the one hand, on the basis of a continuing study of the existing literature, this paper further theorizes how the digital economy can mitigate factor misallocation and thus contribute to carbon emission efficiency. On the other hand, utilizing a database from 30 provincial-level administrative regions for the period from 2011 to 2019 in China as an example, the capital misallocation index and labor misallocation index are introduced as mediating variables to deeply analyze the transmission mechanism and impact effect of factor misallocation between the digital economy and carbon emission efficiency.

3 THEORETICAL ANALYSIS AND RESEARCH HYPOTHESIS

The effect of the digital economy on carbon emission reduction efficiency is manifested in the three major aspects as follows. First, the digital industry represented by electronic equipment manufacturing and information technology services has all the attributes of an environmentally friendly industry. Digital industries are generally greener than traditional industries, whose development is less damaging to the environment (Ghobakhloo and Ching, 2019). Second, digital industrialization can help traditional industries improve their carbon emission efficiency. With the continuous promotion of digital industrialization, digital technologies represented by big data and artificial intelligence will continuously integrate with traditional industries. This will not only help their industries to gradually transform into digital, intelligent, and green, ones but also reduce energy consumption and carbon emissions while improving industrial added value (Qin and Cheng, 2017). Third, the establishment of a carbon emission market encourages enterprises to carry out environmental technology innovation. And the development of the digital economy helps to solve a series of key technical problems that plague the establishment of the carbon market, such as carbon emission monitoring, reporting, and verification (Weng and Xu, 2018). Based on this, this paper proposes hypothesis H1.

Hypothesis H1: The digital economy can significantly improve carbon emission efficiency.

Moreover, as the digital economy develops, the cost of information search decreases significantly, which reduces the information asymmetry between supply and demand, thus improving the price mechanism and reducing the degree of factor misallocation. Simultaneously, the digital economy has substantially strengthened market competition (Chen, 2020). On the one hand, because of the improved efficiency of information access, both the entry barrier of producers and the bargaining power of consumers have been lowered, thus significantly enhancing competition. On the other hand, the rise of the platform economy has blurred the concept of geography and intensified the cross-regional competition of enterprises. It gradually eliminates the less efficient enterprises in the continuous fierce competition, thus realizing the reallocation of factors. Third, the digital economy has obvious high permeability and high synergy. The combination of information, data, and other factors with traditional factors has substantially improved the productivity and allocation efficiency of factors (Zhai et al., 2022). The rise of the digital economy has also transformed traditional organizational structures and business processes towards networking, flattening, and flexibility, thereby improving the degree of factor misallocation (Kretschmer and Khashabi, 2020). Based on this, this paper proposes hypothesis H1.

Hypothesis H2: The digital economy can significantly inhibit factor misallocation.

The digital economy itself has such characteristics as scale effect, network effect, and platform effect, and thus it creates new channels and platforms for the orderly and reasonable flow of production factors associated with the rapid development of the digital economy, which in turn has an indirect role in promoting carbon emission efficiency. Digital economy development assists in lowering information and transaction costs as well as regional industrial upgrading (Lin and Chen, 2018, which in turn contributes to the carbon emission efficiency. On the one hand, the spatio-temporal compression characteristics of the digital economy effectively alleviate information asymmetry, and significantly reduce information costs and transaction costs, thus expanding the market scope while reducing industry and transaction barriers, prompting production factors and commodities to flow in a larger space in an orderly and reasonable manner, thus alleviating the problem of factor misallocation. On the other hand, the digital economy boosts the digital and intelligent transformation of industries, thus optimizing resource allocation. For example, the digital economy eliminates backward enterprises and industries such as low efficiency and high energy consumption through competitive effects and promotes new industries and new business models in the form of digital and intelligent transformation of traditional enterprises (Mattauch et al., 2015). This not only broadens the flow channels and platforms of production factors and improves factor allocation efficiency, but also promotes carbon emission efficiency.

Hypothesis H3: The digital economy improves carbon emission efficiency by ameliorating factor misallocations.

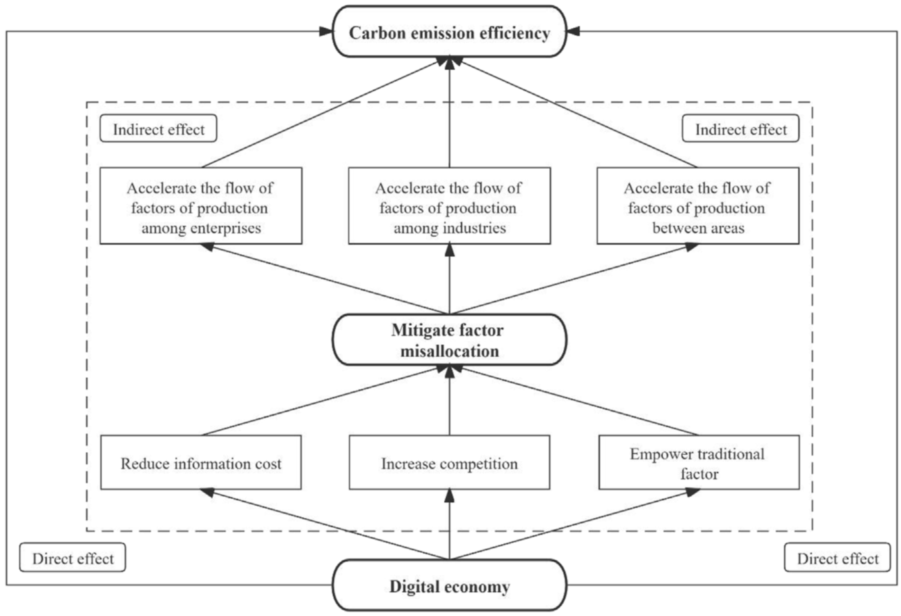

FIGURE 1 | Theoretical mechanism diagram.

The theoretical mechanism of this paper is illustrated on the basis of the above theoretical analysis (**Figure 1**).

4 MODEL SETTING

4.1 Economic Strategies

Referring to Wang et al. (2022), this paper develops the following model to examine the role of the digital economy on carbon efficiency. Specific model setting is given in **Eq. 1**:

$$CEE_{it} = \alpha_0 + \alpha_1 DIG_{it} + \alpha_2 X_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

where $i\,(t)$ denotes the region (time), Cee is the explanatory variable, denoting the carbon efficiency, Dig is the core explanatory variable, denoting the digital economy. X denotes some control variables, such as energy mix (ECS), environmental regulation (ERS), openness (OPE), human capital (HUC), and technological innovation (TEC). μ indicates unobservable area individual effects. ε is a random disturbance term (obeying normal distribution). α is the coefficient to be estimated.

Next, the following equation is developed to examine whether the digital economy can contribute to carbon emission efficiency by mitigating factors misallocation degree.

Step 1: The estimating equations of the digital economy and factor misallocation (including capital misallocation and labor misallocation) is constructed (See **Eqs. 2** and **3**).

$$\tau_{Kit} = \alpha_0 + \beta_1 DIG + \Sigma\theta_j X_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

$$\tau_{Lit} = \alpha_0 + \beta_2 DIG + \Sigma\theta_j X_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

where τK and τL denote the capital and labor misallocation indexes, respectively. The other variables have identical meanings to those defined in **Eq. 1**.

Step 2: To inspect whether the digital economy can contribute to carbon emission efficiency by mitigating factor misallocation (capital factor misallocation and labor factor misallocation) (See **Eqs. 4** and **5**).

$$\tau_{Kit} = \gamma_{0+}\gamma_1 DIG + \gamma_2 \tau_{Kit} + \Sigma\theta_j X_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

$$\tau_{Lit} = \gamma_{0+}\gamma_3 DIG + \gamma_4 \tau_{Kit} + \Sigma\theta_j X_{it} + \mu_i + \varepsilon_{it} \tag{5}$$

Referring to the test of Yang et al. (2021b), the significant β in **Eqs. 2** and **3** is a prerequisites for the test of mediating effects, suggesting that there is an effect of the digital economy on capital misallocation and labor misallocation. If the coefficients γ_1 and γ_2 are significant or when β_2 and γ_4 are statistically significant, a mediation effect exists.

4.2 Variables Selection

4.2.1 Digital Economy

Following the research method of Wang et al. (2021b), this paper employs the scale of the digital economy to characterize the digital economy development degree. Under the definition of the connotation of the digital economy, the digital economy scale is estimated by using digital industrialization and industrial digitization as two parts of accounting for the scale of the digital economy (Li Y. et al., 2021; Wen et al., 2021). Among them, digital industrialization scale is mainly denoted by the added value of the information and communication technology industry (ICT), and the scale of industrial digitization is denoted by the contribution of the information and communication technology industry (ICT) to the added value of other industries. In summary, the scale of the digital economy can be indicated by **Eq. 6**.

$$Digital\ economy\ scale = digital\ industrialization\ scale + industrial\ digitization\ scale \quad (6)$$

Step 1: Digital industrialization scale (CEE), i.e. the total value added to the information and communication technology industry (ICT) sector, is calculated with the formula given in **Eq. 7**.

$$G_{ICT} = \sum_{k=1}^{n} ICT_k \quad (7)$$

where $GICT$ denotes the scale of digital industrialization. $ICTk$ denotes the value-added of each sub-sector in the information and communication technology industry. Computer value-added, communication as well as other electronic equipment manufacturing $ICT1$ and information transmission value-added, software and information technology services $ICT2$ is considered as digital industrialization scale in the input-output table. This paper considers the sum of the value-added of computer, communication, and other electronic equipment manufacturing ($ICT1$) and the value-added of information transmission, software, and information technology services ($ICT2$) in the input-output table to be the scale of digital industrialization.

Step 2: Industry digitalization scale, i.e., the value of ICT the industry's contribution to the value-added of other industries. The volume of information and communication technology industry (ICT) that is employed in the production process of primary industry, secondary industry, and tertiary industry is adopted as an intermediate input. This paper divides the size of the digital economy industry into the value-added of digital basic industries and the value-added of digital auxiliary activities and determines the proportion of the value of ICT intermediate inputs to total intermediate inputs in the accounting period when calculating the value-added of digital auxiliary activities. Meanwhile, this paper determines the proportion of the contribution of the information and communication technology industry (ICT) to other industries value-added using the above method. Considering that price factors can affect the accounting of the size of the digital economy, the price indices of the information and communication technology industry (ICT) and primary, secondary and tertiary industries are introduced in the accounting to convert intermediate inputs into constant prices to correct the contribution share. Therefore, the scale of industry digitalization is calculated as shown in **Eq. 8**.

$$G_I = \sum_{i=1}^{3} G_i \times \frac{I_{ICT1}^i / P_{ICT1} + I_{ICT2}^i / P_{ICT2}}{I_i / P_i + I_{ICT1}^i / P_{ICT1} + I_{ICT2}^i / P_{ICT2}} \quad (8)$$

where the subscript i denotes each industry. G_I denotes the scale of digital industrialization; Gi denotes the value-added of industry i. I_{ICT1}^i denotes the input of computer, communication and other electronic equipment manufacturing industry in industry i. P_{ICT1} denotes the ex-factory price index of industrial producers of communication equipment, computers, and other electronic equipment manufacturing industry. I_{ICT2}^i denotes the input of information transmission, software, and information technology service industry in industry i. P_{ICT2} denotes the ex-factory price of software, information technology service, as well as information transmission. I_i denotes the total intermediate input of industry i. Pi denotes the price index of industry i.

4.2.2 Carbon Emission Efficiency

This paper employs the super-efficient Slack Based Measure (SBM) analysis to measure carbon emission efficiency. Tone (2002) first proposes the SBM model, which is a data envelopment analysis (DEA) model based on slack variables. It has two major advantages over the traditional DEA in that it treats the undesired output more appropriately and can solve the difficulty of comparing multiple efficient units with each other. The equations are set in the following form.

$$\min = \frac{1/m \times \sum_{i=1}^{m} \bar{x}/x_{ik}}{1/(r_1 + r_2) \times \left[\sum_{s=1}^{r_1} \overline{y^d} \Big/ y_{sk}^d + \sum_{q=1}^{r_2} \overline{y^u} \Big/ y_{qk}^u \right]} \quad (9)$$

$$\begin{cases} \bar{x} \geq \sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j & i = 1, \ldots, m \\ \overline{y^d} \leq \sum_{j=1, j\neq k}^{n} y_{sj}^d \lambda_j & s = 1, \ldots, r_1 \\ \overline{y^d} \geq \sum_{j=1, j\neq k}^{n} y_{qj}^u \lambda_j & q = 1, \ldots, r_2 \\ \lambda_j \geq 0 & j = 1, \ldots, n; j \neq 0 \\ \bar{x} \geq x_k & k = 1, \ldots, m \\ \overline{y^d} \leq y_k^d & u = 1, \ldots, r_2 \\ \overline{y^u} \leq y_k^u & q = 1, \ldots, r_1 \end{cases} \quad (10)$$

This paper considers capital stock, energy consumption, and labor as factor inputs, GDP as desired output, and total carbon emissions as non-desired output. Where each province's capital stock was capitalized with 2010 as the base period. The number of urban year-end employment is labor input. Total energy consumption is energy input. Desired output is the real provincial equivalent of GDP transformed taking 2010 years into the base period. Undesired output is the carbon emissions of each province. Drawing on the research methodology of Zhao et al. (2022) and Su et al. (2021), the capital stock is estimated. The specific setting is shown in **Eq. 11**.

$$K_t = I_t / P_t + (1 - \delta_t) K_{t-1} \quad (11)$$

where Kt denotes the fixed capital stock in the current period. It is the total nominal fixed capital formation in the period. The price index of Pt is fixed asset investment. δt denotes the

TABLE 1 | Carbon emissions coefficient.

Energy Types	Coal	Coke	Crude Oil	Gasoline	Kerosene	Diesel	Fuel Oil	Natural Gas
Carbon emissions coefficient	0.7476 t Carbon/t standard coal	0.1128 t Carbon/t standard coal	0.5854 t Carbon/t standard coal	0.5532 t Carbon/t standard coal	0.3416 t Carbon/t standard coal	0.5913 t Carbon/t standard coal	0.6176 t Carbon/t standard coal	0.4479 t Carbon/t standard coal

TABLE 2 | Carbon emission efficiency by province, 2010–2019.

Region	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	1.074	1.140	1.143	1.182	1.184	1.226	1.283	1.319	1.326	1.332
Tianjin	0.702	0.653	0.667	1.071	1.062	1.073	1.093	1.098	1.071	1.030
Hebei	0.501	0.512	0.503	0.643	0.726	0.706	0.644	1.036	0.937	0.695
Liaoning	0.354	0.365	0.365	0.421	0.421	0.399	0.398	0.407	0.421	0.443
Shanghai	0.499	0.505	0.498	1.058	1.073	1.070	1.058	1.036	1.058	1.038
Jiangsu	0.510	0.516	0.522	0.648	0.696	0.702	0.660	0.680	0.700	0.664
Zhejiang	0.467	0.490	0.510	0.614	0.611	0.675	0.681	0.702	0.718	0.670
Fujian	0.442	0.465	0.469	0.552	0.561	0.569	0.582	0.596	0.602	0.601
Shandong	0.781	0.744	0.749	1.017	1.028	1.031	1.034	1.032	1.037	1.038
Guangdong	1.093	1.125	1.146	1.006	0.894	0.916	0.926	0.942	0.983	1.040
Hainan	0.733	0.747	0.758	0.937	0.970	0.967	1.002	1.010	1.030	1.065
Shanxi	0.586	0.606	0.610	0.701	0.628	0.629	0.637	0.648	0.624	0.614
Jilin	0.679	0.669	0.684	0.840	0.724	0.738	0.764	0.766	0.742	0.755
Heilongjiang	0.583	0.585	0.583	0.629	0.588	0.577	0.586	0.600	0.611	0.617
Anhui	0.604	0.621	0.623	1.017	1.027	1.038	1.035	1.014	1.044	1.051
Jiangxi	0.507	0.509	0.521	0.572	0.547	0.550	0.561	0.586	0.651	0.663
Henan	0.553	0.555	0.567	0.700	0.634	0.648	0.655	0.695	0.715	0.694
Hubei	0.549	0.564	0.581	0.779	0.760	0.799	0.784	0.790	0.824	0.729
Hunan	1.144	1.131	1.114	1.068	1.047	1.055	1.051	1.047	1.022	1.012
Inner Mongolia	0.551	0.551	0.549	0.658	0.616	0.603	0.606	0.625	0.643	0.632
Guangxi	0.658	0.648	0.619	0.672	0.632	0.623	0.631	0.628	0.619	0.590
Chongqing	0.521	0.521	0.551	0.683	0.582	0.633	0.657	0.682	0.701	0.691
Sichuan	0.546	0.591	0.609	0.650	0.626	0.685	0.702	0.738	0.785	0.746
Guizhou	0.356	0.371	0.368	0.421	0.374	0.376	0.378	0.376	0.384	0.377
Yunnan	0.392	0.398	0.390	0.452	0.417	0.420	0.424	0.432	0.438	0.456
Shaanxi	0.486	0.497	0.499	0.543	0.495	0.490	0.493	0.500	0.519	0.495
Gansu	0.394	0.409	0.416	0.449	0.412	0.412	0.420	0.419	0.440	0.466
Qinghai	0.363	0.355	0.343	0.404	0.376	0.370	0.358	0.357	0.354	0.334
Ningxia	0.332	0.341	0.331	0.398	0.364	0.349	0.352	0.343	0.342	0.325
Xinjiang	0.360	0.357	0.348	0.387	0.348	0.335	0.329	0.314	0.321	0.303

TABLE 3 | Baseline regression results.

Variables	(1)	(2)	(3)	(4)
	Ols	Ols	Fe	Fe
DIG	0.181***	0.085***	0.164***	0.062**
	(0.015)	(0.013)	(0.020)	(0.031)
ECS		−0.245***		−0.339***
		(0.088)		(0.115)
ERS		0.004***		0.004***
		(0.001)		(0.001)
TEC		0.011***		-0.001
		(0.002)		(0.003)
OPE		0.375***		0.112
		(0.056)		(0.092)
HUC		0.071***		0.090***
		(0.020)		(0.028)
Constant	−1.730***	−1.847***	−1.608***	−1.693***
	(0.108)	(0.159)	(0.140)	(0.227)
N	300	300	300	300
R-squared	0.319	0.690	0.196	0.345

*Note: Standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.*

depreciation rate, which is usually taken as 9.6%. Kt-1 denotes the capital stock of the previous period.

Referring to Li Y. et al. (2021) and Wang et al. (2020b), the IPCC approach is adopted for calculation. The specific calculation process is shown in **Eq. 12**.

$$C_{it} = \Sigma E_{ijt} \times \eta_j \times 44/12 \tag{12}$$

Among them, C_{it} denotes the total carbon emissions of i province in the t year. E_{ijt} denotes the j kind of energy consumption in the t year of i province. η_j denotes the carbon emission coefficient of the j kind of energy. **Table 1** covers each energy source's carbon emission factor. The carbon emission efficiency of each province from 2010 to 2019 is shown in **Table 2**.

4.2.3 Factor Misallocation

Referring to Hao et al. (2020), this paper introduces the capital misallocation index and labor misallocation index to estimate factor misallocation. The specific accounting techniques are shown in **Eqs. 13–15**:

TABLE 4 | Descriptive statistics of variables.

Variables	Variables Name	N	Mean	Sd	Min	Max
Dependent variable	CEE	300	−0.474	0.367	−1.194	0.286
Core explanatory variables	DIG	300	6.921	1.143	4.357	9.670
Mediating variables	τ_K	300	−1.748	1.021	−5.375	-0.282
	τ_L	300	−1.611	0.996	−5.510	0.112
Control variables	ECS	300	0.400	0.149	0.012	0.687
	ERS	300	22.473	21.232	0.435	141.646
	OPE	300	0.275	0.313	0.013	1.548
	HUC	300	9.083	0.930	6.764	12.782
	TEC	300	4.919	7.362	0.012	52.739

$$\gamma_{Ki} = \frac{1}{1+\tau_{Kit}}, \gamma_{Li} = \frac{1}{1+\tau_{Lit}} \tag{13}$$

Equation 13, γ_{ki} and γ_{Li} denote the absolute distortion coefficients of capital and labor factor prices, respectively, which are usually substituted with relative price distortion coefficients.

$$\gamma_{Ki} = \frac{K_i/K}{s_i\beta_{Ki}/\beta_K}, \gamma_{Li} = \frac{L_i/L}{s_i\beta_{Li}/\beta_L} \tag{14}$$

where K_i/K denotes the ratio of the capital stock employed to the total capital stock in the real state. S_i denotes the output of province i as a share of total output. $\beta_{Ki}d$ enotes the capital contribution value of province i. β_K denotes the output-weighted capital contribution value. $S_i\beta_{Ki}/\beta_K$ denotes the ideal proportion of capital in the condition of efficient resource allocation in province i. K_i/K denotes the proportion of capital in province i in the actual situation. L_i/L denotes the ratio of labor force used to the total labor force in province i in the actual state. $\beta_{Li}d$ enotes the value of capital contribution in province i. β_L denotes the output-weighted capital contribution value. $S_i\beta_{Li}/\beta_L$ denotes the ideal ratio of the labor force in the condition of efficient resource allocation in province i. γ reflects the ratio of actual to effective allocation of production factors in each province. If γ is greater than 1 ($\tau < 0$), it indicates that the province has an over-allocation of production factors. γ is less than 1 ($\tau > 0$), it indicates that the province has under-allocation of production factors. To avoid the interference of the regression by inconsistent sign direction, the absolute value of τ is taken from the study of Yang et al. (2022).

Referring to Yang et al. (2022), the Solow residual approach is employed to account for the factor distortion index. The production function in this paper is hypothesized to be a C-D production function that has fixed returns to scale. The specific form is shown in **Eq. 15**.

$$Y = AK_{it}^{\beta_{ki}}L_{it}^{1-\beta_{ki}} \tag{15}$$

where Y denotes output, which is specifically the real GDP of each province in the base period of 2010. K_i denotes capital input of each province, which is the real basic stock of each province in the base period of 2010. L_i denotes labor input, and is measured by the number of employees in each province in urban areas.

4.2.4 Control Variables

Since carbon emission efficiency is influenced by many factors, to be precise and reliable for the study, following Ren et al. (2021), and Hao et al. (2021), this paper identifies energy mix ((ECS), environmental regulation (ERS), openness (OPE), human capital (HUC) and technological innovation (TEC) as unobservable factors for carbon emission efficiency control. The massive burning of fossil fuels is one of the primary contributors to the greenhouse effect and over-reliance on fossil fuels will diminish carbon reduction effectiveness, while a reasonable energy consumption structure can effectively inhibit the increase of carbon emissions. Referring to Wu et al. (2019), using the share of coal consumption in primary energy consumption to characterize the energy consumption structure (ECS). Environmental regulation (ERS) will inhibit carbon emissions and economic aggregates in the short run, however, environmental regulation will eventually reduce carbon intensity in the long run (Zhong et al., 2021). Environmental regulation (ERS) is expressed using the amount of investment

TABLE 5 | Endogeneity results.

Variables	(1)	(2)
	TSLS	TSLS
DIG	0.248***	0.295***
	(0.025)	(0.060)
ECS		0.020
		(0.146)
ERS		0.004***
		(0.001)
TEC		−0.008**
		(0.003)
OPE		0.064
		(0.100)
HUC		−0.041
		(0.041)
	Step 1	
IV	0.0365***	0.024***
	(0.001)	(0.002)
Wald F-value	192.540	89.031
FAR test p-value	668.645	129.879
N	300	300

*Note: Standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.*

TABLE 6 | Robustness test results.

Variables	(1) Replacing Core Explanatory Variables	(2) Removing Municipalities	(3) Eliminating Extreme Values	(4) Estimating Sample Subintervals
DIG	0.112***	0.101***	0.119***	0.111***
	(0.035)	(0.037)	(0.021)	(0.023)
ECS	−0.110	−0.017	−0.653***	0.373
	(0.130)	(0.138)	(0.181)	(0.407)
ERS	−0.001**	0.002**	0.000	−0.004**
	(0.001)	(0.001)	(0.001)	(0.001)
TEC	0.007**	−0.000	−0.001	−0.011**
	(0.003)	(0.003)	(0.004)	(0.005)
OPE	−0.239**	−0.159	0.152	0.039
	(0.103)	(0.205)	(0.278)	(0.285)
HUC	0.071**	0.115***	0.020	0.020
	(0.032)	(0.036)	(0.036)	(0.083)
Constant	−2.142***	−2.139***	−1.172***	−1.310
	(0.255)	(0.249)	(0.416)	(0.859)
N	300	260	259	180

Standard errors in parentheses ***p < *0.01*, **p < *0.05*, *p < *0.1*.

completed in industrial pollution control. Openness is conducive that enterprises with sophisticated equipment and technology are ushered in to engage in economic activities, thus facilitating the reduction of pollutant emissions. However, for some relatively backward regions, they may become "pollution refuges" in the process of foreign investment introduction. Referring to Wang et al. (2022), openness to the outside world (OPE) is measured by dividing the total regional imports and exports by the ratio to GDP. Human capital can overcome the law of diminishing marginal returns, which in turn affects the carbon emissions efficiency. Referring to Yang et al. (2022), human capital (HUC) is denoted by the number of years of education per capita in each region. Technological innovation will both promote environmental protection and increase enterprise productivity, which in turn supports carbon efficiency (Tang et al., 2019; Cao et al., 2021). Technological innovation (TEC) is presented using patent grant numbers.

4.3 Data

This paper selects balanced panel data of 30 Chinese provincial administrative region during the period from 2010 to 2019 as the study sample. The fundamental data are derived from the China EPS database, China Population, and Employment Statistical Yearbook, the Statistical Yearbooks of each province, and relevant data published by the National Bureau of Statistics in each years. Descriptive statistics are presented in **Table 3**.

5 RESULTS AND DISCUSSION

5.1 Baseline Regression Results and Discussion

Table 3 reports the statistical results of the digital economy on carbon emission efficiency. Columns (1) and (3) of **Table 4** demonstrate the estimation results without the inclusion of control variables, columns (2) and (4) demonstrate the estimation results with the inclusion of control variables, columns (1) and (2) use OLS models to estimate the baseline regression model, and columns (3) and (4) use fixed effects models to estimate the baseline regression model. **Table 5** reports that there is a significant positive regression coefficient for the digital economy. (p-value < 0.05), implying that the digital economy significantly drivers carbon emission efficiency. Our results have supported the view of Han et al. (2022), Zhang et al. (2022) and Ma et al. (2022) that digital economy will significantly inhibit carbon emissions and thus influence carbon emission efficiency. Hypothesis 1 is verified. It is easy to interpret that compared with traditional industries, digital industries are emphasized by high added value and environmental

TABLE 7 | Heterogeneity results.

Variables	(1) South Region	(2) North Region
DIG	0.150**	0.182***
	(−0.062)	(−0.066)
ECS	−0.834***	−0.158
	(−0.23)	(−0.18)
ERS	0.005***	0.004***
	(−0.001)	(−0.001)
TEC	0.002	0.002
	(−0.003)	(−0.01)
OPE	−0.152	0.052
	(−0.179)	(−0.149)
HUC	0.013	0.106*
	(−0.048)	(−0.054)
Constant	−1.257***	−2.657***
	(−0.416)	(−0.425)
N	150	150
R-squared	0.478	0.432

Note:Standard errors in parentheses ***p < *0.01*, **p < *0.05*, *p < *0.1*.

TABLE 8 | Influence mechanism results.

Variables	(1)	(2)	(3)	(4)	(5)
	CEE	$\ln\tau_K$	CEE	$\ln\tau_L$	CEE
DIG	0.085***	−0.388***	0.072***	−0.387***	0.061***
	(0.013)	(0.061)	(0.014)	(0.056)	(0.014)
τ_K			−0.033***		
			(0.012)		
τ_L					−0.061***
					(0.013)
ECS	−0.245***	0.599	−0.226**	0.036	−0.243***
	(0.088)	(0.407)	(0.087)	(0.373)	(0.085)
ERS	0.004***	0.000	0.004***	0.001	0.004***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
TEC	0.011***	0.006	0.011***	0.028***	0.012***
	(0.002)	(0.010)	(0.002)	(0.009)	(0.002)
OPE	0.375***	0.001	0.375***	0.154	0.385***
	(0.056)	(0.261)	(0.056)	(0.239)	(0.054)
HUC	0.071***	0.355***	0.082***	0.469***	0.099***
	(0.020)	(0.093)	(0.020)	(0.085)	(0.020)
Constant	−1.847***	−2.558***	−1.930***	−3.421***	−2.054***
	(0.159)	(0.736)	(0.160)	(0.675)	(0.160)
N	300	300	300	300	300
R-squared	0.690	0.137	0.698	0.237	0.711

*Note: Standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.*

friendliness, thus the rise of digital industries has contributed to carbon emission efficiency (Han et al., 2022). Moreover, the development of the digital industry is the basis for the digitization of traditional industries. Along with the leapfrog growth of the digital industry, the digital industry has fuelled the transformation of traditional industry to digitalization, intelligence, and greening (Ma et al., 2022). Meanwhile, the digital economy has solved some technical problems faced by market-based environmental regulation, such as monitoring and verification, which has effectively facilitated the establishment of a carbon market and advanced carbon emission efficiency (Zhang et al., 2022).

5.2 Endogeneity Results and Discussion

The above results demonstrate that the digital economy significantly positive impact on carbon emissions efficiency. However, the above estimation methods may also have some endogeneity problems that cause the results to be biased. Also, the endogeneity problem arising from omitted variables is addressed by adding relevant variables to the control variables as far as possible in this paper. Moreover, considering that carbon emission efficiency represents the production and technology ability of the region while higher production and technology ability may contribute to the digital economy development in the region. Thus, there may be an inverse causality of carbon emission efficiency on digital economy. A properly selected instrumental variable is the most common strategy to tackle the endogeneity problem due to bi-directional causality. Referring to Maydeu-Olivares et al. (2019), this paper re-estimates the baseline regression results using two-stage least squares (TSLS) on the basis of internet penetration employed to generate the instrumental variable for the digital economy (see **Table 5**). Judging from the first-stage results, the coefficients of

TABLE 9 | Unit root test result.

Variables	LLC	IPS	ADF-Fisher
CEE	−7.8652***	−4.3354***	132.4058***
DIG	−17.0122***	−3.2761***	119.5995***
τ_K	−2.651*	−1.4513***	121.7724***
τ_L	−4.3801***	−4.5603***	104.0781***

*Note: Standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.*

the key variables are significant (p-value < 0.01), so that the instrumental variable correlation requirement is achieved. Judging from the second-stage results, the coefficients of the digital economy are still significant (p-value < 0.01),l, and the F-statistics of the weak instrumental variable test are 192.54 and 89.03 (all of them are greater than 10), indicating that there is no weak instrumental variable issue. Consequently, **Table 5** suggests that the digital economy can enhance carbon emissions efficiency when endogenous issues are addressed.

5.3 Robustness Results and Discussion

To investigate that the regression results are stable, this paper employs the robustness tests via replacing core explanatory variables, estimating sample subintervals, eliminating extreme values by shrinking tails, and removing municipalities (See **Table 6**). First, the explanatory variables are replaced. To avoid biased estimation results due to the selection of measurement methods, the carbon emissions efficiency of each province is re-measured by using the ratio of GDP to carbon emissions (see column (1) of **Table 6**). Second, municipalities directly under the central government are eliminated from the sample. Since municipalities directly under the central government and other provincial regions still have significant differences in various aspects, this paper excludes four samples of municipalities directly under the central government, namely Beijing, Shanghai, Tianjin, and Chongqing, to test again above effect (see column (2) of **Table 6**). Third, the data are subjected to a tailoring process. This paper recalculates above effect based on a 2% tailoring of each variable to remove extreme values (see column (3) of **Table 6**). Fourth, the sample subinterval is estimated. As China enters a new stage of digital economy development in 2015, this paper excludes the data from 2010 to 2014 to observe above effect in the sub-sample interval (see column (4) of **Table 6**). **Table 6** demonstrates that the regression coefficients for the digital economy are not significantly different from the baseline regression results in the case of significance and direction, proving that the previous results are robust.

5.4 Heterogeneity Results and Discussion

Given the enormous geographical boundaries in China and the significant diversity among regions in terms of natural endowments and industrial distribution. To elucidate the effects of the digital economy on the heterogeneity of carbon emission efficiency in different regions, referring to Liu et al. (2022), the results are re-estimated by dividing the study region into the south and the north following the Qinling-Huai River

TABLE 10 | Lag order test result.

	Lag Order	AIC	BIC	HQIC
Digital economy and carbon emission efficiency	1	−4.06881	−3.04874	−3.65643
	2	−1.95802	−0.751,789	−1.46894
	3	−5.23886	−3.79376	−4.65176
	4	−5.57042*	−3.80501*	−4.85348*
	5	−4.70407	−2.48201	−3.808
Digital economy and capital misallocation	1	−1.85374*	−0.833,668*	−1.44136*
	2	1.20283	2.40906	1.6919
	3	−0.95046	0.494,642	−0.36336
	4	−1.19091	0.574,501	−0.47397
	5	0.537,636	2.75969	1.4337
Digital economy and labor misallocation	1	1.33566	−0.315,591*	-0.92329
	2	2.96128	4.16751	3.45035
	3	−1.59206*	−0.146,954	−1.00496*
	4	−1.41478	0.35063	−0.69784
	5	−0.20263	2.01943	0.693,435
capital misallocation and carbon emission efficiency	1	−0.43835	0.581,722*	−0.025972*
	2	0.170,844	1.37707	0.659,917
	3	−0.48015	0.964,956	0.106,951
	4	−0.596,416*	1.169	0.120,526
	5	1.62095	3.843	2.51701
labor misallocation and carbon emission efficiency	1	−0.17054	0.849,529	0.241,835
	2	0.145,563	1.35179	0.634,637
	3	−1.04537*	0.399,734*	−0.45827*
	4	−0.65993	1.10548	0.057014
	5	0.587,825	2.80988	1.48389

*Note: * represents the optimal lag order.*

boundary. **Table 7** reports that the coefficients of the digital economy are all significantly positive, but the digital economy has a higher effect on carbon emission efficiency in such a region in the north where energy-producing regions and heavy industries are relatively concentrated. The traditional manufacturing industry in the northern region is relatively concentrated, and its innovation and technology level is comparatively lagging in development. The major advantage of the digital economy is the compressibility of temporal and spatial, which greatly reduces the innovation barriers and R&D costs in the region. This not only provides an effective boost to the green upgrading in the case of the traditional manufacturing industry in the northern region, but also contributes to the economic development and ecological construction. In addition, the economic and social development level of the southern region is generally better than that of the northern region. The innovation-driven and ecological protection strategies are also implemented earlier, resulting in much higher carbon emission efficiency in the southern region than in the northern region.

5.5 Influence Mechanism Results and Discussion

In order to investigate the role mechanism of the digital economy on carbon emission efficiency, this paper examines them in the light of factor misallocations (labor factor misallocation and resource factor misallocation) (See **Table 8**). Column (1) of **Table 8** reveals that the digital economy significantly enhances carbon emissions efficiency, ie., for every unit of growth in the digital economy, there will be a significant 8.5% increase in carbon emission efficiency. Columns (2) and (4) of **Table 8** suggest that the digital economy significantly inhibits capital misallocation and labor misallocation, respectively. Columns (3) and (5) in **Table 9** show that capital misallocation and labor misallocation significantly inhibit carbon emission efficiency. Therefore, the above results confirm that the digital economy can significantly contribute to carbon emissions efficiency via inhibiting factor misallocation (capital misallocation and labor misallocation). Hypotheses 2 and 3 are tested. We can explain the above results from the following aspects. Labor misallocation and capital misallocation reduce the production cost of backward enterprises, so that inefficient enterprises can continue to survive or even expand their scale, resulting in a decrease in carbon emission efficiency. Also, factor misallocation causes low labor and capital prices, which hinders enterprises' technological innovation, and generates an inefficient and low-technology "lock-in effect" (Wang et., 2018). Moreover, the digital economy diminishes the cost of information search, eliminates information asymmetry in the market, and enhances the matching between the supply and demand of labor and capital. Meanwhile, the e-commerce model formed based on digital technology blurs the concept of geography, which strengthens the bargaining ability of consumers. This not only intensifies market competition and accelerates the elimination of less efficient enterprises, but also enables the reallocation of capital and labor, reducing the degree of the

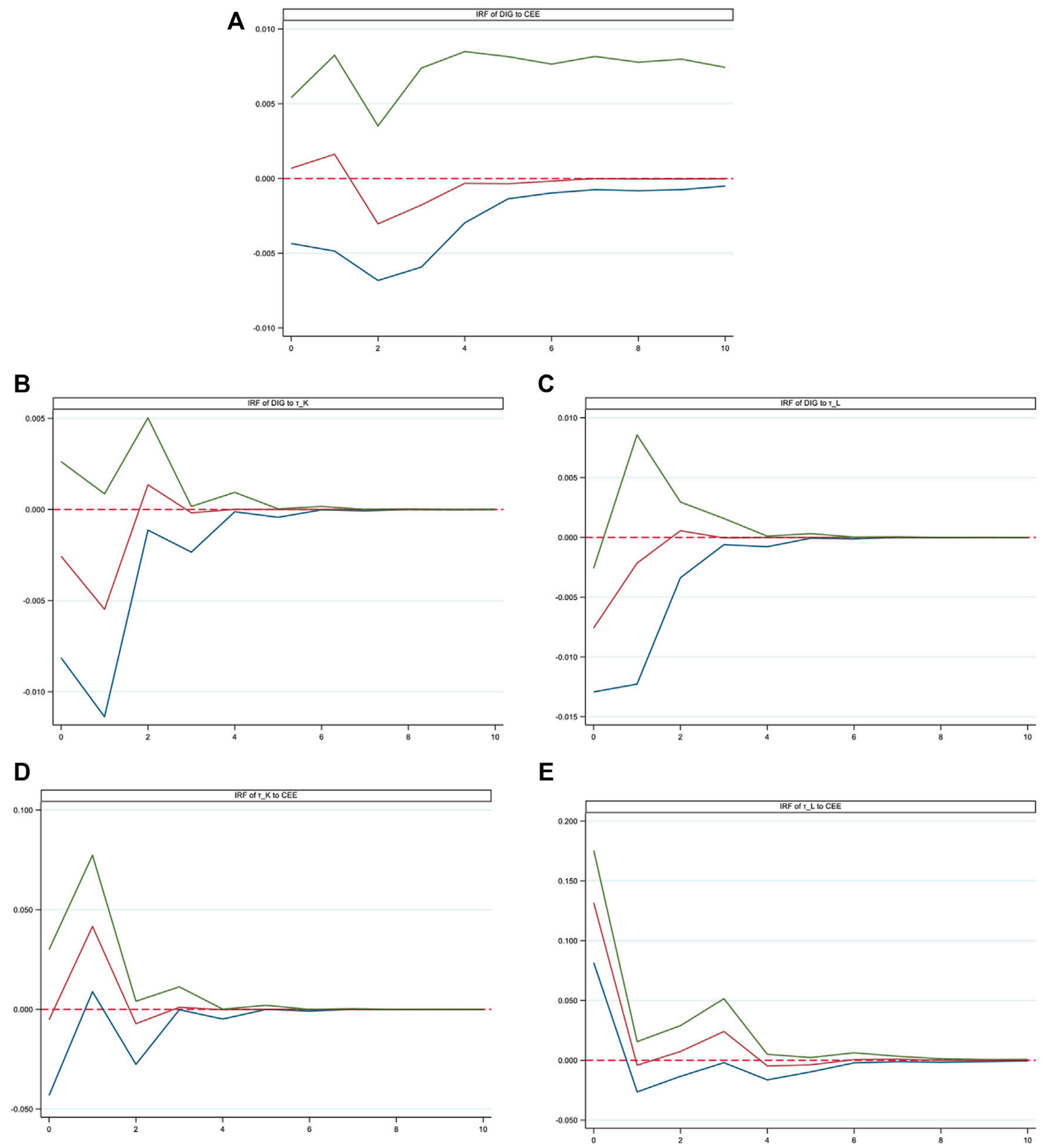

FIGURE 2 | Impulse response function diagram.

misallocation. Finally, the digital economy has significantly improved the productivity of labor and capital by empowering traditional factors with data, thereby improving their misallocation levels.

5.6 Dynamic Effects Results and Discussion

This paper further analyzes the dynamic effect of the digital economy on carbon emission efficiency in the light of factor misallocations (labor factor misallocation and resource factor misallocation) using impulse response functions based on a static study of the effects. The impulse function examines the impact of a random error term of an endogenous variable subjected to a shock of one standard deviation size on the current and future values of all endogenous variables. It describes the trajectory of mutual shocks and responses among the variables in the system, reflecting the dynamic influence relationship among the variables. Referring to Wu et al. (2021), unit root tests are conducted for the target variables using the LLC test, IPS test, and ADF-Fisher test (see **Table 9**). **Table 9** indicates that the first-order difference terms of the digital economy, factor misallocation, and carbon emission efficiency pass the significance test, i.e., the digital economy, factor misallocation, and carbon emission efficiency are smooth. To assure the estimated parameters validity, the number of lags of the impulse response model needs to be determined. Further, three methods, AIC, BIC, and HQIC, are used for the lag order test (see **Table 10**). If the lag order is too high, it will diminish model degrees of freedom and cause unnecessary loss of model data. Conversely, if the lag order is too low, it will reduce the accuracy of the model test results. The final lag order is dominated by the Bayesian criterion, so the lag term orders are chosen as 4th order, 1st order, 1st order, 1st order, and 3rd order, respectively.

Figure 2 illustrates that the horizontal axis reveals the lag order, the vertical axis indicates the response degree, the red solid line in the middle is the impulse response function, and the width between the green solid line and the blue solid line indicates the positive and negative double standard deviation bands. **Figure 2A** shows that the impulse response function curve of the digital economy on carbon emission efficiency is a “U" shape. When the digital economy is subjected to an external positive shock, the change in carbon emission efficiency covers a trend of increasing and then decreasing, and the impact gradually converges to zero from the fourth period. It suggests that the digital economy has a longer-term influence on carbon emission efficiency after an external shock, with a relatively stable impact. **Figures 2B,C** illustrate that the digital economy produces a negative shock to capital (labor)misallocation, and such variation is only present in the first two periods, which exhibits a decreasing trend. A positive shock to the digital economy is transmitted to the capital (labor) misallocation and brings a negative shock to the capital (labor)misallocation, indicating that a positive shock to the digital economy can mitigate the degree of capital (labor) misallocation and that the impact is short term persistent. **Figure 2D** illustrates that after a positive shock to the capital misallocation, the carbon emission efficiency shows a negative change in the current period, but the change in carbon emission efficiency fluctuates up and down around the horizontal axis from the first lag and gradually converges to zero in the third period, indicating that a positive shock to the degree of capital misallocation in the short term may inhibit the improvement of carbon emission efficiency. **Figure 2E** illustrates that after a positive shock is given to labor misallocation, the amount of carbon emission efficiency change fluctuates up and down around the horizontal axis from the lagged period and gradually converges to zero from the eighth period, indicating that a positive shock to the degree of capital misallocation will influence carbon emission efficiency in the long run. In general, the digital economy can contribute to carbon emission efficiency in a certain period and inhibit factor misallocation. As capital misallocation can affect carbon emission efficiency in the short term, while labor misallocation can affect carbon emission efficiency in the longer term. The dynamic analysis results are consistent with the previous analysis, implying that the digital economy can contribute to carbon efficiency by inhibiting capital misallocation and labor misallocation.

6 CONCLUSION AND POLICY IMPLICATIONS

The Chinese economy is in a critical transition period, facing economic pains caused by growth rate shift, structural adjustment, and the absorption of previous stimulus policies, in addition to coping with climate warming due to huge carbon emissions. Therefore, as a new economic form, how to promote economic growth and reduce carbon emissions through the digital economy has become an urgent issue to be investigated. Taking a database from 30 provincial-level administrative regions for the period 2011 to 2019 from 2011 to 2019 in China as an example, the paper examines the effect of the digital economy on carbon emission efficiency, as well as explores its role mechanism deeply in terms of factor misallocation. The results demonstrate that the digital economy can significantly contribute to the improvement of carbon emission efficiency, and this finding is valid when considering both the endogeneity issue and a series of robustness checks. The heterogeneous results show that the digital economy can significantly contribute to carbon efficiency in both southern and northern regions, but more strongly in the northern region. The role mechanism suggests that the digital economy can inhibit the factor misallocation (labor misallocation and capital misallocation) level by reducing the cost of information collection, strengthening enterprise competition, and promoting the integration of information, data, and other high-end data with traditional data, which ultimately enhances carbon emission efficiency. Finally, the dynamic effect results reveal that the digital economy can positively affect carbon efficiency in the long run by mitigating factor misallocation (labor misallocation and capital misallocation). As far as the above findings, this paper provides some policy implications for promoting carbon emission efficiency through the digital economy in the following three aspects.

First, policymakers should further enhance the digital economy scale. While continuously refining the fundamental digital technology, policymakers should strive to expand digital infrastructure construction, accelerate the expansion of the application scenarios of the new generation of digital technology, deepen the integration of the digital economy with the real economy, thereby providing an effective path to fulfil double carbon goal.

Secondly, policymakers should advance the coordinated development of the digital economy among regions by taking into account local conditions and zoning policies. Policymakers, for example, should not only fully balance the heterogeneity between different regions in terms of natural endowment and industrial distribution, but also promote digital industrialization or industrial digitization with a focus on different regions, so as to continuously improve carbon efficiency on the whole.

Finally, policymakers should maximize the factor allocation effect of the digital economy. While utilizing the spatial and temporal compression effect of the digital economy, policymakers should further accelerate the flow of information. By improving the price mechanism, the digital economy is adopted to promote the effective allocation of labor and capital among industries and regions, reduce the degree of factor mismatch, and improve allocation efficiency.

This paper confirms that the digital economy can positive impact on carbon emission efficiency by inhibiting factor misalignment. However, the role paths of the digital economy on carbon emission efficiency are complex and diverse, and some other factors may exist, such as technological innovation, industrial structure, and market segmentation. Scholars in the future can explore more potential paths for the digital economy to influence carbon emission efficiency from the above perspectives.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

WG: Conceptualization, Project administration, Writing - review andamp; editing, Writing - original draft. GL: Formal analysis, Data curation. LL: Software, Visualization. YX: Writing - original draft, Writing - review andamp; editing, Formal analysis. BS: Methodology, Data curation.: Writing - review andamp; editing, Validation. XS: Writing - review andamp; editing, Validation. QR: Writing - review andamp; editing, Writing - original draft, Conceptualization, Methodology, Funding acquisition, Supervision. XY:Writing - review andamp; editing.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.953070/full#supplementary-material

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