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The Impact of the Digital Economy on Carbon Emission Levels and Its Coupling Relationships: Empirical Evidence from China

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Abstract: The development of the digital economy has injected new vitality into the global economy, but the environmental issues it raises cannot be ignored. This paper analyzes the impact of the digital economy on carbon emission levels and their coupling relationships using panel data from 30 provinces, cities, and autonomous regions in mainland China from 2013 to 2021. By employing the coupling coordination degree model and the PVAR model, the study finds that the digital economy in mainland China has shown an upward trend, while carbon emission levels have exhibited a downward trend. The coupling degree between the digital economy and carbon emission levels is relatively good, though the coupling coordination degree is still in its early stages, indicating significant room for development. The digital economy has achieved a positive cumulative effect and can promote itself, and it has a significant negative impact on carbon emission levels.

Keywords: digital economy; carbon emissions; coupling coordination degree model; PVAR model

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1. Introduction

With the advancement of technology and the progress of globalization, the digital economy has become a key driver of modern societal development. This development is reflected not only in the widespread application of digital technologies but also in the significant contribution of the digital economy to global economic value. In 2016, the global digital economy was valued at an estimated USD 11.5 trillion [1], indicating its initial impact on the global economy. Following this, the digital economy experienced rapid growth, reaching an impressive USD 41.4 trillion across 51 major economies in 2022 [2]. This remarkable growth demonstrates the robust development momentum of the digital economy and highlights its potential in driving economic growth. As one of the leaders in the global digital economy, China saw its digital economy grow to USD 6.96 trillion in 2022 [3]. This increasing share of the national GDP underscores China's leadership in the global digital economy and highlights the importance and growth potential of the digital economy in the global economic landscape. Such growth dynamics have sustained the vitality of digital economic development, offering new pathways for economic transformation and upgrading for countries worldwide and bringing new opportunities for sustainable global economic development.

The digital economy, as an essential driver of modern society, is rapidly developing globally, significantly impacting economic growth, social progress, and international competitiveness. However, this phenomenon also brings dual effects on the environment and climate change. On one hand, issues such as the widening digital divide, increasing cybersecurity threats, and the emergence of new carbon emission sources need to be addressed in the development of the digital economy. Statistics show that in 2020, the global electricity consumption of the digital sector accounted for 3.6%, contributing 1.8% of the total global carbon emissions [1]. On the other hand, the digital economy holds enormous potential for promoting sustainable development. By enhancing energy efficiency, optimizing industrial layouts, and driving green technological innovation, the digital economy can help achieve carbon emission reductions and low-carbon development goals. However, the operation and expansion of the digital economy will undoubtedly increase energy and resource consumption, potentially leading to further increases in carbon emissions.

In terms of productivity effects, the digital economy can improve the productivity and efficiency of economic entities by reducing production, transaction, and coordination costs and enhancing the quality and diversity of products and services [4]. This can lower the carbon emissions per unit of output but may also increase output and income, thereby increasing the demand for energy and other carbon-emitting inputs. Regarding dematerialization effects, the digital economy can replace physical products and activities with digital products and activities, such as e-commerce, e-learning, e-government, and remote work [5]. This can reduce the consumption of materials, transportation, and infrastructure, thereby lowering carbon emissions. However, it may also generate rebound effects, such as increasing the demand for other goods and services or shifting emissions to other sectors or regions. In terms of innovation effects, the digital economy can foster the development and dissemination of new technologies and business models that can reduce carbon emissions, such as renewable energy, smart grids, electric vehicles, and the circular economy [6]. This helps to decouple economic growth from carbon emissions and achieve green and low-carbon development, though it may face barriers and challenges, such as market failures, institutional constraints, and social acceptance. Regarding behavioral effects, the digital economy can influence the preferences, attitudes, and behaviors of economic entities towards carbon emissions by providing more information, feedback, and incentives and promoting collective action and social learning [7]. This can lead to voluntary and cooperative changes in behavior, such as the adoption of low-carbon lifestyles, consumption patterns, and production practices. However, this may depend on the availability, accessibility, and reliability of digital technologies, as well as the trust, awareness, and motivation of economic entities.

Therefore, exploring the impact of the digital economy on carbon emission levels and their coupling relationships is of significant theoretical and practical importance for understanding the inherent logic of the digital economy, formulating scientific carbon reduction policies, and achieving the coordinated development of the digital economy and the green economy. The existing literature on the digital economy primarily focuses on the regression relationship between the digital economy and carbon emissions, with less attention paid to the coupling relationship between the digital economy and carbon emission levels. In the context of sustainable development, clarifying the driving mechanisms of the digital economy on carbon emissions and the coupling coordination relationship between the two, and exploring effective paths for sustainable development, have become crucial for promoting the green development of the digital economy.

This paper analyzes the impact of the digital economy on carbon emissions using a panel vector autoregression (PVAR) model and explores the coupling relationship between the two using a coupling coordination degree model. It investigates the mechanisms by which the digital economy affects carbon emissions and proposes policy recommendations to promote the coordinated development of the digital economy and low-carbon emission reduction.

2. Literature Review

The issue of carbon emissions has become a focal point of global concern, as global warming and climate change are direct consequences of these emissions. According to the Sixth Assessment Report (AR6) by the IPCC, ongoing carbon emissions have exacerbated global warming, leading to the increased frequency of extreme weather events, rising sea levels, and glacier melting [8]. These changes have profound impacts on ecosystems, including biodiversity loss and shifts in agricultural production patterns [9]. B. Ekwurzel has found that a significant portion of the increase in atmospheric CO_2, surface temperatures, and sea levels is attributable to the carbon emissions of 90 carbon producers from industrialized and developing countries [10]. Neslihan İyit discovered that increased carbon emissions are linked to a higher percentage of COVID-19 pandemic deaths [11]. Additionally, climate change induced by carbon emissions has negatively impacted the global economy, causing resource shortages, reduced productivity, and damage to infrastructure, thereby threatening economic development [12]. Climate change also causes health problems, migration, and security risks, which particularly affect vulnerable groups and developing countries [13].

As carbon emissions are the primary driver of global climate change, their reduction is crucial for balancing environmental protection and economic development. The rise of the digital economy offers new possibilities for reducing carbon emissions. The digital economy, which is based on digital technologies and is driven by innovation, creates, exchanges, and distributes value through online platforms, forming a new economic paradigm following agricultural and industrial economies [14]. It is characterized by unprecedented reliance on digital technologies in the production, distribution, and consumption of goods and services, transforming traditional economic models [15]. The proliferation of the internet, advancements in data analytics, and the widespread use of mobile devices have played key roles in this transformation, enabling new business models and efficiencies [16].

With the development of artificial intelligence and big data, the digital economy has further promoted the optimization and upgrading of production and service methods, reducing resource consumption and waste generation [17]. Companies use technologies like cloud computing and the Internet of Things (IoT) to improve resource utilization and reduce energy consumption in production processes [18]. Meanwhile, the growth of e-commerce has led to reductions in paper usage, and smart logistics have reduced carbon emissions during transportation [19]. Similarly, the rise of remote work and online education has decreased the travel demand, reducing urban traffic congestion and effectively alleviating greenhouse gas emission pressures [20].

However, while recognizing the positive impacts of the digital economy on environmental protection and economic development, we must also be cautious of potential rebound effects. These effects refer to the possibility that efficiency gains may lead to increased overall consumption, potentially offsetting environmental benefits [21]. Data centers are central to the digital economy, but their substantial energy demands and associated carbon emissions have raised concerns among scholars. Some studies indicate that while digitization promises efficiency gains and energy savings, the underlying infrastructure and operational processes may result in significant carbon emissions. Operations of data centers, cloud computing services, and the production and use of network equipment are energy-intensive activities, increasingly contributing to global energy consumption [22–25]. As data traffic increases and cloud services become more widespread, the energy consumption of data centers is expected to continue growing [26].

Moreover, the digital economy's influence on energy consumption is not only direct but also structural. The expansion of digital labor division and the application of automation technologies have prompted profound changes in employment structures. As robots and artificial intelligence gradually replace labor-intensive jobs in production processes, this may trigger changes in energy demand and consumption patterns at the macroeconomic level, further affecting total carbon emissions [27].

The relationship between the digital economy and carbon emissions has garnered widespread attention from academia and policymakers and is characterized by its multifaceted and complex interactive nature. Hilty et al. (2017) pointed out that digitization can reduce unnecessary resource consumption by optimizing resource allocation [28]. Dong et al. (2022) revealed, through an empirical analysis of 60 countries, that the digital economy has both direct and indirect effects on carbon emissions [29]. Li et al. (2021) explored the relationship between the digital economy, energy structure, and carbon emissions, highlighting the potential role of the digital economy in reducing energy consumption and carbon emissions [30]. Zhu et al. (2022) further analyzed the impact of digital economy development on carbon emissions in China, using the entropy method to assess the level of digital economy development, and found that the digital economy can effectively curb the growth of carbon emissions [31]. Additionally, Zhang et al. (2022) studied the interactions between the digital economy, energy efficiency, and carbon emissions, offering new perspectives on how the digital economy can reduce carbon emissions by enhancing energy efficiency [22].

In summary, the existing literature has actively explored the factors influencing the digital economy's impact on carbon emissions, but less attention has been paid to the coupling relationship between the digital economy and carbon emissions. Therefore, this paper first constructs a measurement system for the digital economy and carbon emissions, quantitatively analyzing the development levels of the digital economy and carbon emissions in China in recent years. It then uses the coupling coordination degree model to explore the coupling relationship between the digital economy and carbon emissions. Subsequently, the PVAR model is employed to empirically examine the actual accumulation mechanism of the digital economy and its impact on carbon emissions. Finally, the paper identifies urgent issues in their coupling coordination and proposes policy recommendations.

3. Mechanism Analysis and Research Hypotheses

The self-reinforcing supply and demand cycle plays a crucial role in driving the development of the digital economy. In this cycle, innovation acts as a catalyst, continuously pushing the creation of new products and services, thereby stimulating market demand. As demand grows, companies respond by increasing investment in technology research and development to meet the expanding market needs and enhance consumer experiences. This ongoing supply-side innovation spurs demand growth, and the sustained increase in demand, in turn, encourages further supply-side innovations, forming a stable and powerful growth loop. Additionally, the cost-reducing effects of economies of scale significantly enhance the market competitiveness of firms. The vast data lakes nurtured by digital transformation become invaluable assets for companies, playing indispensable roles in product optimization and market expansion. Feedback and data provided by users not only guide the innovation of services and products but also serve as crucial inputs for strategic decision making. Ultimately, through platform and network effects, the increasing number of market participants boosts the platform's value, further driving market expansion and product innovation. This closely linked, self-reinforcing supply and demand cycle effectively propels the development of the digital economy and amplifies innovation dynamics.

As the market scale continues to expand, enterprises gain more opportunities and resources to explore and experiment with new business models, further stimulating market vitality and growth potential. With active government guidance and strong support from capital markets, the development of the digital economy is characterized by smooth, orderly, and rapid progression. In conclusion, this self-reinforcing positive cycle mechanism not only lays a solid foundation for the robust and swift development of China's digital economy but also suggests that it will continue to serve as a key force driving socio-economic progress.

Hypothesis 1. *The digital economy in China has achieved a virtuous accumulation mechanism, capable of self-promotion.*

Driven by the digital economy, traditional industries become more efficient and intelligent through technological innovation and application, thereby enhancing productivity and improving energy use efficiency. In this process, labor, capital, and technological resources shift from low value-added agriculture and manufacturing to high value-added service and knowledge-intensive industries. This trend not only promotes industrial structure upgrading but also creates conditions for achieving a low-carbon economy. Optimizing the existing industrial structure can lead to a sustained reduction in energy consumption and improved carbon emission efficiency. From the perspective of industrial upgrading, as the economic structure shifts towards digitalization and informatization, the state and enterprises increasingly rely on data and information technology for decision making and enhancing industrial efficiency and output. During this process, government macro-control and industrial policies will increasingly focus on promoting the development and application of environmentally friendly and low-carbon technologies to achieve the dual goals of economic growth and environmental protection.

However, these changes are not without challenges. Industrial structural adjustments often come with social costs, such as the need for retraining and job placement for some labor forces. Additionally, the rapid development of high-tech industries may increase dependence on scarce resources, posing new pressures on the natural environment. Therefore, comprehensive industrial policy design should consider promoting technological innovation, industrial structure adjustment, and the integration of the circular economy with social equity to ensure truly sustainable development driven by the digital economy.

When analyzing the coupling relationship between the digital economy and carbon emission levels, the rebound effect is a crucial factor, potentially weakening the environmental benefits brought by digital technologies. The rebound effect refers to the phenomenon where improvements in energy efficiency lead to a reduction in the unit cost of energy, which might increase actual energy consumption, thereby offsetting the expected energy savings. Specifically, the rebound effect includes direct rebound effects, where energy-saving technologies make use more economical, leading consumers to use these technologies more or for longer, resulting in no overall reduction in energy consumption, and indirect rebound effects, where saved funds are spent on other energy-consuming goods or services, increasing overall energy demand. Additionally, the economic growth rebound effect occurs when efficiency improvements lower production costs, stimulating overall production growth and potentially increasing total energy demand. Moreover, capital cost rebound effects occur when cost savings from energy efficiency make firms more likely to invest in energy-intensive production, increasing energy consumption. Lastly, switching cost rebound effects may arise, as the sunk costs of existing technologies or equipment might deter consumers or firms from investing in energy-saving technologies, hindering the realization of energy savings.

Hypothesis 2a. *The digital economy has a positive impact on carbon emission levels.*

Hypothesis 2b. *The digital economy has a negative impact on carbon emission levels.*

In summary, the mechanism of the digital economy's impact on carbon emissions is illustrated in Figure 1.

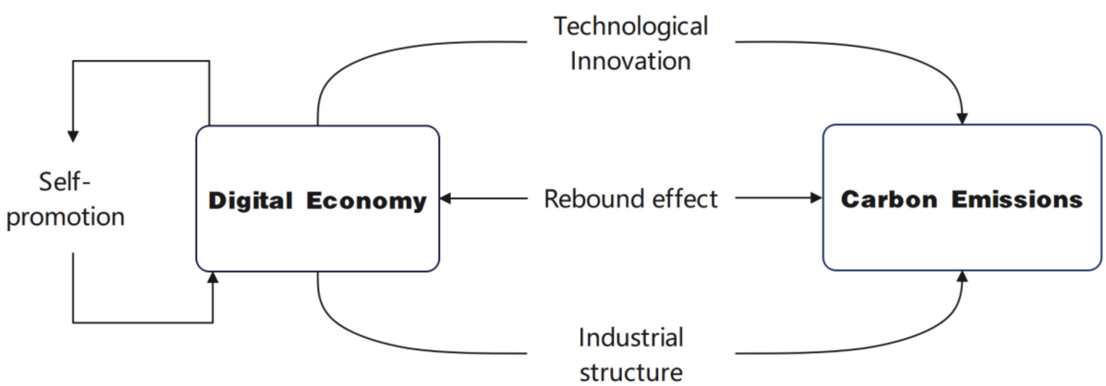

Figure 1. The mechanism of action of digital economy and carbon emissions.

4. Methods and Data Sources

4.1. Data Sources

This study primarily utilizes statistical data. Social statistics were used to calculate the levels of digital economy development and carbon emissions across various provinces and were mainly sourced from the "China Statistical Yearbook" and the National Bureau of Statistics for the years 2013–2021. Some indicators were derived through composite calculations of original data. The carbon emission data were referenced from the research by Shan et al. [32–35].

4.2. Research Methods

4.2.1. Measurement of Digital Economy and Carbon Emission Levels

To measure the level of digital economy development, it is essential to construct an indicator system. Software business revenue is a significant metric since the digital economy relies on the advancement of software technology, and its revenue growth is associated with the level of digital technology application. The length of long-distance optical cable lines reflects the degree of interconnectivity within the digital economy, serving as a critical component of the communication infrastructure that directly influences the speed and scope of digital economic development. The total volume of telecommunications services measures the utilization rate of the communication infrastructure, with the growth of this volume typically correlating with the activity level of the digital economy.

The proportion of the workforce employed in informatization is an important indicator, as the development of the digital economy requires a labor force equipped with relevant skills and knowledge. The penetration rate of mobile phones and the number of mobile phone base stations are crucial communication indicators that directly reflect the prevalence of mobile applications and services within the digital economy, thus impacting its activity level. The number of internet broadband access ports and users indicates the extent of the online activities and services in the digital economy and is closely related to the development of various online businesses, education, and entertainment.

The proportion of enterprises engaged in the digital economy is a key structural indicator, directly influencing the pattern of digital economic development and the proportion of digital economy enterprises within the overall economic system. E-commerce sales are the core indicator of online trading activities in the digital economy, directly reflecting the adoption level of digital business models. The number of computers per 100 people and the number of enterprises with websites per 100 enterprises are fundamental standards for assessing the digitization level among individuals and businesses and directly reflect the participation and penetration rates of the digital economy.

In summary, based on the principles of scientific, practical, and comprehensive indicator construction, and referencing the research by Liu et al. [36,37], this study constructs an indicator system for measuring the level of digital economy development. The system includes three primary indicators—information development, digital infrastructure, and digital transactions—and twelve secondary indicators, all of which are positive impact indicators. The details are provided in Table 1.

For the measurement of carbon emission levels, this study selects five primary indicators. Per capita carbon emissions reflect the contribution of each individual to carbon emissions, providing clarity on which regions have populations that impose a greater environmental burden and thereby offering valuable insights for policy formulation. Carbon emissions per unit of GDP indicate the relationship between a country or region's production efficiency and environmental pressure. Total carbon emissions effectively represent the overall carbon output of a region over a specific period, illustrating the total environmental impact. Total energy consumption reflects a region's level of energy use, directly indicating energy consumption and indirectly indicating carbon emission levels, thus providing essential data support for energy conservation and carbon reduction efforts. Energy consumption per unit of GDP pertains to how much energy is consumed for each unit of economic output, reflecting the relationship between energy efficiency and environmental pressure to some extent.

Table 1. Digital economy measurement indicator system.

First-Level Indicator	Second-Level Indicator	Indicator Attribute	Unit of Measurement	Weight
Information Development	Software Business Revenue	Positive Impact	CNY 100 Million	0.045
	Number of Internet Pages	Positive Impact	10,000	0.033
	Total Telecommunications Business Volume	Positive Impact	CNY 100 Million	0.058
	Proportion of Information Industry Employees	Positive Impact	%	0.060
Digital Infrastructure	Mobile Phone Penetration Rate	Positive Impact	per 100 people	0.117
	Long-haul Optical Cable Length	Positive Impact	10,000 km	0.109
	Internet Broadband Access Ports	Positive Impact	10,000	0.100
	Internet Broadband Access Users	Positive Impact	10,000 households	0.097
Digital Transactions	Proportion of Enterprises Engaged in Digital Economy	Positive Impact	%	0.117
	E-commerce Sales Volume	Positive Impact	CNY 100 Million	0.059
	Number of Computers per 100 People	Positive Impact	Units	0.105
	Number of Websites per 100 Enterprises	Positive Impact	Units	0.100

These indicators comprehensively cover three closely related aspects—population, economy, and energy—thereby accurately and thoroughly revealing and reflecting the carbon emission levels of a region. Drawing on the research by Jiang et al. [38], this study constructs an indicator system for measuring the level of carbon emission development, which includes three primary indicators: population carbon emissions, economic carbon emissions, and energy carbon emissions, along with five secondary indicators. All the indicators are negative impact indicators. The details are provided in Table 2.

Table 2. Carbon emission level measurement indicator system.

First-Level Indicator	Second-Level Indicator	Indicator Attribute	Unit of Measurement	Weight
Population Emissions	Per Capita Carbon Emissions	Positive Impact	Tons	0.225
Economic Emissions	Carbon Emissions per Unit of GDP	Positive Impact	Tons per CNY 10,000	0.289
Energy Emissions	Total Carbon Emissions	Positive Impact	Tons	0.214
	Total Energy Consumption	Positive Impact	10,000 Tons of Standard Coal	0.125
	Energy Consumption per Unit of GDP	Positive Impact	Tons of Standard Coal per CNY 10,000	0.147

Furthermore, the entropy weight TOPSIS method is employed to measure the aforementioned indicators. The specific steps are as follows:

Data Standardization: Due to the different nature and dimensions of each indicator, the positive and negative indicators need to be standardized separately.

For the positive impact indicators:

$$Z_{ij} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

For the negative impact indicators:

$$Z_{ij} = \frac{X_{max} - X}{X_{max} - X_{min}} \tag{2}$$

In Equations (1) and (2), Z_{ij} is the actual value of the j-th indicator in the i-th province after standardization, and the sum is the maximum and minimum value of this indicator.

Determining Weights Using the Entropy Method: The entropy weight method is used to determine the weight of each indicator and calculate the distance between each evaluation indicator and the optimal and worst vectors.

$$D_i^+ = \sqrt{\sum_{j=1}^{m} W_j \left(Z_j^+ - Z_{ij}\right)^2}, D_i^- = \sqrt{\sum_{j=1}^{m} W_j \left(Z_j^- - Z_{ij}\right)^2} \tag{3}$$

Formula (3) is the weight of the j-th attribute, which is obtained by the entropy weight method.

Measuring the Closeness to the Optimal Solution: The degree of closeness of each evaluation object to the optimal solution is measured.

$$DE = \frac{D_i^-}{D_i^+ + D_i^-} \tag{4}$$

The larger the DE value, the better the evaluation object.

4.2.2. PVAR Model

The panel vector auto regression (PVAR) model treats all variables as an endogenous system, combining the advantages of both panel data models and VAR models. This approach is more effective in addressing endogeneity among variables compared to traditional models. The PVAR model constructed in this study is as follows:

$$Y_{it} = \sum_{l=1}^{p} \delta Y_{it} + \eta_i + \theta_i + \lambda_{it} \tag{5}$$

Here, Y_{it} represents the matrix, where Y_{it} = [DE,CE]. DE is the digital economy development index obtained from the entropy weight TOPSIS method, CE denotes the carbon emissions level, p is the lag index, l is the lag length of the variables, η_i represents individual effects, θ_i represents time effects, and λ_{it} stands for the random disturbance term.

4.2.3. Coupling Coordination Model

The coupling coordination model not only reflects the strength of interaction between systems but also demonstrates the relationship of interaction between systems. In this study, the coupling coordination model is selected to reveal the interaction strength and coordination degree between the level of digital economy and the level of carbon emissions. The specific calculation process is as follows:

Calculation of coupling degree C

$$C = 2 \times \left\{ \frac{f(x) \times g(x)}{[f(x) + g(x)]^2} \right\}^{\frac{1}{2}} \tag{6}$$

Calculation of T comprehensive coordination

$$T = \alpha f(x) + \beta g(x) \tag{7}$$

Calculation of D coupling coordination

$$D = \sqrt{C \times T} \tag{8}$$

where $f(x)$ represents the digital economy development level DE calculated by the entropy weight TOPSIS method, $g(x)$ represents the level of carbon emissions CE, α and β denote undetermined weights, reflecting the influence coefficients of the digital economy development level and carbon emissions level. In this paper, it is assumed that both are equally important; thus, let $\alpha = \beta = 0.5$. Referring to existing research [39,40], the coupling degree and coupling coordination are classified into levels, as shown in Table 3.

Table 3. Coupling degree and coupling coordination degree classification.

Coupling Degree Range		Coordination Degree Range			
[0–0.3)	Separation Stage	[0.0–0.1)	Extremely Disrupted	[0.5–0.6)	Barely Coordinated
[0.3–0.5)	Antagonism Stage	[0.1–0.2)	Severely Disrupted	[0.6–0.7)	Marginally Coordinated
[0.5–0.8)	Integration Stage	[0.2–0.3)	Moderately Disrupted	[0.7–0.8)	Intermediate Coordinated
[0.8–1.0)	High-Level Coupling	[0.3–0.4)	Mildly Disrupted	[0.8–0.9)	Good Coordinated
1.0	Good Resonance Coupling	[0.4–0.5)	Near Disrupted	[0.9–1.0)	Excellent Coordinated

5. Analysis of the Coupling Relationship between Digital Economy Level and Carbon Emission Level

5.1. Analysis of Digital Economy Level

5.1.1. Overall Level

In Figure 2, it can be observed that, during this period, except for a slight decrease in growth rate in 2017 and 2021, the level of China's digital economy has shown a significant upward trend. From 2013 to 2021, the digital economy showed an overall growth trend. The data for this period reflect an increase in the digital economy from 0.18 to 0.32 in 2021, indicating a positive development trend. This reflects significant achievements in China's investment in and development of the digital economy over the past few years. The digital economy has not only driven economic growth and innovation, it has also provided more convenience and opportunities for people's lives and business activities.

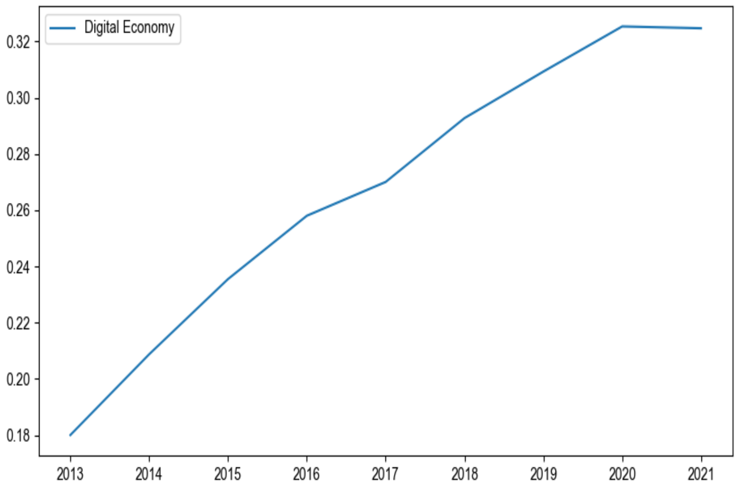

Figure 2. Digital economy level in China from 2013 to 2021.

5.1.2. Regional Level

From the data in Table 4, it is evident that there are regional disparities in the development of the digital economy. The East China region consistently maintained the highest level of digital economy development among all regions during the study period. This may be closely related to the region's stable economic foundation, strong innovation capacity, and early initiation of informatization. Moreover, the East China region also exhibited the fastest growth rate, increasing from 0.2241 in 2013 to 0.3850 in 2021, reflecting the speed and scale of its digital economy development. In contrast, the Northwest China region consistently showed the lowest level of digital economy development among all regions, with its level rising from only 0.1398 in 2013 to 0.2471 in 2021. The relatively underdeveloped digital economy in the Northwest China region could be directly associated with constraints imposed by its geographical location and natural resources, as well as its lagging infrastructure for digital development and overall economic level.

Table 4. Regional digital economy level.

	North China	Northeast China	East China	Central South China	Southwest China	Northwest China
2013	0.1963	0.1368	0.2241	0.1925	0.1466	0.1398
2014	0.2295	0.1674	0.2495	0.2236	0.1773	0.1633
2015	0.2532	0.1838	0.2870	0.2457	0.2110	0.1841
2016	0.2753	0.2039	0.3022	0.2716	0.2461	0.2048
2017	0.2882	0.2183	0.3197	0.2828	0.2579	0.2080
2018	0.3046	0.2325	0.3489	0.3126	0.2805	0.2245
2019	0.3156	0.2382	0.3736	0.3326	0.3122	0.2255
2020	0.3347	0.2574	0.3872	0.3490	0.3282	0.2395
2021	0.3395	0.2522	0.3850	0.3445	0.3223	0.2471

Although the Northeast China region had a relatively low initial level of digital economy, its subsequent growth rate demonstrated an accelerating trend, reflecting the local efforts in policy support and capital investment that promoted rapid digital economy development. Its level increased from 0.1368 in 2013 to 0.2522 in 2021.

Overall, the digital economy levels in all regions exhibited a yearly increasing trend from 2013 to 2021. The East China region showed the most significant growth, while the North China, Central South China, and Northeast China regions also experienced relatively fast growth. In contrast, the Southwest China and Northwest China regions had slower growth. These regional differences could be influenced by factors such as the level of regional economic development, policy support, investment intensity, and the extent of digital infrastructure construction. Each region should develop appropriate strategies based on its conditions to stimulate digital economy development, with the aim of achieving balanced and sustainable regional economic growth.

5.1.3. Provincial Levels

Overall, the digital economy in most provinces has been continuously growing, indicating that the proliferation and development of China's digital economy are still in a rapid upward phase, as shown in Figure 3. The growth in provinces and cities such as Beijing, Guangdong, Shandong, and Jiangsu, has been particularly remarkable, which may be closely related to factors such as economic foundation, policy support, innovation capacity, and the level of informatization. However, some provinces, such as Yunnan, Inner Mongolia, and Jilin, have shown relatively moderate growth and may require more support and policy incentives to promote digital economy growth.

Specifically, the digital economy level in Beijing significantly increased from 0.3563 in 2013 to 0.6320 in 2021. This suggests that the digital economy in Beijing has developed very rapidly, possibly benefiting from the development of high-tech industries and strong government policy support. Guangdong also demonstrated robust growth, rising from 0.3760 in 2013 to 0.6024 in 2021, which could be related to the large economic scale of the region and substantial investment in innovative technologies. The growth trends in Yunnan and Inner Mongolia were relatively stable, increasing from 0.1465 and 0.1724 in 2013 to 0.2860 and 0.2686 in 2021, respectively. Provinces such as Jilin, Guizhou, Chongqing, Heilongjiang, Gansu, Jiangxi, and Guangxi, despite having relatively low initial digital economy levels around 0.12, showed steady growth, all rising to above 0.20 by 2021.

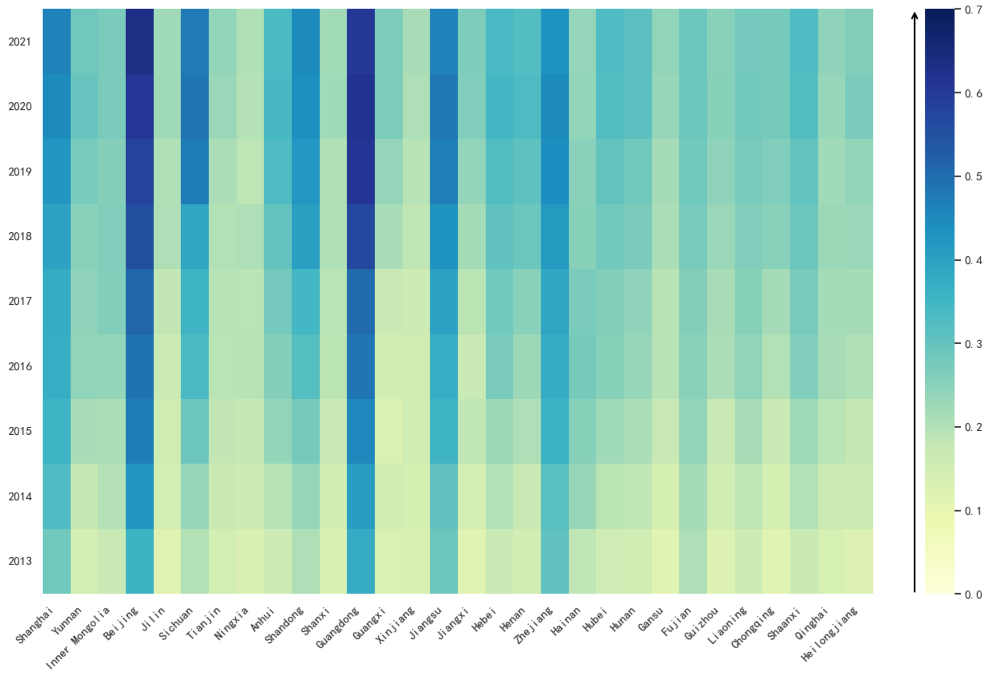

Figure 3. Provincial digital economy levels from 2013 to 2021.

5.1.4. Contribution Proportions of Different Dimensions

Informatization Development. In 2013, the proportion of informatization development was 5.297%. Subsequently, this proportion slightly decreased to 5.163% in 2014 and 5.261% in 2015. By 2016, it had further declined to 4.7538%, indicating a certain degree of slowdown. The proportion slightly rebounded to 5.649% in 2017 and showed significant growth in 2018 and 2019, reaching 7.388% and 9.219%, respectively. In 2020, the proportion peaked at 10.494%, but it decreased to 6.268% in 2021. These fluctuations reflect the varying stages and importance of informatization within the national digital economy strategy, suggesting different periods of emphasis on information technology innovation and updates. Rapid technological development plays a crucial role in driving digital economy growth; however, as technological advancements stabilize, the growth rate begins to slow down, as shown in Figure 4.

Digital Infrastructure. The proportion of digital infrastructure was 42.473% in 2013 and demonstrated a consistent upward trend, indicating increasing investment in digital infrastructure construction. This proportion peaked at 45.616% in 2020 but slightly declined to 39% in 2021. Overall, the trend remains steadily upward, highlighting the importance placed by both the government and the market on digital infrastructure. This is a solid foundation for digital economy development, emphasizing the long-term and fundamental role of digital infrastructure in sustaining digital economic growth.

Digital Transactions. The proportion of digital transactions in the digital economy has been gradually decreasing from 52.230% in 2013, reaching its lowest point at 50.196% in 2017. Subsequently, the proportion remained relatively stable, with 44.421% in 2019, and 43.890% and 45.100% in 2020 and 2021, respectively. This stable trend suggests that the market scale and activity in the digital transactions sector have become relatively mature during this period, entering a phase of steady development.

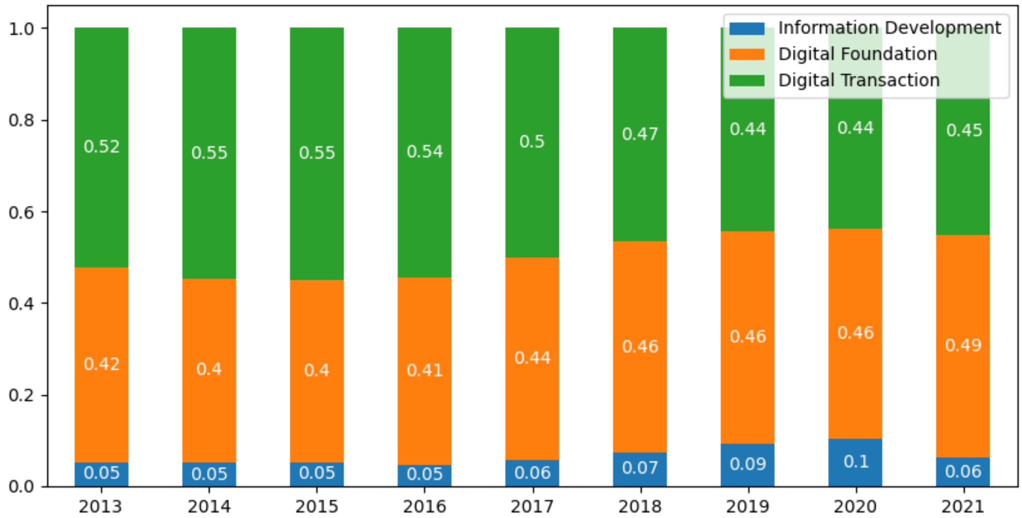

Figure 4. Contribution proportions of different dimensions in the digital economy from 2013 to 2021.

In summary, the changes in informatization development highlight the importance of technological innovation; the continuous growth in digital infrastructure reflects the need for the long-term and stable development of the digital economy; and the stable development of digital transactions indicates the maturity of the transactional activities within the digital economy.

5.2. Carbon Emission Level Analysis

From Figure 5, it is evident that China's carbon emission levels are in a relatively stable phase, exhibiting a U-shaped trend characterized by an initial decline followed by a rise. Specifically, in 2013, the carbon emission level peaked at a high of 0.2. Subsequently, there was a yearly decreasing trend, reaching the lowest value of 0.185 in 2018. This indicates significant changes in China's efforts to control carbon emissions and the effectiveness of its green environmental policies. Although there was a rebound in carbon emission levels after 2018, the overall trend continues to show a decline in China's carbon emission levels.

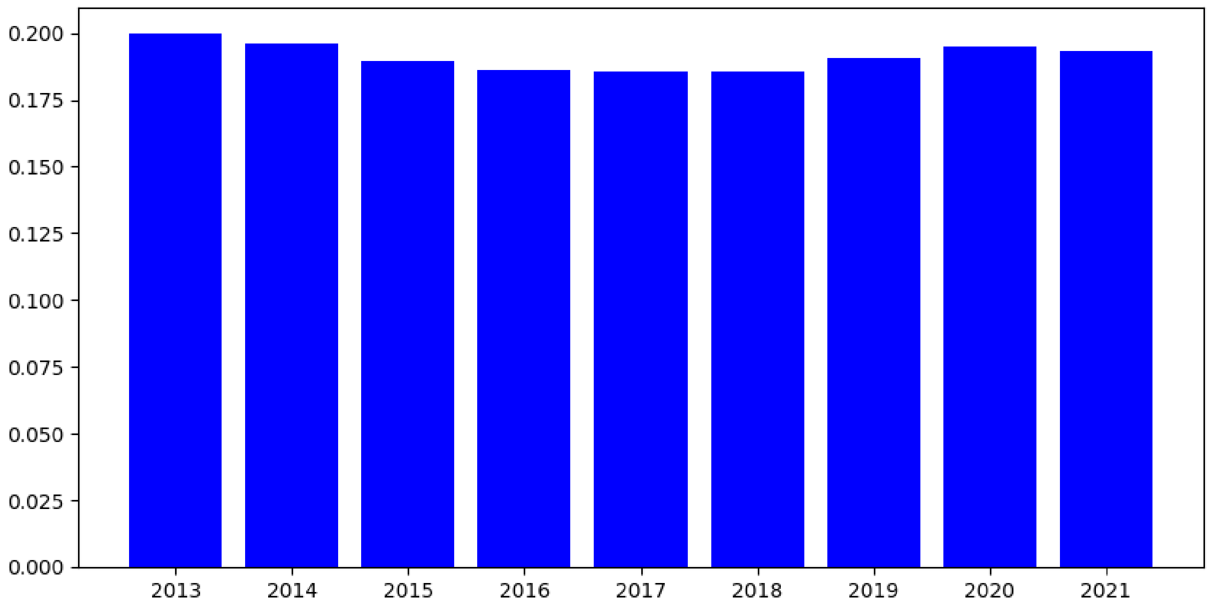

Figure 5. China's carbon emission levels from 2013 to 2021.

5.3. Coupling Coordination Analysis of the Digital Economy and Carbon Emissions

5.3.1. Provincial Coupling Degree Analysis

From Figure 6, it can be seen that the coupling coefficients in most provinces show a declining trend. This may reflect the gradually increasing coordination between digital economy development and carbon emission control. This trend suggests that in promoting the digital economy, relevant provinces might have adopted effective measures to slow the growth rate of carbon emissions or that the growth of the digital economy has to some extent improved carbon emission efficiency.

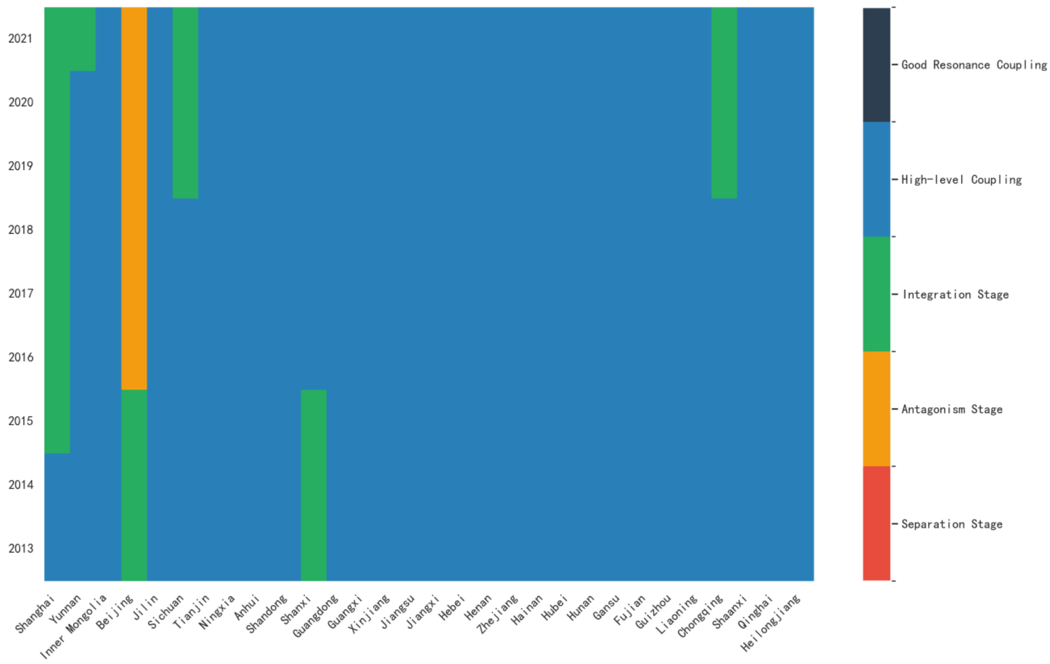

Figure 6. Coupling degree analysis of the digital economy and carbon emissions by province from 2013 to 2021.

There are significant differences in the coupling coefficients between provinces, which could be related to their industrial structures, energy consumption patterns, and environmental protection policies. For instance, the coupling coefficients of Yunnan Province and Jilin Province are consistently close to or equal to 1, implying that the carbon emission levels in these provinces have grown in sync with the development of the digital economy. In contrast, the coupling coefficient for Beijing is relatively low and shows a downward trend, possibly due to the implementation of stricter environmental protection measures alongside the promotion of the digital economy.

Some provinces have shown significant changes in their coupling coefficients in specific years, which may be associated with economic policy adjustments, industrial structure optimization, or technological advancements in those years. For example, Anhui Province saw a significant decrease in its coupling coefficient in 2018 compared to the previous year, possibly due to the implementation of relevant environmental protection policies or industrial structure adjustments that year. Some provinces, such as Hebei, Henan, and Shaanxi, have consistently high coupling coefficients, which may indicate that these provinces have experienced significant carbon emission growth alongside the development of the digital economy.

5.3.2. Provincial Coupling Degree Analysis

According to Table 5, from 2013 to 2021, the coupling coordination degree between the digital economy and carbon emissions across various regions in China generally increased. This indicates that China has been emphasizing environmental protection while advancing its digital economy, thereby achieving a coordinated development between the economy and the environment. Specifically:

Table 5. Regional coupling coordination.

	North China	Northeast China	East China	Central South China	Southwest China	Northwest China
2013	0.4521	0.3996	0.4208	0.3901	0.3774	0.4392
2014	0.4670	0.4162	0.4309	0.4033	0.3933	0.4538
2015	0.4732	0.4179	0.4467	0.4083	0.3978	0.4645
2016	0.4783	0.4325	0.4491	0.4165	0.4104	0.4760
2017	0.4800	0.4386	0.4551	0.4209	0.4076	0.4808
2018	0.4912	0.4432	0.4648	0.4285	0.4115	0.4855
2019	0.5011	0.4616	0.4722	0.4334	0.4128	0.4857
2020	0.5113	0.4719	0.4771	0.4355	0.4124	0.4934
2021	0.5078	0.4690	0.4807	0.4381	0.4058	0.4958

In the North China region, the coupling coordination degree increased from 0.4521 in 2013 to 0.5078 in 2021, indicating that as the digital economy rapidly develops, carbon emission control measures are gradually being strengthened, and the economic development model is progressively shifting towards a low-carbon approach. The Northeast China region exhibits a similar trend, with the coupling coordination degree rising from 0.3996 in 2013 to 0.4690 in 2021, reflecting positive progress in the coupling relationship between digital economy development and environmental protection.

East China, an essential engine of China's economy, saw its coupling coordination degree grow from 0.4208 in 2013 to 0.4807 in 2021, demonstrating that while pursuing economic growth, the region is continuously strengthening its investment and management in environmental protection. The Central South China region showed relatively slower growth in coupling coordination degree, increasing from 0.3901 in 2013 to 0.4381 in 2021, reflecting efforts to improve the coordination between economic development and environmental protection.

The Southwest China region's coupling coordination degree slightly increased from 0.3774 in 2013 to 0.4058 in 2021. Although the increase is modest, it still indicates some coordination between digital economy development and carbon emission control. The Northwest China region's coupling coordination degree also showed an upward trend, rising from 0.4392 in 2013 to 0.4958 in 2021, highlighting the region's efforts to seek coordinated development between the digital economy and environmental protection.

5.3.3. Provincial Coupling Coordination Degree Analysis

Overall, from 2013 to 2021, the coupling coordination degree across provinces in China shows a general upward trend, increasing from 0.4150 to 0.4681. This indicates that during the study period, as the provinces promoted the digital economy, they also gradually improved carbon emission control levels, enhancing the coordination between the two. This trend reflects the Chinese government's firm determination and effective measures in pursuing the dual goals of economic growth and environmental protection, as illustrated in Figure 7.

During this period, 14 provinces were in a state of mild imbalance in 2013, whereas by 2021, only 7 provinces remained in this state. This change indicates that most provinces achieved a better balance between digital economic development and carbon emission control during this period, with a significant improvement in the coupling coordination degree. At the same time, it also suggests that as the provinces promote digital economic development, they are gradually enhancing their control over carbon emissions, with increasing coordination between the two. This is a positive signal, demonstrating that China's efforts to achieve the dual goals of economic development and environmental protection have yielded noticeable results.

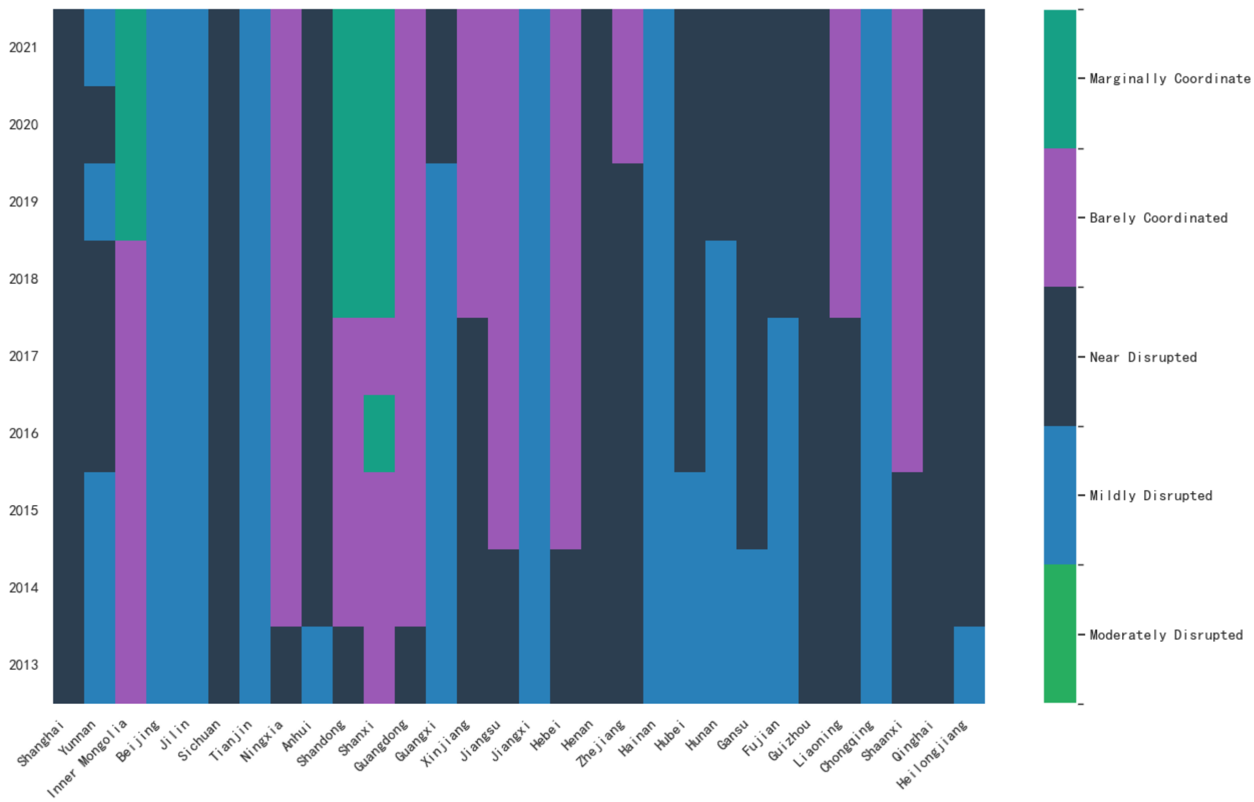

Figure 7. Coupling coordination degree between the digital economy and carbon emissions across provinces from 2013 to 2021.

Specifically, due to the heterogeneity in economic development, population resources, and geographical environment, there are significant differences in the coupling coordination degree between digital economy development and carbon emission levels across regions. Shandong Province progressed from a state of near imbalance in 2013 to a state of primary coordination by 2021, with its coupling coordination degree increasing from 0.4912 to 0.6270, showing significant progress. Inner Mongolia and Shanxi also showed similar trends, transitioning from marginal coordination to primary coordination, with their coupling coordination degrees increasing from 0.4912 and 0.5183 to 0.6327 and 0.6460, respectively. This reflects the positive results achieved in promoting the digital economy and controlling carbon emissions in these regions.

Provinces such as Guangdong, Hebei, Jiangsu, Liaoning, Ningxia, Shaanxi, Xinjiang, and Zhejiang transitioned from near imbalance to marginal coordination. Provinces like Hunan, Hubei, Heilongjiang, Guangxi, Gansu, Fujian, and Anhui moved from mild imbalance to near imbalance. These provinces have also made some progress in improving their coupling coordination degree.

Yunnan, however, experienced fluctuations, moving from mild imbalance to near imbalance and back to mild imbalance, indicating volatility and uncertainty in this area. Sichuan, Shanghai, Henan, Guizhou, and Qinghai remained in a state of near imbalance, suggesting relatively slow progress in coupling coordination. Beijing, Hainan, Jilin, Jiangxi, Tianjin, and Chongqing remained in a state of mild imbalance, possibly indicating challenges in achieving coordinated development between the digital economy and carbon emission control.

Overall, during the study period, there was a significant improvement in the balance between promoting digital economic development and enhancing carbon emission control across various provinces in China. However, the rate of progress in achieving coordination between these two aspects varies among provinces, reflecting regional differences in economic development, population resources, and geographical environments. For regions that remain uncoordinated, it is particularly important to consider the environmental impacts while developing the digital economy to achieve more harmonious development.

6. Analysis of the Impact of Digital Economy Level on Carbon Emission Level

6.1. Stationarity Test

Non-stationarity in data may lead to spurious regression, causing biased results. Before estimating the PVAR model, it is necessary to conduct stationarity tests on the original series. This study adopts both the IPS (Im–Pesaran–Shin) test and the LLC (Levin–Lin–Chu) test to perform panel data unit root tests on each variable, as shown in Table 6.

Table 6. Unit root test results.

Variable	IPS Test	LLC Test	Conclusion
DE	0.2752	−3.3548 ***	Non-stationary
CE	2.6342	−23.0514 ***	Non-stationary
dDE	−5.1188 ***	−27.9203 ***	Stationary
dCE	−5.2883 ***	−41.5822 ***	Stationary

*, **, and *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

Based on the results in Table 6, it is observed that some sequences of DE and CE did not pass the unit root test, indicating that the original sequences are non-stationary. After performing first-order differencing on all variables, the transformed sequences dDE and dCE are stationary, allowing the establishment of a PVAR model.

6.2. Selection of Optimal Lag Order

The optimal lag order of the model is determined based on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan–Quinn Information Criterion (HQIC). The results are presented in Table 7. Considering the criteria collectively, it is evident that the optimal lag order is 1. Hence, a first-order lag PVAR model is established.

Table 7. Optimal lag order selection criteria results.

Lag Order	AIC Criterion	BIC Criterion	HQIC Criterion
1	−10.6267 *	−9.4914 *	−10.1664 *
2	−10.5826	−9.2178	−10.0281
3	−10.2940	−8.6215	−9.6148
4	−9.7487	−7.6378	−8.8975
5	−9.0734	−6.2809	−7.9811

* indicates the optimal lag order selected by this criterion.

6.3. GMM Estimation and Granger Causality Test

Before conducting the GMM estimation, the Helmert transformation is used to eliminate individual fixed effects in order to avoid biased parameters. The GMM estimation results (see Table 8) indicate that when carbon emissions (CE) are the dependent variable (column 2), the lagged digital economy (DE) has a significant negative impact on carbon emissions at the 5% significance level, with a coefficient of −0.112. This suggests that the digital economy has a significant negative effect on carbon emissions. When the digital economy is the dependent variable (column 3), the lagged carbon emissions have a positive but insignificant impact on the digital economy. The lagged digital economy has a significant effect on the current digital economy at the 1% significance level, with a coefficient of 0.529, indicating that China's digital economy can promote itself.

Table 8. GMM estimation.

Variable	dCE		dDE	
	Coefficient	***p*-Value**	**Coefficient**	***p*-Value**
h_dCEL1	0.325 **	0.027	0.002	0.974
h_dDEL1	−0.112 **	0.034	0.529 ***	0.000

*, **, and *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

To further analyze the short-term dynamic impact and causality between the digital economy and carbon emissions, the Granger causality test is used. The results in Table 9 show that at the 5% significance level, DE Granger-causes CE, indicating a significant short-term impact of the digital economy on carbon emissions.

Table 9. Granger causality test.

Null Hypothesis	Test Statistic	*p*-Value	Result
dDE does not Granger-cause dCE	4.499 **	0.034	Reject
dCE does not Granger-cause dDE	0.001	0.974	Accept

*, **, and *** indicate significance at the 10%, 5%, and 1% statistical levels, respectively.

6.4. Impulse Response Analysis

The impulse response function analyzes the dynamic relationship between the digital economy and carbon emissions. Figure 8 reflects the impulse response of the digital economy and carbon emissions for 10 lag periods using Monte Carlo simulations with a confidence level of 95%. The x-axis represents the lag periods of the shock occurrence, and the y-axis represents the response magnitude of the dependent variable to shocks in the explanatory variables. The red line indicates the magnitude of the response of one variable to a shock of one standard deviation in the other variable, while the green and blue lines represent the upper and lower bounds of the 95% confidence interval for the shock response.

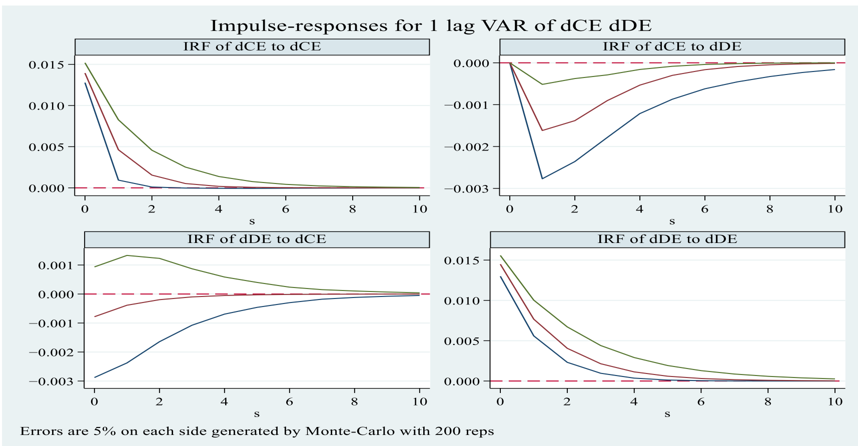

Figure 8. Impulse response analysis.

The figures show that the impulse response of dCE to dCE is primarily positive, indicating that carbon emissions respond quickly to their own shocks. This positive impact is maximal in the initial period and then rapidly declines, with carbon emissions falling back to 0 after a lag of 4 periods. Similarly, the impulse response of dDE to dDE is positive, indicating that the digital economy responds rapidly to its own shocks, and maintains a positive effect even after a lag of six periods. Combining this with the analysis of the impact of the lagged digital economy on the current digital economy in the GMM estimation, it can be inferred that China's digital economy has achieved a virtuous accumulation mechanism and can self-promote, thus validating Hypothesis 1.

The impulse response of dDE to dCE is negative in the 0th period, then continuously rises, reaching 0 after a lag of 5 periods. This indicates a negative impact of the digital economy on carbon emissions, which is consistent with the significant negative impact of the lagged digital economy on carbon emissions in the GMM estimation results, thus validating Hypothesis 2b.

6.5. Variance Decomposition Analysis

Variance decomposition provides insight into the contribution of shocks to endogenous variables to the volatility of a particular variable, helping to further identify the impact of the digital economy on carbon emissions. Table 10 presents the variance decomposition results for periods 1, 3, 6, and 10.

Table 10. Variance decomposition results of each variable.

Variable	Period	dCE	dDE
dCE	1	1.000	0.000
	3	0.980	0.020
	6	0.975	0.025
	10	0.974	0.026
dDE	1	0.000	1.000
	3	0.003	0.997
	6	0.003	0.997
	10	0.003	0.997

From the results, it can be observed that there is little variation in the variance decomposition results after the 10th period, indicating that the variables in the model have achieved relatively good stability by the 10th period. Therefore, based on the corresponding values in the 10th period, this paper explains the relationship between the digital economy and carbon emissions. According to Table 10, in the first period, the changes in carbon emissions are entirely due to their own impact, with the contribution rate of the digital economy to carbon emissions being 0. As the lag period increases, the contribution of carbon emissions to their own changes gradually decreases, while the contribution proportion of the digital economy changes slowly increases. This proportion increases from 0% in the first period to 2.6% in the tenth period, indicating that the changes in carbon emissions are influenced by both themselves and the digital economy. Conversely, changes in the digital economy are affected by both carbon emissions and their own impact. In the first period, the prediction error variance of the digital economy is entirely caused by its own impact. However, by the 10th period, its own contribution to the prediction error is 99.7%, while the impact of carbon emissions is only 0.3%.

7. Conclusions and Discussion

This study is based on panel data from 30 provinces, municipalities, and autonomous regions in mainland China from 2013 to 2021. It constructs an evaluation system for the level of digital economy and carbon emissions. Building on the entropy weight TOPSIS method to measure the levels of digital economy and carbon emissions, the study employs the coupling coordination model and the PVAR model to empirically test the impact of the digital economy on carbon emissions and their coupling relationship. The results indicate that the digital economy in various provinces is on an upward trend, while carbon emissions have been effectively controlled, showing a downward trend. However, the coupling coordination degree between the digital economy and carbon emissions is currently still mainly at a near-disrupted stage, suggesting significant room for improvement in their coordination. Additionally, we observe significant differences in the coupling relationship between the digital economy and carbon emissions across different regions. These differences are mainly due to variations in regional economic structures, the pace of industrial upgrading, innovation capacity, and the rigor of policy implementation.

Compared to other related studies, our findings indicate that in more economically developed regions, the decoupling effect between carbon emissions and economic growth is more pronounced due to higher levels of technology application and policy support. Furthermore, we find that the digital economy has a self-reinforcing mechanism, enabling self-promotion. In the short term, the digital economy has a significant negative impact on carbon emissions, but this impact is not evident in the long term.

Based on the above conclusions, the following policy recommendations are proposed. First, Enhancing the Green Development Orientation of Digital Infrastructure: The government should promote the green transformation of digital infrastructure by providing policy support to encourage data centers to utilize clean energy and optimize network architecture to improve energy efficiency. At the national level, the government should ensure the establishment of clear standards and goals, including regular revisions of energy conservation and environmental protection standards. This should involve mandating data centers to use efficient cooling systems, adopt renewable energy sources, and employ efficient servers. Additionally, the government should support the upgrading and replacement of network equipment and promote efficient data transmission protocols and software algorithms to reduce energy losses during data transmission. Simultaneously, establishing an energy-saving evaluation system and monitoring mechanism to periodically assess data center energy consumption and operational efficiency and promptly disclose assessment results to the public will enhance industry transparency and competitiveness. Encouraging the development of low-carbon technologies and solutions to reduce the carbon footprint of digital economic development is also crucial. The government can implement green credit and investment policies to provide financial subsidies or tax incentives to enterprises using green energy or low-carbon technologies to stimulate market participants' enthusiasm.

Second, Strengthening Cross-Regional Coordination of Energy and Industrial Structure: Given significant differences in the coupling relationship between the digital economy and carbon emissions across different regions, efforts should be made to seek regional cooperation and coordination to promote resource sharing and jointly promote industrial optimization and upgrading. This involves reducing redundant construction and creating an environmentally friendly industrial chain. Firstly, the government should establish a comprehensive regional development plan that includes a comprehensive assessment of regional economic characteristics, resource endowments, and environmental carrying capacity. Based on this assessment, a development roadmap should be designed that aligns with national macroeconomic development strategies while reflecting regional characteristics. Additionally, the government should strengthen information communication and data sharing mechanisms between regions to effectively monitor the flow and allocation of various resources to ensure optimal resource utilization. Encouraging and supporting horizontal links and vertical integration of industrial chains between regions to stabilize cooperative relationships among upstream and downstream enterprises in the industrial chain will not only reduce energy consumption and carbon emissions throughout the industrial chain but also improve industrial efficiency and overall competitiveness.

Third, Continued Investment in Innovation and Research and Development (R&D) to Establish a Long-Term Mechanism: The government should increase investment in R&D of new technologies, particularly in digital technology and its application in the production process, to promote technological innovation as a new driver of economic growth. To establish a long-term mechanism for innovation and R&D, the government needs to not only increase fiscal investment but also build a comprehensive ecosystem that supports innovation. This includes specialized support for R&D funds, tax incentives, intellectual property protection, and the establishment of mechanisms for the transformation of R&D results. To attract enterprises, universities, and research institutions to participate in the country's technology innovation strategy and create a synergistic effect, priority should be given to layout in frontier technology fields, such as artificial intelligence, big data, cloud computing, and the Internet of Things in the digital technology field. Additionally, encouraging enterprises to innovate business models with a focus on services and solutions to promote positive interactions between the digital economy and carbon emissions is essential. By promoting the innovation of business models and supporting enterprises to transition from product sales to service and solution provision, companies can evolve from mere producers and suppliers of goods to comprehensive service providers. This transformation helps to improve resource utilization efficiency and reduce the overall carbon footprint of society.

Although this paper primarily focuses on the impact of the digital economy on carbon emissions and their coupling relationship, we acknowledge that carbon emissions are influenced by a complex array of factors. Beyond the development of the digital economy, several additional factors significantly affect carbon emission levels. Energy structure varies greatly among different regions and countries, and the extent of reliance on fossil fuels directly impacts carbon emissions. Changes in energy consumption patterns, such as the shift from coal to natural gas or renewable energy sources, are also crucial in reducing carbon emissions. Government policies and regulations play a decisive role in guiding and regulating economic activities to reduce carbon emissions. Policy tools, such as carbon taxes, emission trading systems, and energy efficiency standards, are effective measures for promoting emission reductions. Public awareness of climate change and environmental protection, along with their daily behavioral choices—such as energy saving, recycling, and green consumption—also influence carbon emission levels to some extent.

Overall, while this study primarily focuses on China, its findings and recommendations have universal applicability. They can provide useful insights for other countries seeking to balance digital economic development with carbon emission control.

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