Examining the Impact of China's Digital Economy on Carbon Emissions Intensity: Mechanisms, Regional Variations, and Policy Implications

Abstract: Reducing carbon emissions is imperative for achieving sustainable development. Given China's rapid growth in its digital economy, it is necessary to explore the impact of digitaleconomy on emissions intensity. This study employs China’s provincial panel data and uses the fixed effect model to examine thisimpact. The results reveal that digital economy can drop carbon emissions intensity, and the finding remains robust after conducting various endogeneity treatments and sensitivity analyses. This study also explores the mechanisms underlying this effect and finds that the expansion of the digital economy reduces carbon emissions intensity by enhancing green innovation capacity and promoting economic agglomeration. Additionally, we consider electricity consumptionof digital economy, and the analysis reveals regional heterogeneity, with the emissionsintensity reduction effect being significantly stronger in regions with green power generation compared to non-green power generation regions.

Keyword: Digital Economy; Carbon Emissions Intensity; Green Innovation;Economic Agglomeration;Green Power Generation.

1. Introduction

Mitigating global warming and reducing carbon emissions are matters of international significance.As one of the major carbon emitters, China should contribute to global efforts in reducing carbon emissions. During the 75th UN General Assembly in 2020, President Xi of China made a significant announcement, committing China to reach the peak of CO_2 emissions by 2030 and attain carbon neutrality by 2060.[1]. Given China's status as a developing country, it is crucial tobalance high-quality economic development with significant carbon emission reduction. One effective strategy to achieve both objectives simultaneously is to reduce carbon emissions intensity. This approach offers a viable solution for China to meet its international commitments while maintaining economic growth, making it an essential element of China's long-term sustainable development.

China's swift advancement in information technology has propelled the expansion of the

[1]We call these two as “dual carbon goals”.

digital economy, emerging as a pivotal driver for high-quality economic growth within the nation. The digital economy stands as a strategic imperative for China, enabling the nation to harness the opportunities presented by the ongoing technological revolution and industrial transformation. It has evolved into a critical determinant in the allocation of resources, economic restructuring, and the dynamics of competitiveness. Its impact on China's economy and society is far-reaching, as demonstrated by changes in production methods and governance practices, including e-commerce platforms like Taobao and Meituan that have transformed consumption and lifestyle habits. Furthermore, the use of big data analysis has been essential in controlling and governing during the COVID-19 pandemic.Within this context, it is imperative to scrutinize the prospective impact of China's digital economy on the attainment of the nation's dual carbon objectives. In particular, does the evolution of China's digital economy align with the realization of these dual carbon goals? Should it indeed foster a reduction in carbon emissions, what strategies can be implemented to augment and optimize this reduction?

The influence of the digital economy on carbon emissions has been a subject of discussion from various perspectives.Li et al. (2021) conducted a panel data analysis covering from 2011 to 2017 in 30 provinces of China to explore the effect of energy structure and digital economy on carbon emissions.The research revealed a substantial moderating impact of the digital economy on the correlation between a coal-based energy structure and carbon emissions.Similarly, Wang et al. (2022) employed the System-Generalized Method of Moments (SYS-GMM) technique to examine the influence of the digital economy on CO2 emissions. They utilized a digital economy index encompassing data from 30 provinces in China over the period spanning from 2006 to 2017. The findings of the study indicated that the digital economy exerts a negative impact on CO2 emissions. This impact is facilitated through the expansion of the economic scale of the tertiary industry, a reduction in the proportion of coal consumption, and the promotion of innovation in green technology.Yu and Zhu (2023)delved into the examination of the impact of digital economy development on carbon emissions. Their findings revealed that the digital economy contributes to a decrease in carbon emissions through the enhancement of energy intensity. Meanwhile, it also leads to an increase in carbon emissions by stimulating economic expansion.However, despite the abundance of literature on the subject, twolimitations remain in the current studies. First, most existing literature has primarily focused on the influence of the digital economy on total carbon emissions, with scarce attention given to its impact on carbon emissions intensity (i.e., carbon emissions performance). Second, the negative effects of the digital economy's development, which results in substantial electricity consumption and carbon emissions, have not been given adequate emphasis or, in some cases, have been ignored. Therefore, development of digital economy will not surely lead to reduction of carbon emissions intensity. This question should be addressed and our research try to answer it.

The study explores the correlation between China's digital economy and carbon emissions. It does so by primarily employing carbon emissions intensity as the key explanatory variable, with carbon emissions performance used as an additional explanatory variable for the sake of robustness analysis. Carbon emissions intensity quantifies the quantity of carbon dioxide emissions per unit of GDP, while carbon performance is assessed using an enhanced data envelopment analysis (DEA) model that considers both GDP and carbon dioxide output. These two indicators enable us to incorporate both economic development and carbon emissions. Using a fixed effect model, we examine the influence of the digital economy on carbon emissions intensity, and test the robustness of our results by substituting the explanatory and core explanatory variables, as well as by utilizing multiple instrumental variables to reduce the endogeneity issue. Furthermore, the research analyzes the impact of the digital economy on carbon emissions intensity using green innovation capacity and economic agglomeration as the mechanisms, and conduct regional heterogeneity analysis by incorporating the electricity consumption of digital infrastructure. Our findings suggest that (1)the progression of China's digital economy contributes to a reduction in carbon emissions intensity; (2) the improvement of green innovation capacity and promotion of economic agglomeration, reflected by the amount of green patent, also drop carbon emissions intensity; (3) since the developmentof digital economy requires high electricity consumption, the influence of the digital economy on cutting down carbon emissions is significantly stronger in green power generation regions with low electricity carbon emissions factors than non-green power generation areas with high electricity carbon emissions factors, indicating significant regional heterogeneity. Overall, this research offers valuable insights into the intricate relationship between the digital economy and carbon emissions intensity. It underscores the potential for green innovation and economic agglomeration to mitigate carbon emissions while fostering sustainable economic growth.

In previous studies, the main mechanisms for the carbon-reduction effect of the digital economy were argued to be the reduction of the energy consumption structure (coal use share) and the increase in total factor productivity. Additionally, some scholars suggested that the digitalization process of enterprises is accompanied by an increase in green innovation capacity, which in turn leads to a reduction in carbon emissionsintensity. However, the research contributes to the existing studies by proposing that the digital economy also results in economic agglomeration thatdrops carbon emissions intensity, thus complementing the previously mentioned mechanisms. Furthermore, it highlights the importance of considering the role of electricity consumption in the digital economy and its influence on carbon emissions intensity, which has been overlooked in previous studies.This study contributes to the literature in several aspects. Firstly, it offers an analysis of digital economy development and carbon emissions intensity in China, with an attempt to decompose and clarify the mechanisms involved. Secondly, the study introduces a novel influence mechanism by demonstrating that the digital economy leads to improving green innovation capacity and promoting economic agglomeration, resulting in a drop ofemissions intensity. Thirdly, the research underscores the significant regional disparities in the impact of digital economy development on carbon emissions intensity in China. These disparities arise from variations in the environmental cleanliness of power generation across regions, which are a consequence of the substantial electricity consumption associated with the digital economy.This finding highlights the importance of considering regional factors when developing policies related to carbon emissions reduction. Overall, the research fills a gap in the literature and provides new insights to advance the dual carbon goal.

In Section 2, we present the theoretical framework and research hypothesis. Section 3 outlines the research design. Main findings are presented in Section 4. We conduct a mechanism analysis to shed light on the underlying processes that explain the empirical results in Section 5. Section 6 conducts further discussion and highlights electricity consumption of digital economy.In Section 7, we summarize the main conclusions and offer policy implications.

2. Theoretical Analysis and Research Hypothesis

(*a*) Developmentof digital economy reduces carbon emissions intensity

We propose a hypothesis that digital economy development dropds carbon emissions intensity through various mechanisms. Firstly, it is argued that the digital economy benefits from economies of scale as the marginal cost of data as an input factor approaches zero, resulting in increased efficiency, decreased energy consumption, and ultimately reduced carbon emissions intensity. Secondly, digital technology has the potential to transform traditional industries, increasing their added value while simultaneously reducing energy consumption, which can further contribute to the drop of carbon emissions intensity.For instance, AliCloud employs industrial Internet, artificial intelligence(AI), and other digital technologies to serve the production process of Conch Cement, realizing efficient automatic control of the process and reducing comprehensive energy consumption by 2%-3%. Furthermore, in 2011, the implementation of a carbon emissions trading pilot which incorporated the negative externalities of carbon emissions into the costs of enterprises, has further incentivized successful digital transformation and the sale of excess carbon emissions rights.Thirdly, the implementation of digital finance could provide financial support to enterprises, thereby promoting green total factor productivity. Fourthly, digital economy development has the potential to improve the energy structure through the use of advanced process control systems, which could in turn reduce carbon emissions intensity. These mechanisms are supported by literature;therefore, we propose Hypothesis 1.

Hypothesis 1: Development of digital economy reduces carbon emissions intensity.

(b) Digital economy improves green innovation ability, thereby reducing carbon emissions intensity

With the aid of big data analysis, AI, and other digital technologies, many manufacturers are able to implement green innovation, which is helpful for the control of pollution emissions and the reduction of carbon emissions.Using provincial-level panel data from 2006 to 2018, Wang and Cen (2022) develop a spatial econometric model and discover that the digital economy has a strong positive direct effect on the efficiency of innovation as well as a spatial spillover effect on innovation efficiency. Similar findings have been made by Liu et al. (2022), who use data from a sample of Chinese listed companies between 2011 and 2019. Liu et al. (2022) obtain that the digital economy greatly improves organizations' substantive green innovation. Increasing the effectiveness of internal control and encouraging long-term investment are two strategies behind this relationship. Using micro-research data from 215 organizations, El-Kassar and Singh (2019) analyse through empirical analysis that the use of corporate big data further influences firms' ability to compete by influencing their involvement in green innovation. Meanwhile, manufacturers may easily access the steps other manufacturers have taken to cut carbon emissions, which they can then use to better their ideas and further develop their capacity for green innovation. This is made possible by the ease of information exchange in the digital economy era.Mubarak et al. (2021) empirically examine the mechanism by which Industry 4.0 technology affects green innovation behaviors and find that Industry 4.0 technology promotes open innovation practices that helps to further motivate manufacturers to engage in more green innovation activities. Song et al. (2022) argue that enterprise digitalization promotes enterprise green technological innovation by enhancing the level of information sharing and knowledge integration ability of enterprises. Digital finance is conducive to green innovation in new energy enterprises (Jiang et al., 2022). We proposes research hypothesis 2.

Hypothesis 2: The digital economy increases the capacity for green innovation, which in turn reduces the intensity of carbon emissions.

(c) The digital economy promotes economic agglomeration, thereby reducing carbon emissions intensity

Advantages are provided by company concentration, which is a key factor in urban development. A sizable number of digital infrastructures, including 4G and 5G signal stations and numerous data transmission hubs, are the foundation for digital economy development. According to Liu and Hu (2010), infrastructural development has a substantial impact on economic agglomeration, and the digital economy consequently encourages it. There are direct and indirect methods through which economic agglomeration affects carbon emissions. The direct impact includes various externalities, spillover effects, cost savings, centralized regulation, and specialized division of labor, while the indirect impact occurs through the economy of scale effect of centralized energy utilization and green technology spillover for improving energy efficiency. Numerous studies have investigated the relationship between economic agglomeration and carbon emissions intensity. Glaser (2011) argue that cities as economic agglomerations are more environmentally friendly than villages with decentralized production and settlement, and that agglomerations are effective in reducing commuting distances and thus dropping pollution emissions.Zhang and Wang (2014) suggest that spatial agglomeration and cooperation of multiple enterprises are crucial ways to reduce carbon emissions. Shao et al. (2019) find that economic agglomeration has reduced carbon emissions intensity in China in recent years. According to Yan et al. (2023), the growth of the digital economy in urban agglomerations can greatly lower the intensity of carbon emissions through the development of green technology and the information and communications technology (ICT) sector. We propose research hypothesis 3.

Hypothesis 3:Digital economy development facilitates economic agglomeration and reduces carbon emissionsintensity.

(4)Reduction of carbon emissionsintensity exists regional heterogeneity in the digital economydue to the dramatic increase in electricity consumption in digital industries

Here,we examine the regional heterogeneity in China's carbon emissions intensity resulting from the growing electricity consumption of its digital infrastructure and data centers. According to a joint report by Greenpeace and North China Electric Power University, China's data centers consumed 160,889 million kWh of electricity in 2018, representing 2.35% of the country's total social electricity consumption. National data projects that domestic data centers will consume 204.5 billion kWh of electricity in 2020, equivalent to 2.7% of the country's total electricity consumption. While the digital economy contributes to economic efficiency gains, the digital infrastructure and data centers that underpin the digital economy consume significant amounts of electricity, leading to high carbon emissions. The Ministry of Ecology and Environment of China reveals that the average carbon emissions factor of China's power grid was 0.5839 t CO_2/M-Wh in 2021, with the marginal carbon emissions factor of the three major power grids, namely, Northeast Power Grid, Central China Power Grid, and North China Power Grid, ranking among the highest in the past decade. According to the National Bureau of Statistics, thermal power generation using coal as the primary fuel remains the dominant source of power generation, accounting for 71.13% of China's total power generation, followed by hydroelectric power generation (14.6%), wind power generation (6.99%), and nuclear power generation (5.02%). The use of clean and green energy generation, such as nuclear, water, solar, and wind power, is mainly concentrated in the central and western regions. To address the high-power consumption of digital infrastructure and data centers, the "Processing Eastern Data in the West" project has been proposed. The initiative involves building a new arithmetic network system that integrates data centers, cloud computing, and big data. This project aims to redirect arithmetic demand from the east to the west in an orderly manner, optimize the layout of data center construction, and promote synergy between the two regions, thereby enhancing energy utilization efficiency and reducing carbon emissions. The Guizhou Data Center serves as a potential example of this initiative. Consequently, we propose research hypothesis 4.

Hypothesis 4:The consumption of electricity required for the digital economydevelopment may result in heterogeneous effects on the reduction of carbon emissions intensity, contingent on whether the electricity is generated from clean or non-clean energy sources.

3.Research Design

3.1Model Design

To examine the impact of the digital economy on carbon emissions intensity, this paper develops a fixed-effects model.

$$Y_{it} = \alpha + \beta_1 P_{it} + \gamma X_{it} + \mu_i + \varepsilon_{it} (1)$$

where Y_{it} iscarbon emissions intensity of *i* province in *t* period, P_{it} is the level of digital economy of*i* province in *t* period,X_{it} is a set of control variables,μ_i is a provincial fixed effect that does not vary with time,ε_{it} refers to random errorterm.

To examine the mechanism of the digital economy's impact on carbon emission intensity, we set the mediating effect model as:

$$\mathrm{M_{it}} = \alpha + \beta_1 P_{it} + \gamma X_{it} + \mu_i + \varepsilon_{it} \ (2)$$

where $\mathrm{M_{it}}$ is the mediating variables, and other variables could refer to (1). Considering the current controversy over the use of mediating effect models in economics research, this paper refers to Jiang (2022) approach of conducting a mechanism test by identifying the effects of core explanatory variables on mediating variables, i.e., focusing on the causality of equation (2).From the theoretical analysis in the previous section and the viewpoints of the existing literature, it is obvious that the corresponding mediating variables have an impact on carbon emissions. Therefore, if the core explanatory variables have an effect on the mediating variables, it can confirm that the influence mechanism proposed in this paper is effective.

3.2 Variable Selection and Data Description

Constrained by scarcity of data regarding the digital economy and carbon emissions, the present study employs panel data comprising 30 mainland Chinese provinces (excluding Tibet) during the period of 2011 to 2019 to explore the influence of the digital economy on carbon emissions intensity.

1. *Carbon Emissions Intensity*.This variable is measured by the ratio of total carbon emissions to real regional GDP. The measurement of carbon emissions is typically calculated by multiplying the corresponding energy consumption quantities by carbon emissions factors or by using carbon emissions data from the China Emission Accounts and Datasets (CEADs). We opt for the latter approach and utilize the provincial carbon emissions inventory data provided by the CEADs, which is a trusted source of information on the total CO_2 emissions of each province in China.

2.*Digital Economy*. This variable assesses the level of digital economy development, and we adopt the methodology proposed by Huang et al. (2019) andZhao et al. (2020). The methodology focuses on two dimensions: Internet development and digital finance. The number of mobile Internet users, the number of workers working in the internet sector, production related to the internet sector, and the index measuring digital financial inclusion are among the metrics that are chosen. To construct a composite index of digital economy, the principal component analysis is applied. To ensure the robustness of the findings, two additional indexes are utilized: the digital economy index estimated by the entropy weight method and the city digital economy index published by Caixin Insight.

3.Control Variables

Railroad operating mileage. Compared to conventional modes of transportation such as roads, railroads have significantly increased transportation capacity, thereby improving the efficiency of the transportation industry and contributing to the reduction of carbon emissions intensity. Lin et al. (2021) have demonstrated that the expansion of high-speed railroads in China has substantially reduced carbon emissions from the transport sector. The National Bureau of Statistics has provided relevant datain this regard.

Degree of trade openness.We employ the ratio of total exports and imports to regional GDP for each province to measure the degree of openness. Previous research, such as Li and Qi (2018), has demonstrated that trade openness is positively associated with carbon emissions performance and energy conservation, underscoring its potential for facilitating emissions reduction. Therefore, it is expected that a higher level of trade openness will have positive implications for mitigating carbon emissions intensity. The data used in this study is obtained from the National Bureau of Statistics (NBS).

Share of secondary industry.According to He et al. (2021), the secondary industry in China, which generates more than 80% of all carbon emissions in the nation, is the main source of those emissions. Furthermore, according to the Synthesis Report on China's Carbon Neutrality in 2020, China's energy consumption is five to eight times greater than that of industrialized nations per unit of industrial value added. As a result, it is anticipated that decreasing the share of secondary industry will help reduce the intensity of carbon emissions. The data used in this study is obtained from the NBS.

Share of government expenditure on science and technology. This variable captures the extent to which local governments prioritize investment in science and technology in their general budget expenditure. As the public becomes more conscious of the need for energy conservation, emissions reduction, and ecological protection, China has become increasingly attentive to carbon emissions and has reinforced governmental oversight of public expenditure aimed at managing carbon emissions. Prior research has demonstrated that government expenditure on carbon emissions management has a direct and negative effect on carbon emissions, thus contributing to their reduction (Hu et al., 2014; Li and Gao, 2019). The data used to measure this variable is obtained from local finance statistical yearbooks published by the NBS.

4.Mediating variables

Green innovation capacity. The prevailing view in the literature is that the digital economy is conducive to promoting innovation and enhancing productivity, leading to a reduction in carbon emissions. Nonetheless, prior studies on this topic have mainly relied on the number of patents as the primary indicator. In contrast, this study delves into the impact of the digital economy on carbon emissions intensity by analyzing how it improves green innovation capacity. Specifically, we extract the number of green patents in each region and year by searching the patent database of the State Intellectual Property Office of China based on the IPC code of green patents issued by the World Intellectual Industry Organization. The study distinguishes between green invention patents and green utility model patents and utilizes the per capita amount of both types of patents to measure green innovation capacity. This approach better captures the impact of the digital economy on green technological progress and its contribution to reducing carbon emissions intensity. It is noteworthy that previous research has focused on the total number of green invention patents to study the impact on overall carbon emissions (Zhu et al., 2019). However, given the focus of this study on carbon emissions intensity, per capita measures of green invention and utility model patents are employed to assess the effect of the digital economy on green innovation capacity and carbon emissions intensity.

Economic agglomeration. Consistent with the approach adopted by Shao et al. (2019), this study draws on data sourced from the National Bureau of Statistics to operationalize the extent of economic agglomeration. Specifically, we utilize the ratio of non-agricultural output (comprising the aggregate value added of the secondary and tertiary industries) to the area of built-up regions in each province to capture this variable. Centralized production, as opposed to decentralized production, is characterized by several features, including economies of scale, increasing returns to scale, and lower iceberg costs. Economic agglomeration has the potential to help enterprises lower their production costs while encouraging the centralized utilization of energy through channels such as matching, sharing, and learning. This, in turn, can lead to enhanced energy use efficiency, a decrease in energy losses, and ultimately, a reduction in carbon emissions intensity.

3.3 Descriptive Statistics

Table 1 displays the descriptive statistics for the variables employed in this study. The minimum value of carbon emissions intensity is 0.4 tons of CO_2 per 10,000 tons of value added, while the maximum value is 19.17 tons of CO_2 per 10,000 tons of value added, highlighting a substantial difference in carbon emissions intensity among regions.

Table 1Descriptive statistics of variables.

Type of Variables	Variables	Unit	Sample Size	Mean	Std. dev	Min	Max
Explained Variable	Carbon EmissionsIntensity	ton/10000 yuan	270	3.394	3.653	0.401	19.171
Core Explanatory Variables	Digital Economy		270	0.750	1.155	-1.027	6.614
Control Variable	Railroad Operating Mileage	10000 km	270	0.386	0.221	0.050	1.300
	Degree of Trade Openness		270	0.042	0.047	0.002	0.240

	Share of Secondary Industry		270	0.415	0.080	0.160	0.620
	Proportion of Government Expenditure on Science and Technology		270	0.021	0.014	0.004	0.068
Intermediate Variable	Green Invention Patents per capita	quantity / per 10,000 people	270	0.911	1.502	0.026	12.273
	Green Utility Model Patentper capita	quantity / per 10,000 people	270	0.774	0.929	0.044	4.781
	Economic Agglomeration		270	12.115	4.742	4.735	32.847

The scatter plot and linear regression line shown in Figure 1 illustrate a clear negative correlation between two variables. The vertical line represents carbon emission intensity.Specifically, the data suggests that regions with higher levels of digital economy tend to have lower levels of carbon emissions intensity, thus supporting the hypothesis put forth by the authors.

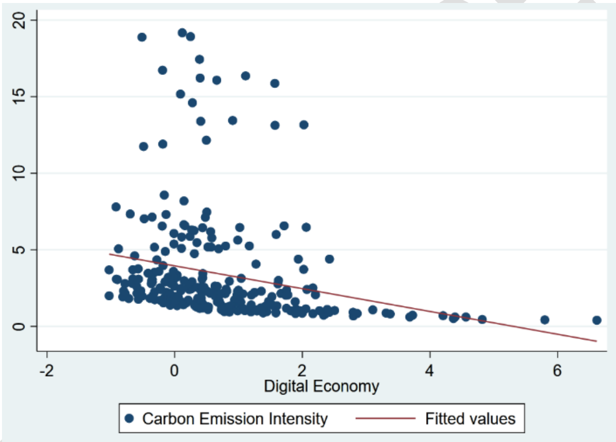

Figure 1 Scatterplot of digital economy and carbon intensity

4. Empirical Results

4.1 Benchmark regression

The results of the baseline regression analysis, presented in Table 2, suggest a significant negative relationship between digital economy development and carbon emissions intensity, with a significance level of 5%. These findings are in line with the initial hypothesis of the study, indicating that the digital economy can potentially reduce carbon emissionsintensity. However, the insignificance of control variables in the model does not necessarily implythat there is no effect of the control variables on the explanatory variable. The lack of significance may be due to issues of multicollinearity and endogeneity, which require further analysis.The use of control variables in this paper does not necessitate the resolution of endogeneity concerns. The control variables are regressed separately from the explanatory variables and yield significant results that align with expectations. The primary purpose of incorporating these control variables is to mitigate the issue of endogeneity arising from omitted variables. For instance, the development of the digital economy, which encompasses e-commerce, is contingent upon well-maintained transportation infrastructure, with railway operating mileage having a discernible impact on this development. Lin et al. (2021) have demonstrated that increased railway operating mileage can reduce carbon emissions, thereby implying that this variable not only affects the development of the digital economy, but also influences the carbon emissionsintensity. Consequently, the lack of accounting for this variable could result in causal identification deviations, and as such, it is essential to use railway operating mileage as a control variable to address the issue of omitted variables.

Table 2Benchmark regression

Variable\Model No.	(1)	(2)	(3)	(4)	(5)
Digital Economy	0.515***	-0.394**	-0.461**	-0.553**	-0.575**
	(0.0969)	(0.147)	(0.179)	(0.201)	(0.211)
Railway Operating Mileage		-2.093	-1.715	-2.684	-2.717
		(1.957)	(2.062)	(1.930)	(1.921)
Degree of Trade Openness			-5.198	-4.077	-4.168
			(3.681)	(4.101)	(3.989)
Share of Secondary Industry				-4.210	-4.375
				(5.358)	(5.546)
Expenditure Share on Science and Technology					6.996
					(11.42)
_cons	3.780***	4.498***	4.620***	6.763**	6.720**
	(0.0727)	(0.677)	(0.650)	(2.554)	(2.501)
N	270	270	270	270	270
r2_w	0.247	0.258	0.264	0.276	0.278

Note that robust standard errors are in parentheses；*represents the corresponding adjoint probability P<10%，**represents the corresponding adjoint probability P<5%，****represents the corresponding adjoint probability P<1%；r2_w refers to r2_within; The following tables are the same as above.

4.2 Robustness and Endogeneity Discussion

4.2.1 Robustness tests

(1)Replacing the explanatory variables. To examine the robustness of the regression results, we replace the carbon emissions intensity variable with carbon emissions performance data calculated by Shao et al. (2022), as demonstrated in models (1)-(2) of Table 3.The findings indicate a statistically significant positive relationship between the digital economy and carbon emissions performance at a 5% level of significance. This suggests that digital economy development has a favorable impact on enhancing carbon emissions performance, thereby reducing carbon emissions intensity.

Table 3 Robustness Analysis

Variable\ Model No.	(1)	(2)	(3)	(4)	(5)	(6)
Type of Robustness	Replacing the explanatory variables		Replacing core explanatory variables			
Replaced variables	Carbon Emissions Performance		Digital Economy (Entropy Method)		Urban Digital Economy Index	
Digital Economy	1.141***	1.604**	-3.029***	-4.019***	-3.106***	-3.311**
	(0.320)	(0.633)	(0.572)	(1.304)	(0.594)	(1.612)
Railway Operating Mileage		1.799		-1.609		-2.373
		(4.436)		(2.124)		(2.107)
Degree of Trade Openness		32.10**		-4.690		-4.818
		(13.56)		(4.119)		(3.288)
Share of Secondary Industry		4.252		-5.553		-2.279
		(9.875)		(5.548)		(4.066)
Expenditure Share on Science and Technology		-14.34		9.750		12.74
		(38.30)		(10.73)		(17.82)
_cons	-0.147	-3.963	4.427***	7.685***	4.233***	6.090***
	(0.181)	(5.504)	(0.195)	(2.608)	(0.164)	(1.876)
N	240	240	270	270	210	210
r2_w	0.134	0.182	0.274	0.305	0.222	0.252

(2)Replacing core explanatory variables.To assess the robustness of the regression results, the digital economic index is calculated using the entropy weight method as a replacement for the principal component analysis method. The regression findings presented in models (3)-(4) of Table 3 reveal a statistically significant negative relationship between the digital economy and carbon intensity at a 5% level of significance. These results underscore the robustness of the conclusion that the development of the digital economy contributes to reducing carbon emissions intensity.Another approach to test the robustness of the findings involves replacing the core explanatory variables with the city digital economy index from Caixin Insight, as demonstrated in models (5)-(6) of Table 3. The results indicate a statistically significant negative relationship between the urban digital economy index and carbon emissions intensity at a 5% level of significance. This supports the robustness of the conclusion.

4.2.2 Endogeneity Discussion

To address the issue of two-way causality and endogeneity arising from unobservable factors, we use an instrument variable approach to avoid endogeneity. Three instrument variables are used to address endogeneity in this paper.

The first instrument variable used is the proportion of private individual employment, which is obtained from the number of private enterprises and self-employed persons divided by the number of total employed persons. This instrument variable is correlated with the development of the digital economy, as the digital economy has induced a new economic model-the odd job economy, generating many flexible workers. *Exogeneity.*The exogeneity of this variable is satisfied since there is no research on the impact of private employment on carbon emissionsintensity. The proportion of privately employed individuals reflects the employment structure, which may be linked to the industrial structure and, consequently, have an impact on carbon emissionsintensity. However, this study has accounted for the industrial structure by using it as a control variable. Furthermore, the proportion of privately employed individuals is unrelated to the disturbance term, thereby meeting the exogeneity requirement.

The second instrument variable used is urban population density. This variable is obtained from urban resident population divided by the built-up area. This instrument variable is correlated with digital economy since digital economy-related companies will increase investment in digital technologies in places with high urban population density for long-term profits. *Exogeneity.*Although certain studies have found that population size is associated with an increase in total carbon emissions (Guo and Sun, 2017), this paper focuses on carbon emissions intensity. Population density may actually decrease carbon emission intensity by enhancing economic efficiency through scaling effects. The digital economy is positively correlated with population density, as higher population density can foster scaling in the digital economy and improve economic efficiency. Furthermore, the omitted variable of economic efficiency at scale is not present in the disturbance term, thereby satisfying the exogeneity condition.

The third instrument variable used is the interaction term of urban population density and topographic slope. Using urban population density still has the possibility of poor exogeneity, and this paper multiplies urban population density with topographic slope, which is relatively exogenous and can improve the exogeneity of the instrument variables to some extent.

To enhance the robustness of the instrument variables method, and the regression results using robust standard errors and bootstrap standard errors (1,000 times) are presented in Table 4. The coefficients of models (1)-(6) for the digital economy are all significantly negative at the 5%

level and exhibit similar magnitudes. Moreover, both the robust standard errors and bootstrap standard errors do not demonstrate significant differences, while also satisfying the unidentifiable test and the weak instrument variable test. Collectively, these findings support the robustness of the conclusion.

Table 4Endogeneity Analysis

Variable\ Model No.	(1)	(2)	(3)	(4)	(5)	(6)
Instrument Variable	Proportion of private individual employment		Urban population density		Interaction term of urban population density and topographic slope	
Type of Standard Error	Robust Standard Error	Bootstrap	Robust Standard Error	Bootstrap	Robust Standard Error	Bootstrap
Digital Economy	-0.920***	-0.920***	-1.050***	-1.050***	-1.080***	-1.080**
	(0.197)	(0.223)	(0.312)	(0.367)	(0.369)	(0.439)
Railway Operating Mileage	-1.232	-1.232	-0.676	-0.676	-0.545	-0.545
	(1.623)	(1.740)	(1.669)	(1.914)	(2.199)	(2.516)
Degree of Trade Openness	-8.476**	-8.476*	-10.09**	-10.09**	-10.47*	-10.47
	(4.277)	(4.772)	(4.225)	(5.029)	(5.782)	(6.905)
Share of Secondary Industry	-7.282*	-7.282*	-8.369	-8.369	-8.626*	-8.626
	(3.902)	(4.157)	(5.245)	(5.897)	(4.858)	(5.387)
Expenditure Share on Science and Technology	16.42*	16.42	19.95*	19.95	20.78*	20.78
	(9.916)	(11.03)	(11.76)	(14.04)	(11.95)	(15.08)
N	270	270	270	270	270	270
r2_w	0.249	0.249	0.223	0.223	0.216	0.216
Unidentifiable Test	33.886***	33.886***	21.305***	21.305***	14.327***	14.327***
Phase 1 F-value	55.005	55.005	44.296	44.296	26.725	26.725

5.Mechanism Analysis[2]

5.1 The digital economy increases the capacity for green innovation and thus reduces carbon emissions intensity

To test research hypothesis 2, we examine the impact of the digital economy on green

[2]This paper also discusses the mechanism of the energy consumption structure, which has been included in the appendix as it is not an innovative point. In the traditional three-part mediation, the third step regression poses a challenge of endogeneity of the core explanatory and mediating variables, making it difficult to address the endogeneity of both variables simultaneously. Therefore, the mediating variable is typically employed as the explanatory variable to examine the effect of the core explanatory variable on the mediating variable. In this paper, various mechanism analyses have been carried out using the instrumental variable approach to address endogeneity. These analyses have been included in the appendix due to the length of the paper.

innovation capability, using green invention patent per capita and green utility model patent per capita as explanatory variables. The results are shown in Table 5. Gradually adding control variables using the stepwise regression method, the coefficient of the digital economy remains positive and significant at the 5% level. This suggests that the digital economy has a positive effect on the improvement of green innovation capability. Moreover, the improvement of green innovation capability is found to reduce carbon emissions intensity, thereby verifying the mechanism by which the digital economy reduces carbon emissions by promoting green innovation capability.

Table5Mechanism 1——Green Innovation Capability

Variable\ Model No.	(1)	(2)	(3)	(4)	(5)	(6)
Explained Variable	Green Invention Patents per capita			Green Utility Model Patent per capita		
Digital Economy	0.600***	0.451***	0.468**	0.528***	0.441***	0.415***
	(0.165)	(0.135)	(0.177)	(0.0731)	(0.0799)	(0.0720)
Railway Operating Mileage		-2.054	-1.606		-0.825	-0.797
		(1.453)	(1.171)		(0.601)	(0.973)
Degree of Trade Openness		-30.81***	-31.50***		-15.49***	-15.72***
		(4.691)	(5.398)		(2.347)	(2.180)
Share of Secondary Industry			1.912			0.0849
			(2.379)			(1.888)
Expenditure Share on Science and Technology			9.324			10.73**
			(11.36)			(5.137)
_cons	0.462***	2.661***	1.519	0.379***	1.413***	1.175
	(0.124)	(0.609)	(0.938)	(0.0548)	(0.197)	(1.128)
N	270	270	270	270	270	270
r2_w	0.407	0.723	0.729	0.587	0.731	0.738

5.2The digital economy promotes economic agglomeration, thereby reducing carbon emissions intensity

To test research hypothesis 3, we examine the effect of the digital economy on economic agglomeration by using economic agglomeration as the explanatory variable. We show the results in Table 6. After adding control variables using the stepwise regression method, the coefficients of the digital economy in models (1)-(5) are all positive at a 1% significance level. This suggests that the digital economy is conducive to promoting economic agglomeration. It is widely accepted in existing literature that economic agglomeration reduces carbon emissionsintensity. Therefore, this paper verifies that the digital economy reduces carbon emissions intensity by promoting economic agglomeration.

Table6 Mechanism2——Economic Agglomeration

Variable\ Model No.	(1)	(2)	(3)	(4)	(5)
Digital Economy	1.910***	1.991***	1.496***	1.685***	1.570***
	(0.196)	(0.302)	(0.196)	(0.189)	(0.182)
Railway Operating Mileage		-1.409	1.381	3.376	3.207
		(2.964)	(2.054)	(2.321)	(2.401)
Degree of Trade Openness			-38.39***	-40.70***	-41.18***
			(10.74)	(11.76)	(12.06)
Share of Secondary Industry				8.662	7.805
				(5.669)	(5.373)
Expenditure Share on Science and Technology					36.34
					(28.43)
_cons	10.68***	11.17***	12.07***	7.663**	7.440**
	(0.147)	(0.973)	(0.841)	(3.203)	(3.362)
N	270	270	270	270	270
r2_w	0.668	0.669	0.733	0.743	0.751

5.3 Reduction of carbon emissions intensity exists regional heterogeneitydue to differences in carbon emission factors for generationelectricity

To test research hypothesis 4, we empirically demonstrate that digital economy development increases electricity consumption. The logarithm of electricity consumption is used as the explanatory variable, and we show the results in Table 7. The explanatory variable in model (1) is the logarithm of electricity consumption, and the coefficient of the digital economy is positively significant at the 1% level. Model (2) employs the instrumental variable method, and the instrumental variable used is the interaction term of urban population density and topographic slope. The coefficient of the digital economy in the instrumental variable estimation is also positively significant at the 1% level. Both model (1) and model (2) provide evidence that digital economy development generates more electricity consumption. It is worth noting that carbon dioxide emissions from electricity consumption are larger than other energy-consuming carbon emissions. Thus, the sharp increase in electricity consumption due to digital economy weakens the reduction effect of the digital economy on carbon emissions intensity.

Table 7 Mechanism 3——Electricity Consumption

Model No.	(1)	(2)
Variable	Logarithm of Electricity Consumption	Instrumental Variable Method
Digital Economy	0.720***	0.174***
	(0.127)	(0.0397)

Railway Operating Mileage	0.668**	0.561**
	(0.251)	(0.221)
Degree of Trade Openness	-0.0518	0.741
	(0.445)	(0.767)
Share of Secondary Industry	0.0805	0.467
	(0.391)	(0.452)
Expenditure Share on Science and Technology	2.352	0.907
	(1.924)	(1.511)
_cons	6.769***	
	(0.174)	
N	270	270
r2_w	0.776	0.728
Unidentifiable test		14.327***
Phase I F-value		26.725

Notethat model (1) in parentheses is the robust standard error, and model (2) in parentheses is the bootstrap 1000 times standard error.

We examine sub-regional heterogeneity by analyzing the magnitude of carbon emissions factors of the six power grids. The Northeast Power Grid, Central China Power Grid, and North China Power Grid are identified as regions with high power carbon emissions factors, while the East China Power Grid, South China Power Grid, and Northwest China Power Grid are regions with low carbon emissions factors. The findings, presented in models (1) and (2) in Table 8, reveal that the coefficient of digital economy in model (1) is not statistically significant, suggesting that the digital economy may not necessarily reduce carbon emissions intensity in regions with high power carbon emissions factors. Conversely, the coefficient of digital economy in model (2) is negative at a 5% level of significance, indicating that the conclusion that the digital economy reduces carbon emissions intensity in regions with low power carbon emissions factors is reliable.The study undertakes a regional heterogeneity analysis by splitting the eastern, central, and western regions because the majority of clean energy generation is located in these areas. The results, presented in models (3) and (4) in Table 8, show that the coefficient of digital economy in model (3) is not statistically significant, while the coefficient of digital economy in model (4) is significant. This shows that it is more reliable to draw the conclusion that the digital economy lowers the intensity of carbon emissions in the central and western areas.

Table8 Mechanism3——Regional Heterogeneity

Variable\ Model No.	(1)	(2)	(3)	(4)
Regional Classification	High carbon emissions factor of electricity	Low carbon emissions factor of electricity	Eastern	Central and Western

Digital Economy	-0.523	-0.602**	-0.0675	-0.842**
	(0.381)	(0.228)	(0.0432)	(0.294)
Railway Operating Mileage	-3.516*	0.356	-2.570*	-3.706
	(1.950)	(4.323)	(1.258)	(2.935)
Degree of Trade Openness	-1.397	-18.65	-0.639	19.69
	(4.879)	(11.47)	(1.014)	(16.11)
Share of Secondary Industry	-6.340	5.687	4.623***	-12.85
	(7.996)	(8.451)	(1.408)	(7.691)
Expenditure Share on Science and Technology	30.17	-9.314	10.26**	-3.073
	(37.07)	(13.18)	(4.165)	(17.51)
_cons	7.328**	2.775	0.235	11.75***
	(3.242)	(4.063)	(0.777)	(3.823)
N	135	135	90	153
r2_w	0.213	0.436	0.797	0.299

The findings show that while the digital economy as a whole helps to reduce the intensity of carbon emissions, the significant increase in electricity consumption brought on by the growth of the digital economy may limit its ability to reduce emission intensity. In regions where the electricity carbon emission factor is low, the carbon emission issues arising from high electricity consumption in the digital industry are relatively less severe. Conversely, in regions where the electricity carbon emission factor is high, the carbon emission problems due to high electricity consumption in the digital industry are relatively more pronounced. Therefore, digital economy development has a considerable emission reduction effect in reducing carbon emission intensity in regions with a low electricity carbon emission factor, while the emission reduction effect is not significant in regions with a high electricity carbon emission factor.

6.Further discussion

The digital economydevelopment has brought about a significant increase in carbon emissions generated by digital industries. According to Yi et al. (2022), based on OECD international input-output tables for 66 countries from 2005 to 2018, while the process of digital industrialization itself increases carbon emissions intensity, industrial digitization can effectively promote the development of national low-carbon transformation by empowering upstream and downstream industrial technological innovation.Digital industry's unique characteristics and the future of the digital era determine that its total carbon emissions are higher than in other industries,it is also capable of achieving a more significant emissions reduction effect on carbon emissions intensity.

The digital economy development has resulted in significant greenhouse gas emissions, primarily from the production of digital equipment and the supporting infrastructure of digital centers. Specifically, in terms of equipment production, China's carbon emissions from production of digital communication equipment exceed those of developed countries such as the United States, indicating the potential for China's digital industry to reduce its overall carbon emissions and carbon intensity. Besides emissions from communication equipment and electronic devices, emissions from China's large data centers should not be overlooked.The supporting facilities of digital centers consist of eight subsystems, including power supply and distribution systems, cooling systems, and cabinet systems. Energy consumption from IT equipment and cooling equipment alone accounts for 80% of the total energy consumed, resulting in significant electricity usage. Given China's enormous consumer market for digital products and the continuous digital transformation of various industries, the demand for digital centers is expected to increase significantly over a long period of time, resulting in a rise in the number of data processing centers, cloud computing centers, and other digital facilities. Consequently, digital economydevelopment has resulted in a surge in energy and electricity demand, leading to a rapid increase in total carbon emissions from the digital industry.

To address this issue, reducing heat dissipation from digital center-related equipment and increasing the proportion of clean energy in power generation are two potential solutions for promoting green and low-carbon digital economydevelopment. This could be achieved by improving the efficiency of heat dissipation in digital center-related equipment and by reducing carbon dioxide emissions associated with electricity generation, thereby reducing the carbon emissions generated by digital centers.

7. Conclusions and policy implications

China made clear in 2020 that it intended to reach "carbon peak" by 2030 and "carbon neutrality" by 2060, and the digital economy is now seen as a new force and crucial component in achieving these objectives. The research yields the following key findings: First off, the growth of China's digital economy helps to lessen the intensity of carbon emissions. Second, through enhancing green innovation capabilities and encouraging economic agglomeration, the growth of China's digital economy can lower the intensity of carbon emissions. Thirdly, there is a lot of geographical variation in this area.Given that digital economy development requires a substantial amount of electricity, its impact on carbon emissions intensityis considerably stronger in areas with clean energy generation (areas with low electricity carbon emissions factor) than in regions with non-clean energy generation (areas with high electricity carbon emissions factor). This study carries significant implications for the development of China's digital economy and the achievement of the dual carbon goals.

The policy implications of this paper can be summarized as follows.

First, it is advised that China keep pushing for the high-quality growth of the digital economy. The digital economy has the ability to alter existing industries and support the development of a contemporary economic system as a highly inventive, porous, and expansive sector. Although the quality of China's development is still lacking, the country's digital economy is currently among the fastest-growing in the world in terms of both its size and growth rate. The level and quality of China's economic development can be improved by further fostering high-quality development in this field. This will also help to reduce the intensity of China's economy's carbon emissions.

Secondly, China should enhance the carbon emissions trading mechanism and strengthen incentives for green innovation among enterprises. Carbon emissions trading involves incorporating the negative externalities of enterprises that previously emitted carbon dioxide into their costs, thereby facilitating green transformation and green inventions. By further improving the carbon emissions trading mechanism, China can increase incentives for enterprises to innovate in environmentally friendly ways.

Thirdly, China should expedite the "Processing Eastern Data in the West" project, relocating some data centers to the western region and taking advantage of clean energy generation in that area. In the era of the digital economy, data processing is a core activity that consumes a large amount of electricity, while power generation in the east is less environmentally friendly than in the west. Therefore, a reasonable spatial layout of digital centers can be made to improve energy utilization efficiency and reduce carbon emissions intensity. Accelerating the "Processing Eastern Data in the West" project is not only beneficial for China's digital economy to better promote economic growth, but also helps to achieve the dual carbon goals.

The study exhibits three main limitations. First is the sample size: The data on secondary indicators used to measure the development of the digital economy are only available from the National Bureau of Statistics from the year 2011. This study relies on data from 2011-2019 for 30 provinces, resulting in a small sample size. Second is theoretical mechanism. This study does not account for the potential impact of the digital economy on the industrial structure. A well-designed industrial structure and optimized layout can contribute to low-carbon development. This issue will be considered in future research.Third is the setting of the model.We have tested the impact of the digital economy on carbon emissions intensity using only a one-way individual fixed effects model. The use of other models to identify the causal utility of the digital economy on carbon emissions will be considered in future studies to improve the robustness of the findings.

One potential extension for future research is to explore the impact of digital industries on carbon emissions intensity. Digital industries empower traditional industries and facilitate the process of digital transformation. The digitalization of industries can improve economic efficiency, reduce business costs, and lower energy consumption. However, it's important to note that the digital industry itself can also produce a significant amount of carbon dioxide, which may not be conducive to reducing carbon emissions intensity.Therefore, future research could focus on how to effectively coordinate the development of digital industries and industrial digitalization in order to minimize carbon emissions intensity.

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Appendix.

As the present study has confirmed that the digital economy enhances the energy consumption structure by decreasing the proportion of coal in the overall energy consumption. This mechanism is presented in the appendix, with the corresponding results reported in Table 1. Model (1) serves as the baseline regression, while model (2) utilizes an instrumental variable approach to address endogeneity issues. The outcomes indicate that the digital economy has a positive impact on improving the energy consumption structure.

Table 1Mechanism——Energy Consumption Structure

Variable\ Model No.	(1)	(2)
Digital Economy	-0.0378***	-0.0903***
	(0.0107)	(0.0130)
Railway Operating Mileage	-0.228	-0.00260
	(0.141)	(0.0908)
Degree of Trade Openness	0.0251	-0.630**
	(0.317)	(0.258)
Share of Secondary Industry	-0.0454	-0.487***
	(0.235)	(0.166)
Expenditure Share on Science and Technology	-0.693	0.740
	(1.030)	(0.656)
_cons	0.543***	
	(0.133)	
N	270	270
r2_w	0.626	0.465
Unidentifiable Test		33.886***
Phase 1 F-value		55.005

Note:：The robust standard errors are in parentheses. In this paper, the standard errors were obtained by bootstrap 1000 times at the same time, and the conclusions are basically the same. The following table is the same as above.

Because of the endogeneity problems associated with the traditional three-step mediated regression (mainlyin the third step), many studies opt to perform only two-step regressions, with the third step used for theoretical analysis and literature citation to support their arguments. However, both the first and second regressions may also have endogeneity issues, necessitating endogeneity treatment for both. To this end, this paper employs the instrument variables method, with the share of private enterprises and self-employed persons serving as instrument variables, to address the endogeneity problems in the mechanism used in this study. Table 2 presents the results of the endogeneity treatment, which are consistent with the use of the other two instrument variables used in this study. Models (1) and (2) show that after endogeneity treatment using the instrument variable method, the coefficient of the digital economy remains positive at the 1% significant level and passes the unidentifiable test and weak identification test, indicating the reliability of the conclusion that the digital economy improves green innovation capacity. Model (3) is an endogeneity treatment of economic agglomeration, and the results also indicate that the digital economy is beneficial to economic agglomeration. Model (4) uses an instrument variable approach regression for regions with high electricity carbon emissions factor, and model (5) uses an instrument variable approach regression for regions with low electricity carbon emissions factor. The results indicate that the digital economy has a stronger emissions reduction effect on regions with low electricity carbon emissions factor. In summary, after the endogeneity treatment, the findings of the mediating mechanism and regional heterogeneity analysis in this paper are robust.

Table 2Mechanism Analysis--Instrument Variable Approach

Variable\ Model No.	(1)	(2)	(3)	(4)	(5)
Explained Variable	Green Invention Patents per capita	Green Utility Model Patent per capita	Economic Agglomeration	Carbon emission intensity	Carbon emission intensity
Digital Economy	0.332***	0.541***	1.985***	-0.572**	-1.213***
	(0.0998)	(0.102)	(0.344)	(0.254)	(0.307)
Railway Operating Mileage	-1.021	-1.342*	1.421	-3.308*	2.717
	(0.621)	(0.689)	(1.995)	(1.888)	(2.643)
Degree of Trade Openness	-33.20***	-14.14***	-36.00***	-2.079	-24.57***
	(5.065)	(2.233)	(6.852)	(5.042)	(7.862)
Share of Secondary Industry	0.766	1.151	11.30***	-6.714	-1.268
	(1.237)	(1.052)	(3.638)	(4.482)	(5.528)
Expenditure Share on Science and Technology	13.04*	7.273	25.01	32.30	1.118
	(7.014)	(4.778)	(16.94)	(21.53)	(11.67)
N	270	270	270	135	135
r2_w	0.724	0.729	0.743	0.213	0.326
Unidentifiable Test	33.886***	33.886***	33.886***	16.594***	15.626***
Phase 1 F-value	55.005	55.005	55.005	29.232	22.799