Study on the Impact of the Digital Economy on Carbon Emissions

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Abstract. Utilizing provincial panel data spanning from 2013 to 2022, the paper delves deeper into the function of industrial structure upgrading as an intermediary variable within the relationship between the digital economy and carbon emissions, employing the intermediary effect model. The research indicates that the digital economy has a considerable restraining effect on carbon emissions, with industrial structure advancement serving as a pivotal intermediary in the pathway from the digital economy to reduced carbon emissions.

Keywords: digital economy; industrial structure upgrading; carbon emission; intermediary effect

1 Introduction

In the current global technological and industrial shift, the digital economy, fueled by advancements in artificial intelligence, big data, cloud computing, and other technologies, along with digital productivity, is demonstrating robust dynamism as a nascent economic modality. However, behind this prosperity, we must face up to the problem of environmental protection. Citing the IEA's 2023 report on carbon dioxide emissions, China accounts for 30.93% of global CO2 emissions. To tackle the developmental carbon emission challenge, China has introduced the "double-carbon" target. Consequently, the question arises: Can the digital economy contribute to reducing these emissions?

The digital economy, due to its rich connotations, lacks a unified global definition. Institutions such as BEA (2019)[1] and ABS (2019)[2] have all released insights into the digital economy, while scholars have also measured it from various angles.Liu Jun et al. (2020)[3] establish an index system focusing on informatization, internet, and digital transaction development. Zhao Tao (2020)[4] selects sub-indicators from internet penetration, employment, output, mobile users, and digital financial inclusion. The carbon emission coefficient method, commonly used, is employed by Li et al. (2019)[5] for fossil fuels like coal, LPG, and gas, while Yang et al. (2019) [6]estimate provincial energy-related emissions across 11 fuel types.And regarding the impact of the digital economy on carbon emissions,Wu Caixia et al. (2020) [7]discovered that the digital

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economy significantly drives the development of low-carbon industries, primarily through two channels: energy flow and resource flow. Xie Yunfei (2022)[8]analyzed the intermediary role of energy structure in the relationship between the digital economy and carbon emissions, concluding that improving energy structure is a crucial mechanism for reducing carbon emission intensity due to digital economy development.

Existing literature primarily emphasizes energy structure and seldom considers industrial structure upgrading as an intermediary variable to explore the interconnections between the three. Therefore, this paper will employ the intermediary effect model to investigate the relationship between digital economy development, industrial structure upgrading, and carbon emissions using panel data from 30 provinces and autonomous regions spanning 2013 to 2022. The aim is to support the policy framework for the digital economy in promoting industrial structure upgrading and achieving low-carbon development.

2 Rsearch Design

2.1 Mediation Effect Model

$$\mathrm{LnCO2}_{it} = \alpha_0 + \beta_1 D\mathrm{IG}_t + \beta_2 X_{it} + \varepsilon_{it} + \delta_t + \eta_i \quad (1)$$

$$IS_{it} = \alpha_0 + \beta_3 D\mathrm{IG}_{it} + \beta_4 X_{it} + \varepsilon_{it} + \delta_t + \eta_i \quad (2)$$

$$LN\mathrm{CO2}_{it} = \alpha_0 + \beta_5 D\mathrm{IG}_{it} + \beta_6 IS_{it} + \beta_7 X_{it} + \varepsilon_{it} + \delta_t + \eta_i \quad (3)$$

Specifically, i and t represent the province and year respectively; $LN\mathrm{CO2}it$ is carbon emission; Digit is digital economy index; $ISit$ is industrial structure; Xit is control variable group; εit is random error term; δt is time non-observation effect; and ηi is regional non-observation effect.

2.2 Variable Selection

2.2.1 Explained Variables.
Carbon emissions (LnCO2) in this paper refer to liu (2018)[9], by measuring the provinces eight energy consumption total energy consumption, then according to the IPCC provide carbon accounting basic equation: carbon emissions = activity data* emission coefficient,Calculate the carbon emissions for each province, and then perform logarithmic processing on the data. The calculation formula is provided below:C $=\sum_{i=1}^{n} E * SCC_i * CEC_i$.Among them, C is the total emission, E_i represents the consumption of the first energy, SSC_i represents the discount standard coal coefficient of the first energy, and CEC_i represents the carbon emission coefficient of the first energy.

2.2.2 Core Explanatory Variables.
Digital economy development (Dig) digital economy index system including basic design, digital industrialization, digital, digital governance four level indicators and 18 secondary index, Drawing inspiration from Wang Jun et al. (2021)[10],this paper utilizes

the entropy method to determine the weight of digital economy indicators and calculate the comprehensive score, ultimately assessing the development level of the digital economy through a comprehensive index.

2.2.3 Intermediary Variables.

Industrial Structure Upgrading (IS): This paper adopts the research approach of Wang Wei et al. (2015)[11], calculating the hierarchy coefficient of industrial structure by determining the weighted proportion of the primary industry, secondary industry, and tertiary industry.The specific calculation method is as follows: IS=$\sum_{i=1}^{3} X_i * i$,This represents the proportion of the output value of the first xi industry in the total output value, where i also denotes the weight assigned to each output value in the weighted ratio.

2.2.4 Control Variable.

(1) Energy consumption intensity. This paper uses the proportion of total energy consumption to GDP, and the symbol is ECI. (2) Technical innovation. This paper employs the natural logarithm of the number of patents granted as a representation of "technological innovation". The symbol is denoted as the LnRD. (3)density of population. In this paper, the population of each province is divided by the population density obtained at the end of the region to measure the population level, and take the logarithm, and the symbol is denoted as LnPD. (4)Level of economic development. In this paper, the logarithm of regional GDP will be used as an indicator to measure economic development, denoted by the symbol LnGDP.

2.2.5 Data Sources.

The empirical process utilizes data sourced exclusively from the China Statistical Yearbook and China Energy Statistical Yearbook spanning multiple years.

3 Empirical Analysis

3.1 Mediation Effect Analysis

According to the above model, the provincial panel data from 30 provinces from 2013 to 2020 are shown in Table 1:

Table 1. Analysis results of mediating effects

	$LnCO_2$	IS	$LnCO_2$
Dig	-2.890***	0.676***	-1.782***
	(-11.621)	(12.793)	(-6.118)
IS			-1.638***
			(-6.356)
ECI	1.591***	0.016	1.618***
	(23.603)	(1.146)	(25.503)
LnRD	-0.044	0.028***	0.002
	(-0.946)	(2.822)	(0.038)

LnPD	0.069***	0.046***	0.145***
	(3.066)	(9.604)	(5.955)
LnGDP	1.361***	-0.106***	1.188***
	(22.355)	(-8.160)	(18.765)
_cons	-5.108***	2.816***	-0.496
	(-13.270)	(34.418)	(-0.612)

Source(s): The Authors' computation.

The variables Dig and IS in Models 1 through 3 successfully achieved statistical significance at the 1% threshold, yielding the subsequent insights: (1) As evident from the regression outputs in Columns 1 and 3, the negative coefficient of Dig signifies that the proliferation of the digital economy exerts a notable suppressive effect on carbon emissions. (2) Conversely, Column 2's positive coefficient of Dig underscores the stimulatory impact of the digital economy's development on advancing industrial structure transformation. (3) Additionally, Column 3's negative coefficient of IS underscores the substantial and adverse effect that industrial structure upgrading has on carbon emissions.

To delve deeper, the subsequent stepwise regression analysis underscores the pivotal intermediary function of industrial structure, accounting for 38.322% of the influence exerted by the digital economy on carbon emissions reduction.

4 Robustness Test

4.1 Robustness Test of the Mediation Effect

In this research, we have introduced an innovative metric, IS2, to assess industrial structure, replacing the conventional measurement approach. IS2 represents the ratio of the tertiary industry's added value to that of the secondary industry.Furthermore, we have employed the previously utilized gradual regression methodology to scrutinize the mediating role of this revised industrial structure measure. The empirical findings derived from this analysis are summarized in Table 2.

Table 2. Robustness test results of the mediation effect model

	LnCO2	IS	LnCO2
Dig	-2.890***	5.555***	-2.405***
	(-11.621)	(15.235)	(-7.278)
IS2			-0.087**
			(-2.208)
ECI	1.591***	-0.761***	1.525***
	(23.603)	(-7.693)	(20.772)
LnRD	-0.044	-0.207***	-0.062
	(-0.946)	(-3.038)	(-1.323)
LnPD	0.069***	0.138***	0.081***
	(3.066)	(4.166)	(3.521)
LnGDP	1.361***	-0.666***	1.303***
	(22.355)	(-7.460)	(19.752)
_cons	-5.108***	9.269***	-4.299***
	(-13.270)	(16.422)	(-8.119)

Sample capacity	300	300	300
R2	0.83	0.595	0.833

Note(s):*Significant at 0.1 level; **significance at 0.5 level;***significance at 0.01 level
Source(s): The Authors' computation

The empirical results demonstrate that the digital economy has a substantial positive effect on industrial structure upgrading, indicating that the advancement of the digital economy can propel the upgrading of industrial structure. Concurrently, the upgrading of industrial structure exhibits a significant negative impact on carbon emissions, suggesting that the upgrading and optimization of industrial structure contribute to carbon emission reduction.The outcomes of the gradual regression analysis indicate that industrial structure upgrading exerts an intermediary effect of 16.72%, suggesting that it accounts for 16.72% of the reduction in carbon emissions attributed to the digital economy, thereby strengthening the robust conclusions drawn in this study.

5 Conclusions and Revelation

5.1 Conclusion

The main conclusions are summarized as follows:

1. The development of the digital economy has a substantial potential to mitigate carbon emissions. 2. The digital economy fosters a positive impetus for the upgrading of industrial structures. 3. The process of industrial structure upgrading functions as a mediator between the digital economy's influence and carbon emissions reduction, ultimately facilitating a decrease in carbon emissions.

Drawing upon these conclusions, this paper presents the following insightful observations: (1) To bolster progress, provinces should escalate investments in pivotal technological research and development, encompassing big data, cloud computing, artificial intelligence, the Internet of Things, and blockchain.This would enhance their autonomous innovation capabilities, foster an open and collaborative innovation platform, facilitate deep integration between industry, academia, research, and application, and expedite the transformation of technological achievements. Additionally, emphasis should be placed on critical technology domains such as clean energy, energy conservation, emission reduction, carbon capture, and storage, with a focus on strengthening technology research, development, promotion, and application. (2) The provinces should devise a green, low-carbon industry development plan that outlines clear development goals and key tasks. This strategy should foster the growth of clean energy, energy efficiency, environmental protection, new energy vehicles, and other eco-friendly, low-carbon industries.Fiscal subsidies and preferential tax policies should be provided to encourage enterprises to adopt advanced energy conservation and emissions reduction technologies, thereby improving energy efficiency and reducing carbon intensity. In addition, the carbon emission rights trading market should be established and refined to promote the optimal allocation of carbon emission rights through market mechanisms. (3) Provincial authorities must rigorously manage the capacity of industries characterized by high energy consumption and emissions, incrementally phasing out obsolete production capabilities. Additionally, they should harness digital technologies to transform and elevate traditional industries, thereby augmenting their value-added and market competitiveness, while guiding enterprises towards environmentally sustainable, low-carbon, and energy-efficient development paths. Moreover, the industrial layout should be optimized, with a rational distribution of digital economy industries based on regional resource endowments and industrial foundations, fostering the emergence of digital economy industrial clusters with distinct characteristics and complementary advantages.

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