Digital Industry Agglomeration, Green Technology Innovation and Carbon Productivity

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Abstract. The synergistic development of digitalization and greening represents an inescapable option for propelling the advancement of economy and society. Using the panel data of 30 provinces spanning from 2010 to 2021 in China, this research conducts the effect and path of digital industrial agglomeration on carbon productivity from a multi-dimensional perspective. The study reveals that a non-linear inverted U-shaped correlation exists between digital industrial agglomeration and carbon productivity. The threshold effect test indicates that once the level of green technology innovation surpasses a specific threshold, the agglomeration of digital industries exerts a positive influence on carbon productivity. The research results hold substantial practical importance for the effective utilization of digital industrial agglomeration to empower efficiency-enhancing carbon reduction.

Keywords: Digital industry agglomeration; green technology innovation; carbon productivity; threshold effect

1 Introduction

Since the 18th CPC National Congress, China has made historic progress in its low-carbon transformation development. The economy grew at an average annual rate of 6.5%, while energy consumption increased by only 3% per year. This resulted in a 26.2% reduction in energy consumption intensity and a decrease of 2.94 billion tons in carbon emissions, exceeding the autonomous target for carbon intensity reduction [1]. As the globe's largest developing nation, China has committed to reaching a carbon peak by 2030 and attaining carbon neutrality by 2060. The primary obstacle during the green transformation lies in achieving a balance between carbon emissions and economic expansion. Moreover, enhancing carbon productivity is of vital importance for reconciling the "economic value" and "environmental friendliness" within the development process. Simultaneously, the digital economy is experiencing rapid growth in China. With the integration of digitalization and green development, the digital industry has become a crucial impetus in driving the growth of the green economy. The digital

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industry exhibits clear spatial agglomeration, and China's digital industry clusters have entered a new stage of centralized collaboration and comprehensive development.

At present, the research on digital industry agglomeration is still in its infancy, mainly focusing on the dimensions of spatio-temporal evolution [2], influencing factors [3], and innovation effects [4]. While several scholars have taken note of the green influence of digital industry clustering, no study has yet unraveled the "black-box enigma" of how carbon productivity impacts the agglomerative development of the digital industry, given that it is an emerging sector. It has been recognized that the impact of various traditional industrial agglomerations on carbon productivity is complex, and the relationship between the two has not reached a unanimous conclusion. Previous research has fruitfully probed into the connection between the agglomeration of the digital industry and green technology innovation [5], as well as the link between green technology innovation and carbon productivity [6], but has not included all three in the same research framework.

The potential contributions of this study are manifested in these areas: (1) Taking the agglomeration of the digital industry as a starting point, this study delves into the catalytic effect of digitalization on green development from the vantage point of agglomeration economic theory, thereby augmenting the body of research on the factors influencing carbon productivity. (2) It puts forward the “digital industry agglomeration-carbon productivity “and analyzes the critical point and key channels of digital industrial agglomeration affecting carbon productivity, and incorporates green technology innovation into the same theoretical framework. (3) It explores the new kinetic energy of efficiency enhancement and carbon reduction and provides empirical evidence for the further promotion of digitalization and greening.

2 Theory and Hypotheses

2.1 Digital Industrial Agglomeration and Carbon Productivity

Based on the industrial agglomeration life-cycle theory, in the growth and maturation phases of digital industrial agglomeration, the positive externalities of carbon productivity are greater than the negative externalities. Digital industry agglomeration boosts carbon productivity through several mechanisms. First, the economies of scale effect: the digital industry's inherent permeability enhances operational efficiency through agglomeration. Sharing pollution treatment equipment lowers unit costs, allowing companies to invest more in research and development. Additionally, the shared use of green technologies drives regional advancements in carbon productivity. Second, information spillover effect: Digital industry agglomeration, through digital platforms, improves communication efficiency and data processing, reducing information asymmetry between enterprises. This optimizes resource allocation, resulting in energy and resource savings [7]. Learning green emission reduction technology among enterprises accelerates the development of a green production technology network and boosts overall carbon productivity. Third, industrial structure effect: The agglomeration of the digital industry spurs industrial upgrading via the industrial chain mechanism. It propels industries to expand towards low-pollution and high-value-added sectors and restructures the industrial framework to boost carbon productivity.

However, once digital industry agglomeration surpasses a certain threshold, it enters a decline phase, where the negative externalities on carbon productivity outweigh the positive ones. As the agglomeration scale expands and local governments pursue a "GDP Championship," diseconomies of scale arise, causing a loss in production efficiency and a rebound in carbon emissions [8], which hampers the enhancement of carbon productivity. Based on this, Hypothesis 1 is proposed:

H1: There exists an inverted "U"-shaped correlation between the agglomeration of the digital industry and carbon productivity, where carbon productivity increases initially and then decreases as agglomeration intensifies.

2.2 Threshold Effects of Green Technology Innovation

The theory of biased progress views green technological innovation as a means to balance environmental protection and economic growth, serving as a key driver of improved carbon productivity. It enhances carbon productivity by fostering industrial structure upgrades, promoting sustainable agriculture, and enabling transportation substitution. Nevertheless, studies indicate that the influence of digital industry clustering on green technological innovation presents a dual-nature characteristic. Moderate agglomeration can foster green innovation, while excessive agglomeration may hinder it. Consequently, the connection between the agglomeration of the digital industry and carbon productivity could differ according to the degree of green technological innovation. In regions with higher levels of green innovation, businesses can absorb green technologies through innovation networks, thereby enhancing carbon productivity. Based on the above-mentioned analysis, Hypothesis 2 is put forward:

H2: Green technology innovation acts as a moderator in the relationship between digital industry agglomeration and carbon productivity, whereby agglomeration positively influences carbon productivity more significantly at elevated levels of green technology innovation.

3 Research Design

3.1 Empirical Model

In this study, the following benchmark regression model is constructed:

$$\mathrm{CP}_{i,t} = \alpha_0 + \alpha_1 \mathrm{DIA}_{i,t} + \alpha_2 \mathrm{DIA}_{i,t}^2 + \lambda \sum \mathrm{Control} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{1}$$

where subscript i refers to province and t denotes year. The explanatory variable CP is carbon productivity at the provincial level, and the core explanatory variables DIA and DIA^2 capture the degree of digital industry agglomeration at the provincial level, and Control encompasses a set of control variables at the provincial level. μ_i and δ_t represent province and year fixed effects, and $\varepsilon_{i,t}$ is the random error term.

The model estimates are adjusted with robust standard errors, clustered at the provincial level.

This paper draws on the research idea of Hansen (1999) [9] to construct the following panel threshold model:

$$CP_{i,t} = \beta_0 + \beta_1 DIA_{i,t} I(GTI_{i,t} \le \gamma_1) + \beta_2 DIA_{i,t} I(\gamma_1 < GTI_{i,t} \le \gamma_2) + \cdots + \beta_{n+1} DIA_{i,t} I(GTI_{i,t} > \gamma_n) + \lambda \sum Control + \mu_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

where GTI represents a threshold variable that denotes the extent of green technology innovation, $\gamma_1 \ldots \gamma_n$ is the threshold value, $I(\cdot)$ is a schematic function that equals 1 when the conditions within the parentheses are met, and 0 otherwise.

3.2 Variables

3.2.1 Explained Variable

Carbon productivity (CP). In this paper, it is quantified as the rate of GDP to CO_2 emissions in each province:

$$CP_{i,t} = \frac{GDP_{i,t}}{CO_2} \quad (3)$$

where GDP is the real GDP at the provincial level, which is price-deflated to remove the impact of inflation. CO_2 is the CO_2 emissions at the provincial level.

3.2.2 Core Explaining Variable

Digital Industry Agglomeration (DIA). The definition of the digital industry proposed by the China Academy of Information and Communication Research (CAICR) is broadly recognized in academic circles. This definition, along with the Statistical Classification of Digital Economy and Its Core Industries (2021) from the National Bureau of Statistics (NBS), as well as the study by Han Jun and Gao Yinglu (2022) [10], forms the basis for this study, the digital industry in this paper is defined to cover digital industry manufacturing and digital industry services. This study employs the location entropy index to gauge the agglomeration of the digital industry:

$$DIA_{i,t} = \frac{DEM_{i,t}}{EM_{i,t}} / \frac{\sum_{i=1}^{n} DEM_{i,t}}{\sum_{i=1}^{n} EM_{i,t}} \quad (4)$$

In Eq (4), $DEM_{i,t}$ is the number of urban units employed in the digital industry in province i during year t, $EM_{i,t}$ denotes the total number of urban units employed in province i in year t, $\sum_{i=1}^{n} DEM_{i,t}$ refers to the total number of urban units employed in the digital industry across the country in year t, and $\sum_{i=1}^{n} EM_{i,t}$ represents the number of urban units employed nationwide.

3.2.3 Threshold Variable

Green Technology Innovation (GTI). To account for population differences, this research adopts the number of green patent authorizations per 10,000 individuals as a substitute variable for green technological innovation.

3.2.4 Control Variables

Building upon existing literature, this paper incorporates several variables that may influence carbon productivity: (1) Economic development level (PRGDP), measured by real GDP per capita (constant 2010 prices). (2) Urbanization level (URB), measured by the proportion of the non-rural population to the total population at year-end. (3) Industrial structure (STR), measured by the share of value added from the secondary industry in GDP. (4) Openness to the outside world (OPEN), measured by the ratio of foreign direct investment (FDI) to GDP. (5) Energy consumption structure (ECS), measured by the share of coal consumption in total energy consumption. (6) Environmental regulation (ER) is measured by the ratio of completed industrial pollution control investment to GDP.

3.3 Descriptive Statistics

The data utilized in this study is sourced from 30 provincial regions across China, spanning the time frame from 2010 to 2021, with the Tibet Autonomous Region excluded due to significant data gaps, as well as Hong Kong, Macao, and Taiwan. Data was sourced from multiple official and academic databases, including the Statistical Yearbook and databases like CEADs and CSMAR. For missing data, interpolation was used, and all continuous variables underwent Winsorization.

4 Empirical Results and Analysis

4.1 Baseline Regression Results

Table 1 shows the regression results of digital industry agglomeration on carbon productivity. In column (2), the digital industry agglomeration coefficient is significantly positive at the 1% level, and its squared term is significantly negative. The "U" - shaped test shows a positive slope at the lower limit and a negative one at the upper limit, with the inflection point within the observed range. This indicates the existence of an inverse "U" relationship, validating hypothesis H1.

Table 1. The impact of digital industry agglomeration on carbon productivity.

	(1)	**(2)**
Variable	CP	CP
DIA	1.0903**	0.9395***
	(0.4262)	(0.3147)
DIA^2	-0.4135**	-0.2706***

	(0.1567)	(0.0962)
PRGDP		0.1016***
		(0.0316)
URB		-1.6850**
		(0.6434)
STR		-1.3402*
		(0.7561)
OPEN		0.0366
		(0.0998)
ECS		-0.0059
		(0.0950)
ER		6.8462*
		(3.9310)
constant	0.0406	1.0736*
	(0.2302)	(0.5710)
Fixed effects	Yes	Yes
N	360	360
Adj_R^2	0.545	0.687

Note
Clustering robust criterion errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

4.2 Threshold Effect Test Results

The bootstrap self-sampling method with 500 repeated samples tested the threshold effect. The single-threshold effect was significant at the 1% level. In Figure 1, the red dashed line shows the critical value of 7.3523, while the single threshold value of 4.0774, much lower than the critical value, validates the threshold estimate. Thus, a single-panel threshold model is developed.

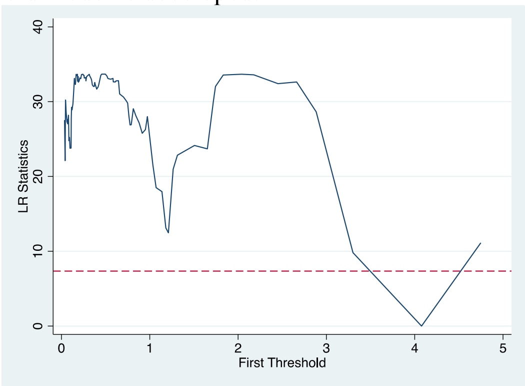

Fig. 1. Single threshold estimates of green technology innovation LR figure.

Table 2 shows the threshold-effect regression results of green technology innovation. On the time that green technology innovation is below the threshold (GTI≤4.0774), the coefficient on carbon productivity is insignificant. Once GTI exceeds the threshold (GTI>4.0774), the coefficient is significantly positive at the 10% level. This means that after green technology innovation crosses a certain threshold, the digital industry agglomeration carbon productivity relationship is on the left of the inverted "U" curve, validating hypothesis H2.

Table 2. The panel threshold effects regression results.

Variable	CP
DIA （GTI ≤ 4.0774）	0.0881 (0.1354)
DIA （GTI > 4.0774）	0.2815* (0.1457)
Constant	0.9959*** (0.3425)
Controls	Yes
Fixed effects	Yes
N	360
Adj_R^2	0.713

Note
Clustering robust criterion errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10%, respectively.

5 Conclusions and implications

We identify an inverted “U”-shaped link between digital industry agglomeration and carbon productivity, with green technology innovation exhibiting a significant and evident threshold effect. When green technology innovation exceeds a certain threshold, digital industry agglomeration boosts carbon productivity. These findings yield policy implications. First, boost digital industry agglomeration and speed up the growth of digital industry clusters. Second, enhance green technology innovation for carbon-reducing efficiency. Third, deepen the enhancement of the digital economy and finance to underpin digital industry clustering.

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