Pol. J. Environ. Stud. Vol. 32, No. 5 (2023), 4919-4929
DOI: *10.15244/pjoes/166345* ONLINE PUBLICATION DATE: 2023-08-03

Original Research

Does Digital Economy Promote Enterprise Green Innovation? Evidence from Listed Heavy-Polluting Enterprises in China

Rui Zhao[1]*, Zhipeng Ren[2]

[1]School of Government, University of International Business and Economics, Beijing,100029, China
[2]Center for Innovation-Driven Development, NDRC, 100038, P.R. China

Received: 13 December 2022
Accepted: 20 May 2023

Abstract

In the digital era, enterprises need to explore the green development path to achieve sustainable development. Whether the digital economy can promote enterprises' green innovation has thus become an important issue. Based on the panel data of heavy-polluting enterprises in 352 cities in China from 2015 to 2019, this article analyzes the impact of the digital economy on enterprises' green innovation and yields three main findings: A positive relationship between the digital economy and heavy-polluting enterprises' green innovation is confirmed and accompanied by the lag effect. Mechanism analysis indicates that absorption capacity plays an important mediating role in this process. Further, the hypothesis concerning the U-shaped relationship is proved empirically, indicating that heavy-polluting enterprises' green innovation can be improved under the digital economy shocks but with a specific level context. This article suggests that the government should pay attention to the digital economy development, and encourage enterprises to increase investment in scientific research. This research provides empirical evidence for the effectiveness of applying the digital economy in advancing green innovation in China's heavy-polluting enterprises.

Keywords: digital economy, heavy-polluting enterprises, green innovation, absorption capacity, inverted U-shaped relationship

Introduction

Environmental issues are inevitable derivatives in the process of industrial development [1-2]. In response, western industrialized countries began the social-ecological movement in the 1960s and sparked the green revolution worldwide. Despite over half a century of exploration, balancing the relationship between the environment and economic development is still a global concern [3]. Multiple international organizations advocated for green technology innovation, such as the World Intellectual Property Organization, to deal with the environmental problem. The importance of green innovation has gradually been mentioned, which has become a global trend [4]. Meanwhile, the digital economy emerging in the fourth revolution promoted resource allocation with intelligent and networked

*e-mail: ZGZJKZR@163.com

information technology. The rapid development of digital economy generates positive link with the environmental protection [5-7], demonstrating the enormous potential for green transformation [8-9].

From an international perspective, advanced economies represented by the United States and the European Union are accelerating the integration of data elements and the green economy. For example, The US Environmental Protection Agency and the Energy Department also launched the Energy Star Program to further promote the wide application of digital technologies in green innovation. In December 2019, the European Commission announced the "European Green Agreement", which devoted to accelerating the green economy through increased digital technology R&D investment. Those international practices have provided valuable experiences for China's environmental governance and green innovation. As the world's largest energy producer and consumer [10], China is going through a critical period of green transformation and has shown great potential. Although China's energy consumption structure has shown a definite trend toward low carbon and cleanliness driven by the "double carbon" policy, China's heavy-polluting enterprises still face a green transformation dilemma due to the long-term resource dependence and weak technical capabilities [11]. As a result, drawing on the experience of the developed country to promote the green innovation effects of digital economy is more urgent than ever. Although existing research has supported the positive relationship of digital economy and environment performance or green innovation on macro-level, little attention has been paid to the micro perspective of heavy-polluting enterprises [12]. At the same time, several different sounds argued that may not always be magic cure for innovation, and it is necessary to further examine its multiple benefits. This largely unexplored case leads us to further explore the relationship between the digital economy and enterprises' green innovation as well as its intrinsic mechanisms.

This article estimates the specific impact of the digital economy as a main driving force on green innovation based on the Tobit model and the Chinese A-Share listed heavy-polluting enterprises panel data. The contributions of this article are mainly in bridging previous unclear views to provide the inspiration concerning the digital paradox. Specifically, first this article introduces the nonlinear relationship into the discussion by presenting evidence that excessive development of the digital economy can be a double-edged sword for heavy-polluting enterprises green innovation. Second, compared with previous literature, the research method is a relatively rigorous paradigm as it considers the time lag effect of the digital economy, which will contribute the understanding the real role of digital economy in actual microeconomic entities. Third, this article identifies the intermediary effect of absorptive capacity between the digital economy on heavy-polluting enterprises' green innovation, which enriches the literature stream related to enterprises' sustainable development.

Theoretical Analysis and Hypothesis

The digital economy has shown great potential in improving the overall green innovation performance of heavy-polluting enterprises in the following aspects. Firstly, the digital economy has the inherent characteristic of being green at its beginning because it brings cutting-edge information technology and reduces the reliance on natural resources. The digital economy advocates a greener lifestyle and encourages environmental protection. As a result, enterprises are compelled to develop green innovation strategies and engage in environmental activities. Secondly, with the widespread adoption of information technologies such as big data, cloud computing, and blockchain, the digital economy has brought high-tech innovation, which increases social productivity [13]. In this process, the efficient information transfer and knowledge spillover allow enterprises to develop pollution control and resource recycling technology [14], contributing to green sustainable development [15]. Thirdly, the digital economy accelerates the sharing of green innovation resources among enterprises and reduces transaction costs caused by the information asymmetry [16-17], which will strengthen the enterprises' green innovation dynamics. Finally, the digital economy promotes market competition to a certain extent. Under the pressure of the peer group effect [18], enterprises would inevitably seek opportunities from the digital economy to maintain competitive advantage and master differentiated core technologies. In this way, they may be able to resist the economic transformation risk. Hence, the digital economy is expected to have a positive impact on enterprise green innovation. We propose the first hypothesis:

H1: Digital economy positively promotes heavy-polluting enterprises' green innovation.

Although the digital economy has the potential to provide opportunities for enterprise green transformation, its integration into enterprises' green innovation is a complex and long process. Firstly, heavy-polluting enterprises tend to adopt the extensive development mode relying on fossil energy [19]. It implies that green innovation is a profound reformation for heavy-polluting enterprises, which would need the precondition including the leaders' conscience change as well as the green development strategy formulation, both of which take time. Secondly, from a cost-effectiveness perspective, green innovation management activities undoubtedly bring huge costs to heavy-polluting enterprises, which will slow down the integration speed of new technologies penetration. Finally, enterprises green innovation is considered the complex exploration accompanied by dynamic adjustment [20], usually including technological transformation, designing new products, or applying for green patents, which take time for incubation and production [21]. Therefore, considering the lag effect, this article puts forward the second hypothesis:

H2: The effect of digital economy on heavy-polluting enterprises' green innovation represents the lag effect.

Absorptive capacity refers to an enterprise's capacity to obtain, assimilate, transform, and exploit technical knowledge to support sustainable innovation [22]. These four dynamic capacities interact to form absorptive capacity. According to innovation absorption theory, absorptive capacity is considered as one of the most valuable enterprises' resources, as it plays an important role in transforming knowledge spillover into innovation. Specifically, in the knowledge acquisition stage, enterprises can easily obtain valuable technical information from external sources through digital search approaches like knowledge maps, which subsequently optimize their knowledge reserves. Once acquired green technology knowledge, enterprises shall assimilate it, otherwise, it becomes exceedingly challenging to utilize such information. It is the emergence of the digital economy that provides enterprises with the convenient information technology management tool to evaluate, analyze, store, and integrate technical knowledge into every stage of production processes [23]. In the knowledge transformation stage, the digital economy allows enterprises to cross organizational boundaries, minimize uncertainty and opportunistic behavior of green innovation collaboration, and avoid resource mismatch, which is unfavorable for the green technology transfer performance [24]. Finally, in the knowledge exploit stage, heavy-polluting enterprises can utilize digital platforms to fulfill green innovation demands and optimize the entire production chain, then build a more effective, cleaner, and more efficient advanced digital technology utilization system. Hence, we propose the third hypothesis.

H3: Absorptive capacity plays a mediating role in the process of the digital economy promoting heavy-polluting enterprises' green innovation.

Regarding the relationship between the digital economy and green innovation, there are important but mixed findings in the existing research [22]. Some scholars argued that this alleged relationship is a complex rather than a simple linearity. These disagreements involve both empirical data and theoretical ambiguity [25]. That is, the further development of the digital economy may have a non-linear spillover effect on high-quality green development [26-27]. It might be caused by the following factors. Firstly, the digital economy development has promoted fiercer market competitiveness with more active economic activities. This may lead to large amounts of energy consumption, such as electricity, and increase exhaust gas emissions. The environmental pollution caused by the digital economy may exceed the generated benefits. Secondly, emerging digital technologies may not be effectively or safely applied by enterprises, such as digital resources waste [28], public opinion interference [29], information diversification, and overload [30], leading to low returns and high risks [31]. Accordingly, hypothesis 4 is further proposed:

H4: When the digital development level exceeds the specific threshold, it will cause negative effects, in other words, there is an inverted U-shaped relationship between the digital economy and the heavy-polluting enterprises' green innovation.

Material and Methods

Sample Selection and Data Source

Sample Selection

The research sample of this article is Shanghai and Shenzhen A-share manufacturing listed heavy-polluting enterprises in 352 Chinese cities from 2015 to 2019. We take 2015 as the starting year of the sample period because the Chinese government successfully issued the Internet Plus Strategy and National Big Data Strategy in 2015. So far, the rapid expansion of the digital economy has driven China's high-quality green innovation exploration. The heavy-polluting industries are derived from Environmental Information Disclosure Guidance for listed companies issued by The Ministry of Environmental Protection, mainly covering thermal power, steel, cement, electrolytic aluminum, coal, metallurgy, chemical industry, petrochemical industry, building materials, papermaking industry, brewing, pharmaceutical industry, fermentation, textile, tannery, and mining industry, and the industry classification codes are compiled according to the Classification Guidelines for Listed Companies (2012) issued by the China Securities Regulatory Commission (CSRC). To ensure the accuracy of the research results, we delete the sample companies of Special Treatment (ST) and Particular Transfer (PT), as well as the enterprises with the assets-liabilities ratio of more than 1. And Hong Kong, Macau, and Taiwan are excluded due to the lack of relevant data. Finally, the 773 company samples were screened out, and a total of 2541 observations were obtained. In this article, all variables are winsorized by up and down 1%. Considering the lag effect of digital innovation, the independent variables were treated with a one-stage lag to eliminate the deviation of the research results.

Variable Selection

(1) Dependent Variables

As invention patents are generally considered to be the most representative of the technological innovation capability of enterprises, we select the number of green patents to stand for the enterprises' green innovation. We obtain the related datasets from the State Intellectual Property Office (SIPO), then matched and extracted the green invention patents data according to the IPC codes developed by the World Intellectual Property Organization (WIPO). We take the logarithmic of patent variables to minimize the deviation caused by the data that does not follow the normal distribution.

(2) Independent Variables

The independent variable of this article is the digital economy. All data are from the digital China Index report released by China Tencent Research Institute, which has been widely used in related research. The index includes four parts, i.e., the basic sub-index, the industrial sub-index, the innovation and entrepreneurship sub-index, and the smart livelihood sub-index. These data are released by a third-party authoritative organization and jointly compiled by experts invited by Tencent Research Institute through the multidimensional weighted average method, which scientifically and objectively reflect the development capacity of the digital economy in various cities. The specific calculation steps are shown in Eqs (1)-(3).

Step 1: Experts assign weight to the index:

$$\alpha_j = \sum_{i=1}^{n} \alpha_{ij} / \sum_{i=1}^{m} \sum_{j=1}^{m} \alpha_{ij} \tag{1}$$

Where, *i* represents expert; *j* represents the indicators; α_{ij} represents the experts' scores on indicators; *n* represents the total number of expert groups; *m* represents the total number of scored indicators.

Step 2: Data standardization:

$$t_{cj} = x_{cj} / \sum_{c=1}^{k} x_{cj} \tag{2}$$

Where: *c* represents the city; *j* represents the indicator; t_{cj} represents the De-quantitative value of the indicators; x_{cj} represents the indicators' original value; *k* represents the total number of sample cities.

Step 3: Digital Economy Index Measurement:

$$\begin{bmatrix} x_{c_1 j_1} & \cdots & x_{c_1 j_m} \\ \vdots & \ddots & \vdots \\ x_{c_k j_1} & \cdots & x_{c_k j_m} \end{bmatrix} \begin{bmatrix} x_{total\ j_1} \\ \vdots \\ x_{total\ j_m} \end{bmatrix}^{-1} = \begin{bmatrix} t_{c_1 j_1} & \cdots & t_{c_1 j_m} \\ \vdots & \ddots & \vdots \\ t_{c_k j_1} & \cdots & t_{c_k j_m} \end{bmatrix} \xrightarrow{x \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_m \end{bmatrix}} \begin{bmatrix} T_{c_1} \\ \vdots \\ T_{c_m} \end{bmatrix} \tag{3}$$

(3) Control Variables

Considering the potential impact of other factors on the enterprise's green innovation, we select the following control variables to overcome the omitted variables bias: enterprise age (Age), the total assets (Size), leverage ratio (Lev), the social wealth creation ability (TobinQ), fixed assets ratio (Fa), the number of employees (Staff), the shareholding proportion of the largest shareholder (Largest), and intangible assets ratio (Iar). All data are from the CSMAR database.

(4) Mediating Variable

In this article, the mediating variable is the technology absorption capacity. We use the proportion of R&D investment in operating income to represent the technology absorption capacity. The data can be obtained from the CSMAR database.

Model Specification

To verify the hypothesis of this article, the following models are shown in Eqs (4)-(8):

$$Gre_{i,k,t} = \alpha_0 + \alpha_1 Dig_{i,t} + \gamma Control_{i,k,t} + u_k + \delta_t + \varepsilon_{i,k,t} \tag{4}$$

$$Gre_{i,k,t} = \alpha_2 + \alpha_3 Dig_{i,t-1} + \gamma Control_{i,k,t} + u_k + \delta_t + \varepsilon_{i,k,t} \tag{5}$$

$$Absorb_{i,k,t} = b_0 + b_1 Dig_{i,t-1} + \theta Control_{i,k,t} + u_k + \delta_t + \varepsilon_{i,k,t} \tag{6}$$

$$Gre_{i,k,t} = c_0 + c_1 Dig_{i,t-1} + c_2 Absorb_{i,k,t} + \vartheta Control_{i,k,t} + u_k + \delta_t + \varepsilon_{i,k,t} \tag{7}$$

$$Gre_{i,k,t} = d_0 + d_1 Dig_{i.t-1} + d_2 \left(Dig_{i,t-1}\right)^2 + \sigma Control_{i,k,t} + \mu_k + \delta_t + \varepsilon_{i,k,t} \tag{8}$$

Model (4) corresponds to the first hypothesis, which is used to test the linear relationship between the digital economy development and the green innovation of enterprises. Model (5) is used for examining the lag effect in the second hypothesis. Models (5), (6), and (7) form the intermediary effect model and correspond to the third hypothesis. Model (6) explores the effect of the digital economy on the intermediate variable and Model (7) examines the effect of the digital economy and technology absorptive capacity on enterprises' green innovation. Model (8) can be employed to prove the nonlinear relationship between the digital economy and enterprises' green innovation. Here, $Gre_{i,k,t}$ represents green innovation, $Dig_{i,t}$ represents the digital development of city i in t year, $Dig_{i,t-1}$ represents the one-period lag in digital economy development, $Control_{i,k,t}$ represents a series of control variables. $Absorb_{i,k,t}$ is the intermediate variable, i represents the city (i = 1, 2, 3…31), *k* represents enterprise, t denotes the year. μ_k is the industry fixed effect, δ_t is the time fixed effect, α_0, α_2, b_0, c_0 and d_0 denote the constant term, α_1, α_3, b_1, c_1 and d_1 are the estimated coefficient of the independent variables, γ, θ, ϑ and σ denote the coefficient of the control variables, $\varepsilon_{i,k,t}$ is the error term.

Methods

The article uses the Tobit model for regression analysis, and the reason is that we obtain non-zero continuous variables by taking the logarithm of enterprise green patents, which are greater than zero, and the Tobit model is better suited to handle truncated variables than other models. Thus, the Tobit model is selected as it more accurately matches the distribution characteristics of the dependent variables.

Regression Results Analysis

Data Descriptive Statistics

The definitions and descriptive statistics of all the variables are shown in Table 1. The green innovation average is only 0.178, which indicates that Chinese heavy-polluting enterprises' green innovation is low and there are obvious gaps between enterprises. The standard deviation of the digital economic development index is 7.843, which indicates that regional digital development is unbalanced. Regarding Lev, the average value is 0.416, which is in a reasonable range due to that the asset-liability ratio is 40%-60% in general, so the research samples selected can be used for further examinations.

Linear Influence and Lag Effect Test

Table 2 presents the regression results concerning the relationship between the digital economy and heavy-polluting enterprises' green innovation. Regarding the first hypothesis, the corresponding results of estimating Eq (4) are reported in Columns (1)(2). The estimated coefficient of the Dig is 0.0193 and 0.0225, respectively, which are both significantly positive. The increase of the digital economy by 1% can promote enterprises' green innovation by 2.25%, hence, hypothesis 1 is verified. Furthermore, the lagging influence of the digital economy on the green innovation of enterprises is listed in columns (3)(4). The coefficient of Dig_1 is both significantly positive, indicating that the lagging influence of the digital economy on green innovation of heavy-polluting enterprises is verified.

Regarding the control variables, the listing age and ownership concentration negatively affect enterprises' green innovation. This indicates that with the increase of listing age, the ownership tends to be concentrated, which is unfavorable for the improvement of enterprises' green innovation ability. The size and staff positively affect green innovation, which is consistent with the research results of other scholars [32-33].

Mechanism Analysis

With respect to the intermediary effect, the results are shown in Table 3. Column (1) presents the benchmark regression, and column (2) shows the impact of the digital economy on the enterprises' absorption ability, the estimated coefficient is 0.0086, which is significantly positive, indicating that the digital economy development can improve the green technology absorption capacity of enterprises. In column (3), the coefficient of *Dig_1* and *Absorb* is 0.0218 and 0.0767, respectively, which are both significantly positive, that is, the technology absorption is an evident transmission channel for boosting green innovation in the digital economy, thus the third hypothesis is verified.

Table1. Definition and Description of Variables.

Variables	Definition	Obs.	Mean	Std. Dev.	Min	Max
Gre	Ln (green invention patents+1)	2,541	0.178	0.495	0.000	2.773
Dig	Digital development index	2,541	4.968	7.843	0.072	35.734
Dig_1	Digital development index in t-1	2,541	5.418	7.547	0.072	29.992
$(Dig\_1)^2$	The digital development index of the previous year is taken as the square	2,541	86.292	190.261	0.005	899.531
Age	Ln (the current year-year of listing +1)	2,541	2.312	0.759	0.693	3.296
Size	The logarithm treatment of the assets	2,541	22.508	1.366	20.245	26.415
Lev	Ratio of total liabilities to total assets	2,541	0.416	0.190	0.066	0.866
TobinQ	Ratio of enterprise market value to total assets	2,541	2.015	1.201	0.814	6.872
Fa	Ratio of fixed assets to total assets	2,541	0.308	0.166	0.030	0.770
Staff	The logarithm of the number of employees	2,541	6.484	1.683	2.398	10.462
Largest	Proportion of the largest shareholder	2,541	0.353	0.148	0.096	0.770
Iar	Ratio of net intangible assets to total assets	2,541	0.052	0.048	0.001	0.307
Absorb	Ratio of R&D investment to operating income of the enterprise	2,254	2.730	1.929	0.040	9.170

Notes: Obs. stands for the variable number, Mean represents the mean value of the variables, Std. Dev. represents standard deviation, Min and Max refer to the minimum and maximum values of the variables, respectively.

Table 2. Regression Results.

	(1)	(2)	(3)	(4)
Variable	Gre	Gre	Gre	Gre
Dig	0.0193**	0.0225***		
	(0.0078)	(0.0074)		
Dig_1			0.0192**	0.0231***
			(0.0076)	(0.0074)
Age		-0.2575**		-0.2757**
		(0.1132)		(0.1134)
Size		0.5453***		0.5513***
		(0.0797)		(0.0798)
Lev		0.4854		0.5087
		(0.4254)		(0.4267)
TuobinQ		0.0576		0.0544
		(0.0614)		(0.0615)
Fa		0.5500		0.5505
		(0.4627)		(0.4631)
Staff		0.2594***		0.2566***
		(0.0503)		(0.0501)
Largest		-1.7029***		-1.6964***
		(0.5094)		(0.5093)
Iar		1.8013		1.9502
		(1.4720)		(1.4751)
Constant	-1.8174***	-15.8449***	-1.7488***	-15.8679***
	(0.3277)	(1.7715)	(0.3227)	(1.7743)
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Sigma_u	1.7213***	1.3878***	1.7264***	1.3915***
	(0.1058)	(0.0923)	(0.1059)	(0.0924)
Sigma_e	0.8946***	0.8912***	0.8944***	0.8914***
	(0.0431)	(0.0430)	(0.0431)	(0.0430)
Wald chi2	16.37	135.03	16.69	135.19
Log-likelihood	-1178.406	-1103.9382	-1178.2503	-1103.580
Obs.	2,541	2,541	2,541	2,541
Rho	0.787	0.706	0.788	0.709

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

Table 3. Intermediary Effect Regression Results.

Variable	(1)	(2)	(3)
	Gre	Absorb	Gre
Dig_1	0.0231***	0.0086**	0.0218**
	(0.0074)	(0.0039)	(0.0077)
Absorb			0.0767*
			(0.0389)
Age	-0.2757**	-0.509***	-0.1519
	(0.1134)	(0.0747)	(0.1178)
Size	0.5513***	-0.1866***	0.5549***
	(0.0798)	(0.0553)	(0.0823)
Lev	0.5087	-0.6419***	0.4607
	(0.4267)	(0.2443)	(0.4504)
TuobinQ	0.0544	-0.0380	0.0514
	(0.0615)	(0.0268)	(0.0650)
Fa	0.5505	0.1847	-0.1593
	(0.4631)	(0.2764)	(0.4972)
Staff	0.2566***	0.0044	0.3107***
	(0.0501)	(0.0306)	(0.0536)
Largest	-1.6964***	-0.6163*	-1.4529**
	(0.5093)	(0.3273)	(0.5197)
Iar	1.9502	-2.5335***	2.6000
	(1.4751)	(0.9404)	(1.5765)
Constant	-15.8679***	7.4840***	-16.4334***
	(1.7743)	(1.2155)	(1.8797)
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Sigma_u	1.3915***	1.5020***	1.3059***
	(0.0924)	(0.0442)	(0.0890)
Sigma_e	0.8914***	0.6633***	0.9304***
	(0.0430)	(0.0120)	(0.0460)
Wald chi2	135.19	369.68	151.85
Log-likelihood	-1103.580	-3251.332	-1049.917
Obs.	2,541	2,254	2,254
Rho	0.709	0.837	0.663

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

Check for Nonlinear Relationship

Although the linear relationship between the digital economy and enterprises' green innovation was verified, we need to do more investigation to examine the non-linear relationship. We add the square term $(Dig\_1)^2$ and the results are shown in columns (1)-(2) in Table 4. Column (2) adds control variables to column (1).

Table 4. Results of Non-linear Regression Analysis.

	(1)	(2)
Variable	Non-linear Regression	
	Without all control variables	With all control variables added
Dig_1	0.0704***	0.0733***
	(0.0262)	(0.0258)
$(Dig\_1)^2$	-0.0015*	-0.0015*
	(0.0008)	(0.0008)
Age		-0.2781
		(0.1772)
Size		0.5118***
		(0.0946)
Lev		0.8588*
		(0.5177)
TuobinQ		0.0452
		(0.0736)
Fa		0.7112
		(0.5495)
Staff		0.2745***
		(0.0599)
Largest		-2.3180***
		(0.6254)
Iar		0.0219
		(1.8386)
Constant	-1.7616***	-14.8179***
	(0.3902)	(2.0707)
Industry FE	YES	YES
Year FE	YES	YES
Sigma_u	1.8238***	1.4641***
	(0.1243)	(0.1065)
Sigma_e	0.8753***	0.8735***
	(0.0443)	(0.0447)
Wald chi2	20.78	108.63
Log-likelihood	-954.215	-899.754
Obs.	1,938	1,938
Rho	0.813	0.712

Notes: Standard errors in parentheses
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

In column (2), the estimated coefficient of *Dig_1* is 0.0733, which is significantly positive, and the coefficient of $(Dig\_1)^2$ is significantly negative. However, the inverted U-shape cannot be proved by a single fact with a negative coefficient of the squared term [34]. We need to observe the turning point and marginal effect after adding the square term. The following conditions must be met: Firstly, the value corresponding to the turning point must be within the values range of independent variables, i.e., $Dig\_1 \in [Dig\_1_{mix}, Dig\_1_{max}]$. Secondly, there must be enough samples on either side of the turning point to explain the nonlinear relationship. If there are samples are available on only one side of the turning point, the assumption that the inverted U-shaped relationship may not hold. Finally, the marginal effect value ought to transform from positive to negative. As such, it is necessary to introduce a curvilinear model (see Fig. 1). Following the examination, the related results fulfilled the inverted U-shaped criteria. In Fig. 1, the turning point value is 24, which is within the value range of the digital economy. So, we conclude that there is an inverted U-shaped relationship between the digital economy and enterprises' green innovation, and hypothesis 4 is verified.

Robustness Analysis

We performed a series of tests to check the robustness of the research results, including replacing methods, and variables, and changing the sample capacity.

Replace Regression Methods

To further verify the robustness of the results at the method level, we retest the relationship between the digital economy and heavy-polluting enterprises' green innovation by using the OLS method. The empirical results are shown in the first three columns (1)-(3) of Table 5. The estimated coefficient of the *Dig, Dig_1*, and $(Dig\_1)^2$ are 0.0058, 0.0047, and-0.0004, respectively, and are all significant, which implies that the digital economy can significantly enhance the enterprises' green innovation with a lagged effect, and shows the nonlinear relationship. This implies the credibility and reliability of the regression results at the method level.

Replace Variable

We replace the original absolute value index with a proportional index, i.e., the proportion of enterprises' green patents in all patents is used as the dependent variable to re-estimate the relationship between the digital economy and green innovation. The results are shown in columns (4)-(6) in Table 5. The estimated coefficients of the dependent variables *Dig, Dig_1* and $(Dig\_1)^2$ were 0.0101, 0.0109, and -0.0011, respectively, which are all significant. It proves the robustness of regression results in variable levels.

Change Sample Capacity

There are four municipalities directly under the central government in China, including Beijing, Tianjin, Shanghai, and Chongqing. These regions have important status in politics, economy, science, culture, and transportation, in which the development level significantly surpasses the ordinary prefecture-level

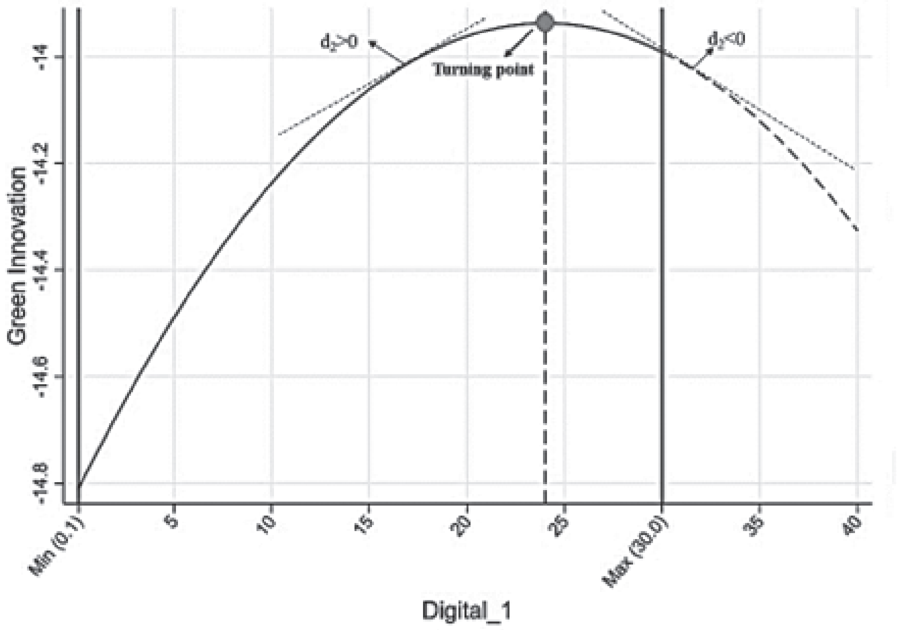

Fig. 1. Inverted U-shaped Curve.
Note: According to Table 1, the minimum and maximum values of Dig_1 are 0.072 and 29.992, respectively. And we rounded the two values in Fig.1. It does not affect the non-linear relationship to hold.

Table 5. Robustness Analysis Results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	Replace the methods			Replace the variable			Change sample capacity		
Dig	0.0058***		0.0158***	0.0101*		0.0468***	0.0266**		0.1143***
	(0.0014)		(0.0048)	(0.0061)		(0.0176)	(0.0117)		(0.0367)
Dig_1		0.0047***			0.0111*			0.0257***	
		(0.0013)			(0.0056)			(0.0085)	
$(Dig\_1)^2$			-0.0004**			-0.0011*			-0.0025**
			(0.0002)			(0.0006)			(0.0010)
Age	-0.0167	-0.0197	0.0112	-0.1264	-0.1223	-0.1888**	-0.2174*	-0.2342**	0.0610
	(0.0186)	(0.0186)	(0.0348)	(0.0852)	(0.0787)	(0.0790)	(0.1181)	(0.1177)	(0.1796)
Size	0.1135***	0.1152***	0.1195***	0.3481***	0.3200***	0.2766***	0.4803***	0.4798***	0.3390***
	(0.0139)	(0.0139)	(0.0194)	(0.0599)	(0.0551)	(0.0525)	(0.0881)	(0.0881)	(0.0986)
Lev	-0.0139	-0.0108	0.0104	0.2223	0.2500	0.4974*	0.7013	0.7332	1.5878***
	(0.0709)	(0.0710)	(0.0976)	(0.3269)	(0.3030)	(0.2887)	(0.4500)	(0.4495)	(0.5477)
TuobinQ	0.0110	0.0102	0.0081	0.0301	0.0276	0.0474	0.0618	0.0587	0.0851
	(0.0090)	(0.0090)	(0.0115)	(0.0493)	(0.0458)	(0.0458)	(0.0650)	(0.0648)	(0.0788)
Fa	0.0455	0.0364	0.0579	0.0215	0.0263	0.0648	0.5953	0.5784	0.6476
	(0.0777)	(0.0777)	(0.1052)	(0.3578)	(0.3313)	(0.3214)	(0.4836)	(0.4814)	(0.5423)
Staff	0.0398***	0.0382***	0.0445***	0.1881***	0.1739***	0.1014***	0.2306***	0.2303***	0.1475**
	(0.0081)	(0.0081)	(0.0110)	(0.0393)	(0.0361)	(0.0359)	(0.0535)	(0.0532)	(0.0600)
Largest	-0.1556*	-0.1544*	-0.2483**	-1.2501***	-1.1875***	-0.8966***	-1.7034***	-1.7211***	-2.9031***
	(0.0890)	(0.0892)	(0.1238)	(0.3876)	(0.3587)	(0.3415)	(0.5286)	(0.5276)	(0.6326)

Table 5. Continued.

Iar	0.1007	0.1212	-0.1470	-0.1936	-0.0653	1.5205	2.3892	2.5671*	-1.2535
	(0.2649)	(0.2655)	(0.3675)	(1.2032)	(1.1153)	(1.0607)	(1.5171)	(1.5144)	(2.0345)
Constant	-2.6083***	-2.6052***	-2.7613***	-9.9696***	-9.3254***	-7.7928***	-14.5831***	-14.5183***	-8.1674***
	(0.2955)	(0.2961)	(0.4207)	(1.3242)	(1.2176)	(1.1545)	(1.9449)	(1.9426)	(2.3005)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Sigma_u	--	--	0.4188	0.9893***	0.9126***	0.7302***	1.3272***	1.3291***	0.7577***
	--	--		(0.0689)	(0.0623)	(0.0598)	(0.0979)	(0.0977)	(0.0792)
Sigma_e	--	--	0.2809	0.7735***	0.7260***	0.7394***	0.9154***	0.9093***	0.9113***
	--	--		(0.0352)	(0.0315)	(0.0350)	(0.0484)	(0.0481)	(0.0537)
Wald chi2	--	--	134.35	98.77	101.21	85.27	98.11	100.88	179.48
Log-likelihood	--	--	--	-1032.486	-1008.7783	-921.804	-947.256	-945.301	-644.414
Obs.	2,541	2,541	1,938	2,503	2,503	1,599	2,208	2,208	1,664
Rho	0.610	0.611	0.690	0.621	0.612	0.494	0.678	0.681	0.409

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

cities. To avoid the influence of special administrative status on the regression results, we exclude the sample that enterprises locate in municipalities directly under the central government regions, and the regression results are shown in columns (7)-(9) of Table 5. The estimated coefficients of the dependent variables *Dig, Dig_1* and $(Dig\_1)^2$ were 0.0266, 0.0257, and -0.0025, respectively, and are all significant, indicating that the regression results are still robust.

Conclusions and Discussion

This article presents a study using a Tobit model to investigate the relationship between the digital economy and green innovation in China's heavy-polluting enterprises from 2015 to 2019. The research shows that the digital economy has a positive impact on the green innovation of heavy-polluting enterprises, with a time lag effect. Absorptive capacity plays an important role as an intermediary variable in this process. However, there is an inverted U-shape relationship between the digital economy and enterprises' green innovation, i.e., along with the increase in the digital economy until a specific threshold is exceeded, it will gradually decrease the heavy-polluting enterprises' green innovation. Moreover, based on the above results, there remain two critical concerns that need further discussion.

The Paradox of Digital Economy and Green Innovation

There is a green innovation paradox in the digital economy, i.e., the digital economy can be regarded as a double-edged sword [35-37]. On the one hand, the digital economy enable benefit the green innovation of heavy-polluting enterprises within a certain development level.On the other hand, the digital economy at greater levels may also result in the imbalance of information overload and management skills, inducing the curse of the digital economy in enterprises' sustainable green innovation. From the perspective of the green patent output, China's heavy-polluting industries' green innovation ability is weak. There are two primary reasons. First, the long-term extensive development model of heavy-polluting enterprises has caused excessive reliance on resources, which hinders further green innovation practices. Second, the heavy-polluting enterprises are not fully integrated with the virtual economy and information technology, which results in the steady hemorrhage of technological resources and R&D talents. According to the open innovation theory [38], enterprise innovation requires a large amount of resource investment, and cannot be achieved by relying solely on internal resources for innovation. Instead, external learning from the environment is crucial. It is undeniable that the digital economy offers great benefits for green innovation, but this link may be more complicated than it appears. Despite the usual viewpoints that tend to focus on either the positive or negative consequences, this article demonstrates the dynamic green innovation performance of heavy-polluting enterprises that results in practice from the digital economy. These findings provide practical implications for micro-enterprises to understand the dialectical and objective effects of the digital economy, broaden the research scope of the digital economy, and provide empirical support to develop specific digital transformation strategies and green innovation initiatives.

Management Inspiration

According to the resource-based theory [39], internal organizational elements such as technological absorptive capacity are the foundation for enterprises' innovation to maintain sustainable competitive advantage, and the research results also strongly support it. That is, although the digital economy has brought innovation resources for enterprises, valuable digital knowledge can only be transformed into green innovation motivators after being absorbed and internalized by enterprises. Hence, heavy-polluting enterprises should fully optimize green innovation management strategies to embrace the challenges and opportunities in the digital era. More investment in R&D capital and R&D personnel should be put to improve technological absorption capacity and promote knowledge transformation. More importantly, enterprise managers should reexamine the "double-edged sword" effect of the digital economy, and choose the application depth of digital technology based on the characteristics of the enterprise itself, to avoid information overload and resource wastage. Such insight can help managers establish a better dialectical perspective to mitigate the negative results.

Policy Recommendations

The research results enlighten us on the important role of government in regulating green innovation of heavy-polluting enterprises in the digital economy era. This article proposes the following policy recommendations.

First, the value of data resources is worthy further explored by the government to promote the deep integration of emerging technologies such as big data, artificial intelligence, and 5G with green and low-carbon industries. More particularly, a catalytic role of government should be full played, encourage heavy-polluting enterprise to integrate digital technology into the low-carbon process synthesis application, intelligent production system construction, and green innovation management.

Secondly, the insufficient absorptive capacity of enterprises hinders the transmission and integration of digital economy in the green innovation field. There is a need to focus on the technical challenges in the green innovation process of heavy-polluting enterprises, explore a model for governments, enterprises, and social capital to cooperate in tackling key issues in green digital core technology. In addition, policy tools including tax incentives and digital technology talent cultivation policies as well as the information sharing mechanisms deserve to be fully considered to remove barriers to the adoption of digital technology.

Third, given the robust evidence of digital economy innovation paradox, equal emphasis should be placed on both regulations and technology. The Chinese government ought to step up efforts on basic research of digital security utilization, optimize the formulation of national standards. In doing this, the healthy development of the digital economy bid fair to be form to create a safe and sound data environment for the green development of heavy-polluting enterprises. Additionally, the government should be more cautious when formulating policies concerning the digital economy. It should not only play a leading role in encouraging the digital technology transformation, but also a supervisory and guiding role in preventing the blind promotion of the digital economy by heavy-polluting enterprises.

Limitations

This article only selects heavy-polluting enterprises, it may limit the generalizability of research results. In further research, data from different industries should be considered to reveal the impact of the digital economy on the green innovation of different types of enterprises. In addition, this article measures the enterprises' green innovation from the green patents output perspective, the future research should try to optimize the green innovation measurements from multiple dimensions.

Conflict of Interest

The authors declare no conflict of interest.

References

1. KOULOUKOUI D., MARINHO M.M. DE O., GOMES S.M. DA S., KIPERSTOK A., TORRES E.A. Corporate climate risk management and the implementation of climate projects by the world's largest emitters. Journal of Cleaner Production, **238**, 117935, **2019**.
2. YU T., CHANG Y., CHANG L. A pro-environmental behavior model for investigating the roles of social norm, risk perception, and place attachment on adaptation strategies of climate change. Environmental Science and Pollution Research, **26** (24), 25178, **2019**.
3. LEE T., KOSKI C. Multilevel governance and urban climate change mitigation. Environment and Planning C: Government and Policy, **33** (6), 1501, **2015**.
4. SHA Y., ZHANG P., WANG Y., XU Y. Capital market opening and green innovation – Evidence from Shanghai-Hong Kong stock connect and the Shenzhen-Hong Kong stock connect. Energy Economics, **111**, 106048, **2022**.
5. HORBACH J., RAMMER C., RENNINGS K. Determinants of eco-innovations by type of environmental impact – The role of regulatory push/pull, technology push and market pull. Ecological Economics, **78**, 112, **2012**.
6. HORBACH J., RAMMER C., RENNINGS K. Determinants of eco-innovations by type of environmental

impact – The role of regulatory push/pull, technology push and market pull. Ecological Economics, **78**, 112, **2012**.
7. REN S., HAO Y., XU L., WU H., BA N. Digitalization and energy: How does internet development affect China's energy consumption? Energy Economics, **98**, 105220, **2021**.
8. GONG X., ZHANG J., ZHANG H., CHENG M., WANG F., YU N. Internet use encourages pro-environmental behavior: Evidence from China. Journal of Cleaner Production, **256**, 120725, **2020**.
9. LI Z., WANG J. The Dynamic Impact of Digital Economy on Carbon Emission Reduction: Evidence City-level Empirical Data in China. Journal of Cleaner Production, **351**, 131570, **2022**.
10. CHENG Y., AWAN U., AHMAD S., TAN Z. How do technological innovation and fiscal decentralization affect the environment? A story of the fourth industrial revolution and sustainable growth. Technological Forecasting and Social Change, **162**, 120398, **2021**.
11. YI H., LIU Y. Green economy in China: Regional variations and policy drivers. Global Environmental Change, **31**, 11,**2015**.
12. QIN R. Overcoming the digital transformation paradoxes: a digital affordance perspective. Management Decision, **2023**.
13. NAMBISAN S., LYYTINEN K., MAJCHRZAK A., SONG M. Digital Innovation Management: Reinventing Innovation Management Research in a Digital World. Mis Quarterly, **41** (1), 223, **2017**.
14. DALENOGARE L.S., BENITEZ G.B., AYALA N.F., FRANK A.G. The expected contribution of Industry 4.0 technologies for industrial performance. International Journal of Production Economics, **204**, 383, **2018**.
15. LI Y., DAI J., CUI L. The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model. International Journal of Production Economics, **229**, 107777, **2020**.
16. AGYAPONG D. Implications of digital economy for financial institutions in Ghana: An exploratory inquiry. Transnational Corporations Review, **13** (1), 51, **2021**.
17. DEMERTZIS M., MERLER S., WOLFF G.B. Capital Markets Union and the Fintech Opportunity. Journal of Financial Regulation, **4** (1), 157, **2018**.
18. XIONG H., WANG P., BOBASHEV G. Multiple peer effects in the diffusion of innovations on social networks: A simulation study. Journal of Innovation and Entrepreneurship, **7** (1), 2, **2018**.
19. HE Z., KUAI L., WANG J. Driving mechanism model of enterprise green strategy evolution under digital technology empowerment: A case study based on Zhejiang Enterprises. Business Strategy and the Environment, 1, **2022**.
20. YIN C., SALMADOR M.P., LI D., LLORIA M.B. Green entrepreneurship and SME performance: The moderating effect of firm age. International Entrepreneurship and Management Journal, **18** (1), 255, **2022**.
21. MVULIRWENANDE S., WEHN U. Opening the innovation incubation black box: A process perspective. Environmental Science & Policy, **114**, 140, **2020**.
22. PACHECO L.M., ALVES M.F.R., LIBONI L.B. Green absorptive capacity: A mediation-moderation model of knowledge for innovation. Business Strategy and the Environment, **27** (8), 1502, **2018**.
23. HENARD D.H., MCFADYEN M.A. The Complementary Roles of Applied and Basic Research: A Knowledge-Based Perspective. Journal of Product Innovation Management, **22** (06), 503, **2005**.
24. MONDEJAR M.E., AVTAR R., DIAZ H.L.B., DUBEY R.K., ESTEBAN J., GÓMEZ-MORALES A., HALLAM B., MBUNGU N.T., OKOLO C.C., PRASAD K.A., SHE, Q., GARCIA-SEGURA S. Digitalization to achieve sustainable development goals: Steps towards a Smart Green Planet. Science of The Total Environment, **794**, 148539, **2021**.
25. WEN H., LEE C.-C., SONG Z. Digitalization and environment: How does ICT affect enterprise environmental performance? Environmental Science and Pollution Research, **28** (39), 54826, **2021**.
26. MA D., ZHU Q. Innovation in emerging economies: Research on the digital economy driving high-quality green development. Journal of Business Research, **145**, 801, **2022**.
27. SAVCHENKO A.B., BORODINA T.L. Green and Digital Economy for Sustainable Development of Urban Areas. Regional Research of Russia, **10** (4), 583, **2020**.
28. AVOM D., NKENGFACK H., FOTIO H.K., TOTOUOM A. ICT and environmental quality in Sub-Saharan Africa: Effects and transmission channels. Technological Forecasting and Social Change, **155**, 120028, **2020**.
29. EDGERLY S., THORSON K. Political Communication and Public Opinion: Innovative Research for the Digital Age. Public Opinion Quarterly, **84** (S1), 189, **2020**.
30. DONG J.Q., NETTEN J. Information technology and external search in the open innovation age: New findings from Germany. Technological Forecasting and Social Change, **120**, 223, **2017**.
31. GHISETTI C., MANCINELLI S., MAZZANTI M., ZOLI M. Financial barriers and environmental innovations: Evidence from EU manufacturing firms. Climate Policy, **17** (sup1), S131, **2017**.
32. LAI H., WANG F., GUO C. Can environmental awards stimulate corporate green technology innovation? Evidence from Chinese listed companies. Environmental Science and Pollution Research, **29** (10), 14856, **2021**.
33. USMAN M., JAVED M., YIN J. Board internationalization and green innovation. Economics Letters, **197**, 109625, **2020**.
34. SADORSKY P. Information communication technology and electricity consumption in emerging economies. Energy Policy, **48** (SEP.), 130, **2012**.
35. WATANABE C., TOU Y., NEITTAANMÄKI P. A new paradox of the digital economy-Structural sources of the limitation of GDP statistics. Technology in Society, **55**, 9, **2018**.
36. WATANABE C., NAVEED K., TOU Y., et al. Measuring GDP in the digital economy: Increasing dependence on uncaptured GDP. Technological Forecasting and Social Change, **137**, 226, **2018**.
37. AHMADOVA G., DELGADO-MÁRQUEZ B.L., PEDAUGA L.E., LEYVA-DE LA HIZ D.L. Too good to be true: The inverted U-shaped relationship between home-country digitalization and environmental performance. Ecological Economics, **196**, 107393, **2022**.
38. ALEXY O., BASCAVUSOGLU-MOREAU E., SALTER A.J. Toward an aspiration-level theory of open innovation. Industrial and Corporate Change, **25** (2), 289, **2016**.
39. LIAO Y.C., TSAI K.H. Innovation intensity, creativity enhancement, and eco-innovation strategy: The roles of customer demand and environmental regulation. Business Strategy and the Environment, **28** (2), 316, **2019**.