



Journal of Information Economics

Homepage: <https://anser.press/index.php/JIE>



Does the digital economy promote industrial green transformation? Evidence from spatial Durbin model

Mingyue Du ^{a, b}, Siyu Ren ^{c, *}

^a School of Social Science, Swinburne University of Technology, Melbourne, Australia

^b School of Economics, Beijing Technology and Business University, Beijing, China

^c School of Economics, Nankai University, Tianjin, China

ABSTRACT

The digital economy based on digital technology is an important force for high-quality economic growth and industrial transformation, and has great potential for value creation. Based on the data of 30 provinces in China from 2007 to 2017, this paper uses entropy method to calculate the industrial green transformation (IGT), and empirically analyzes the impact of Digital economy on IGT. The DE can significantly reduce IGT of local and neighboring areas after excluding the influence of macro system factors and replacing the spatial weight matrix. The DE can indirectly reduce the IGT by accelerating the accumulation of human capital, and green technology innovation. The impact of digital economy on IGT is a non-linear relationship. With the further improvement of environmental regulation, financial development and intellectual property protection, the role of digital economy in IGT is more obvious. To this end, it is necessary to speed up the construction and improvement of digital infrastructure, build an integrated layout of "digital infrastructure", give full play to the radiating role of the digital economy, and implement differentiated development paths based on regional comparative advantages.

KEYWORDS

Digital economy; Industrial green transformation; Environmental Regulation; Spatial Durbin model; China

*Corresponding author: Siyu Ren
E-mail address: rensiyuking@126.com

ISSN 2972-3671

doi: 10.58567/jie01010001

This is an open-access article distributed under a CC BY license
(Creative Commons Attribution 4.0 International License)



Received 12 December 2022; Accepted 12 January 2023; Available online 16 January 2023

1. Introduction

As one of China's five major development concepts, green development is an inevitable requirement for building a high-quality modern economic system and a fundamental policy to solve the pollution problem (Nadal et al., 2015; Zandalinas et al., 2021). The statistics data released by the Ministry of Ecology and Environment in 2020 show that nearly 200 large and medium-sized cities generate 1.38 billion tons of general industrial solid waste. Among them, the output of general industrial solid waste in key cities is 725 million tons, an increase of 0.94% compared with that in 2018. Economic development at the expense of ecological environment not only causes ecological loss and extreme climate change, but also seriously reduces residents' happiness (Sulemana, 2016; Yang et al., 2022; Liu et al., 2022a). With the increasingly prominent ecological environment problems, the traditional industrial ecological model is difficult to sustain development (Meng et al., 2022; Wang et al., 2022). The green transformation of industry oriented by green technology innovation is a new industrial development path to achieve the dual goals of economic benefits and environmental benefits (Scoones et al., 2015), which not only has broad prospects for development, but also has sustainable growth effects (Li and Lin, 2017).

As an emerging economic form, the digital economy is flourishing globally and gradually becoming an important factor in driving high-quality economic development. The volume of digital economy has increased from 11 trillion RMB to 45.5 trillion RMB during the period of 2012-2021, and the proportion of GDP has increased from 21.6% to 39.8%. The digital economy is gradually becoming an important part of China's national economy and a growth driver, and the integration of new generation information technology with traditional industries, with artificial intelligence as the core, is promoting the informatization, intelligence and cleanliness of traditional industries (Xu et al., 2022; Hao et al., 2023). Moreover, it is not only the key to promote digital industry clusters and resource allocation efficiency, but also gradually become an important factor to break the constraints of environmental pollution on industrial green transformation (Wu et al., 2021a; Mergel et al., 2019; Yang et al., 2021). Therefore, analyzing the impact of digital economy development on industrial green transformation is an important reference value for promoting high-quality economic development and the construction of beautiful China.

The global economy is currently in a new era of digital transformation (Rogers, 2016). It represents an emerging industrial revolution that relies on high-tech digital technologies and is expanding rapidly around the globe (Ustundag and Cevikcan, 2017). Previous studies have focused on the impact of the green innovation impact on industrial development and economic transformation brought about by the development of the digital economy (Feng and Chen, 2018). With the new generation of information technology, the economies of scale, scope and long-tail effects generated by the digital economy continue to accelerate the upgrading of traditional industries (Teece, 2018). As global pollution increases, digital technology reduces environmental pressure and creates a new endogenous growth engine (Dong et al., 2022). More importantly, typical features of the digital economy, such as permeability, platforming and sharing, can effectively improve resource utilization and promote the deep integration of traditional industries with green and low-carbon development (Luo et al., 2022). In addition, the rapid development of next-generation information technology is driving changes in production and lifestyle, which can enhance sustainable development by increasing the dematerialization of economic activities, improving resource utilization efficiency. To this end, this study empirically tested the effect of digital economy on industrial green transformation. It is conducive to exploring new ways of energy conservation and provides suggestions for the achievement of sustainable energy development.

This paper attempts to do further research as follows. Firstly, we incorporate the Internet and energy saving potential into a same research framework. It contributes a new view for further understanding how to reduce IGT. Secondly, considering the actual Digital economy of China, Internet comprehensive development level is constructed from multiple perspectives. Finally, a spatial econometric model was constructed to explore the spatial effect of the Internet on IGT. It provides scientific basis for China to use information technology to control environmental

pollution. Considering the "Metcalfe's Law", we verify the nonlinear effect and spatial spillover effect of digital economy development on industrial green transformation.

The rest are as follows. Section 2 reviews the related literature. Section 3 briefly explains the mechanism analysis. Section 4 calculates China's IGT. Section 5 shows the model and data interpretation. The last is the conclusion.

2. Literature review

The existing literature related to industrial green transformation is mainly focused on three aspects. First, about the connotation of industrial green transformation. Industrial green transformation refers to the dynamic evolutionary process of achieving resource consumption saving and environmental pollution emission constraints in industrial development, and promoting efficient and ecological development of industry (Mao et al., 2019; Hou et al., 2018). Second, about the measurement of industrial green transformation. The existing literature mainly focuses on the measurement of industrial green transformation efficiency and the construction of multidimensional evaluation indexes, and the main measurement methods include non-parametric method and parametric method (Hou et al., 2022). The non-parametric methods are data envelopment analysis (DEA) and its improved forms, such as DEA-DDF model, Malmquist-Luenberger productivity index, super efficiency-SBM model and Luenberger productivity (Ren et al., 2022b). The parametric method is implemented by setting the production function and the distribution of efficiency terms (Kumbhakar and Tsionas, 2006). Based on the connotation of industrial green transformation, some scholars develop a multi-dimensional evaluation index system and use a comprehensive evaluation method to measure it (Qi et al., 2022). For example, Qi et al. (2022) established an evaluation index system from the dimensions of energy resource intensive utilization, pollution reduction, industrial structure upgrading, production efficiency improvement, and sustainable development. Fu et al. (2018) used industrial wastewater emissions, industrial dust emissions and other pollutant emissions to reverse characterize the degree of industrial green transformation. Third, for the driving factors and achievement paths of industrial green transformation, scholars believed that green technology progress promotes the main factors of industrial green transformation. Increasing investment in technological innovation, environmental management and industrial structure upgrading can effectively improve the level of industrial green transformation (Han et al., 2020; Tian et al., 2022; Zhao et al., 2021). In addition, the ways to promote the green development of industry include building a strict environmental regulation and improving the level of human capital (Zhai and An, 2020; Wang et al., 2021; Liu et al., 2022b).

The digital economy has been an important area of academic research in recent years, but it still does not have a unified concept. Rouse (2016) considers the digital economy as a global network of economic activities supported by information and communication technologies, which can also be defined more simply as an economy based on digital technologies. Dahlman et al. (2016) argue that the digital economy incorporates a variety of general-purpose technologies and is a set of economic and social activities carried out by people through the Internet and related technologies. With the deepening of the digital economy (DE), DE has permeated all industrial fields and has increasingly become an important driving force for economic growth and emission reduction (Ren et al., 2022a; Deng et al., 2022). China has implemented several new policies such as "Broadband China" and "Internet+" to promote digital economy development (Hao et al., 2023; Wu et al., 2022). It is widely believed that DE has a positive impact on energy efficiency, environmental supervision, and carbon reduction (Yang et al., 2021, Wu et al., 2021b, Ren et al., 2021).

In the existing literature, scholars have mainly studied the effects of digital economy on high-quality development, economic growth, technological innovation, industrial structure upgrading, and total factor productivity (Murthy et al., 2021; Lange et al., 2020; Jin et al., 2020; Ding et al., 2021). It provides an important

reference for an in-depth study of the impact effects and channels of action of the digital economy on economic activities. For high-quality development, most scholars have found that the digital economy releases new dynamics of economic development and actively promotes high-quality development of China's economy (Ding et al., 2021). Ding et al (2021) empirically tested the impact mechanism of the digital economy on the level of high-quality economic development by using a mediating effects model and a spatial Durbin model (Ding et al., 2021). It was found that the digital economy can significantly contribute to the high-quality development of China's regional economy. In terms of industrial structure upgrading and economic growth, as the digital economy develops, new factors and resources are allocated to more efficient technology-intensive industries can promote the industrial structure to achieve optimization, transformation, and economic growth (Li et al., 2020; Sorescu and Schreier, 2021). Teece (2018) showed that the digital economy can use digital technology to significantly reduce transaction costs, and stimulate firms to engage in technological innovation and increase competitive advantage. Several studies have also examined the impact of the digital economy on total factor productivity, arguing that the digital economy can contribute to total factor productivity (TFP) by improving factor allocation distortions (Meng and Zhao, 2022). Pan et al. (2022) investigated the innovation-driven effect of the digital economy on TFP in China. The results showed that the digital economy has a positive non-linear relationship with provincial TFP, and the digital economy is considered as an innovation driver of TFP.

3. Methodology and data

3.1. Econometric Methodology

3.1.1. Spatial Durbin model

Previous studies focused on the IGT under non-spatial spillover factors, but ignored the spatial interaction. Therefore, referring to the research of Du et al. (2022), this paper uses the spatial panel model to analyze the space of DE and IGT. The following dynamic space Durbin model is constructed:

$$IGT_{it} = \alpha_0 + \rho \sum_{j=1}^N W_{ijt} Ecp_{it} + \alpha_1 IGT_{it-1} + \alpha_2 DE_{it} + \alpha_3 \sum_{i \neq j}^N W_{ijt} DE_{it} + \sum_{k=1}^5 \delta_k X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (1)$$

Among them, IGT_{it} is the industrial green transformation; DE_{it} is the digital economy index; X is a series of control variables; W_{it} is an $N \times N$ order space weight matrix.

3.1.2. Mediation effect models

The DE may have an impact on IGT through human capital accumulation, and green technology innovation. In order to test the existence of mediation variables, this paper constructs the estimation of mediation effects shown in equations (2), (3), and (4) (Hao et al., 2022).

$$IGT_{it} = \gamma_0 + \gamma_1 DE_{it} + \sum_{k=1}^5 \gamma_k X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (2)$$

$$med_{it} = \vartheta_0 + \vartheta_1 DE_{it} + \sum_{k=1}^5 \vartheta_k X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (3)$$

$$IGT_{it} = \varphi_0 + \varphi_1 DE_{it} + \varphi_2 med_{it} + \sum_{k=1}^5 \varphi_k X_{it} + \mu_i + \theta_t + \varepsilon_{it} \quad (4)$$

Among them, med_{it} is the mediator variables, including three variables: human capital accumulation (HUM_{it}), and green technology innovation (GTI_{it}).

3.1.3. Threshold effect models

In order to further test the non-linear relationship between the DE and IGT, this paper uses the threshold panel model of Hansen (1999).

$$IGT_{it} = \beta_0 + \beta_1 DE_{it} \cdot I(Threshold_{it} \leq \gamma) + \beta_2 DE_{it} \cdot I(Threshold_{it} > \gamma) + \beta_c X_{it} + \lambda_i + \varepsilon_{it} \quad (5)$$

3.2. Explanation of variables

3.2.1. Industrial green transformation

This paper draws on the definition of industrial green transformation by the research group of institute of industrial economics CASS. Combined with the main indicators of the industrial green development plan (2016-2020) issued by the Ministry of industry and information technology in 2016, and the "14th Five-year plan" of China's industrial development strategy, we build an industrial green transformation index from seven aspects: pollution emission, pollution treatment, resource intensification, green innovation, structural optimization, production efficiency and sustainable development. The industrial green transformation index system is shown in Table1.

Table 1. Industrial green transformation index system.

First index	Secondary index	Variation
Pollution Emission	Sulfur dioxide emission per unit of industrial added value	-
	NOx emission per unit of industrial added value	-
	COD emission per unit industrial added value	-
	Ammonia nitrogen emission per unit of industrial added value	-
	Smoke (dust) emission per unit of industrial added value	-
	Wastewater discharge per unit of industrial added value	-
	Carbon dioxide emissions per unit of industrial added value	-
Pollution Treatment	Solid waste output per unit of industrial added value	-
	Removal rate of industrial sulfur dioxide	+
	Removal rate of Industrial smoke and dust	+
	Proportion of industrial wastewater pollution treatment investment in pollution treatment investment	+
Resource Intensification	Proportion of industrial solid waste pollution control investment in pollution control investment	+
	Energy consumption per unit of industrial added value	-
	Land use per unit of industrial added value	-
	Power consumption per unit of industrial added value	-
Green Innovation	Water consumption per unit of industrial added value	-
	Green product innovation	+
	Green process innovation	+
	Proportion of R&D expenditure in main operating income of Industrial Enterprises above Designated Size	+
	Proportion of R&D personnel in employees of Industrial Enterprises above Designated Size	+
	Number of patent applications authorized by industrial enterprises	+
Structural Optimization	Technology market turnover	+
	Proportion of main business income of high-tech industry in industry	+
	Proportion of exports of high-tech products in commodity exports	+

	Proportion of total output value of six high energy consuming industries in industrial added value	-
	Proportion of natural gas consumption in total energy consumption	+
	Proportion of non-fossil energy in primary energy consumption	+
	Agglomeration level of strategic emerging industries	+
	Proportion of added value of tertiary industry in GDP	+
Production Efficiency	Cost profit margin of Industrial Enterprises above Designated Size	+
	Contribution rate of total assets of Industrial Enterprises above Designated Size	+
	Total factor productivity	+
Sustainable Development	Comprehensive utilization rate of industrial solid waste	+
	Ratio of industrial water reused	+
	Greening coverage rate of built-up area	+
	Per capital park green are	+

3.2.2. Digital economy

This paper constructs the comprehensive development level of China's digital economy from four aspects: basic indicators, industrial indicators, integration indicators and development environmental indicators (Table 2).

Table 2. China Digital economy measurement system.

First index	Secondary index	Measure method
Internet infrastructure	Internet penetration	Internet penetration
	Website quantity	Number of Internet sites
	Number of domain names	Internet domain name
	Page update frequency	Internet page update frequency
Internet industry development	Number of Internet enterprises	Number of online trading enterprises
	Scale of electronic information manufacturing industry	Data of electronic information manufacturing scale
Internet business application	E-commerce scale	Proportion of e-commerce transactions in GDP
	Total express business	Number of express collection business
Internet development environment	Per capita GDP	Ratio of provincial GDP to total population
	Per capita disposable income of urban residents	The ratio of the total income of each province to the population of urban residents

3.2.3. Mediation variable

This paper selects human capital accumulation (HUM), and green technological innovation (GTI) as mediation variable to empirically test the indirect impact mechanism of DE on industrial green transformation. Among them, human capital accumulation is measured by the average years of education between provinces (Zhou et al., 2022); green technological innovation is measured by the number of green patents granted in each province (Luo et al., 2021).

3.2.4. Control variables

Considering many factors affecting IGT, this paper introduces a set of related control variables, including economic openness (OPEN): using the proportion of FDI in GDP of each province to measure the degree of economic opening of each province. Urbanization level (URB): use the proportion of non-agricultural population in each province to measure the urbanization level of the region. R&D investment intensity (RD): R&D investment intensity is measured by the proportion of R&D investment to GDP of each province. R&D personnel intensity (RDP) is measured by the number of R&D personnel. The descriptive statistics of the variables are reported in Table 3.

Table 3. The statistical description of variables.

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
IGT	Industrial green transformation	360	3.0041	0.7481	1.1940	4.4730
DE	Connected Development Level	360	0.1928	0.1655	0.0199	0.7416
URB	Financial development	360	0.5353	0.1371	0.2746	0.8960
FDI	Human capital accumulation	360	0.0568	0.0735	0.0080	0.7500
RD	Urbanization level	360	0.0145	0.0107	0.0020	0.0601
RDP	Open to the outside world	360	6.2481	8.9534	0.0085	45.7342
OPEN	Corporate labor	360	0.3122	0.3750	0.0086	1.7215

4. Empirical Results

4.1. Estimation results of spatial model

4.1.1. Spatial correlation test

We use stata 14.0 to calculate the Moran index of variables under the geographic weight matrix. It can be seen from table 4 that the Moran index of China's IGT and digital economy in 2006-2017 is positive. According to the Moran scatter Figure 3, most provinces are distributed in the first and third quadrants. It shows that the IGT has significant spatial agglomeration characteristics.

Table 4. Global correlation test.

Year	I	sd(I)	z	p-value	I	sd(I)	z	p-value
2006	0.385	0.119	3.512	0.000	0.532	0.133	-3.525	0.000
2007	0.397	0.119	3.617	0.000	0.522	0.134	-3.576	0.000
2008	0.369	0.120	3.375	0.000	0.547	0.132	-3.431	0.000
2009	0.389	0.120	3.535	0.000	0.534	0.132	-3.537	0.000
2010	0.421	0.119	3.832	0.000	0.499	0.135	-3.704	0.000
2011	0.361	0.119	3.331	0.000	0.535	0.136	-3.415	0.000
2012	0.381	0.119	3.489	0.000	0.540	0.135	-3.409	0.000
2013	0.396	0.119	3.607	0.000	0.493	0.133	-3.806	0.000
2014	0.353	0.119	3.245	0.001	0.548	0.133	-3.402	0.000
2015	0.430	0.119	3.896	0.000	0.486	0.134	-3.836	0.000
2016	0.39	0.120	3.549	0.000	0.510	0.132	-3.722	0.000
2017	0.424	0.119	3.838	0.000	0.490	0.133	-3.836	0.000

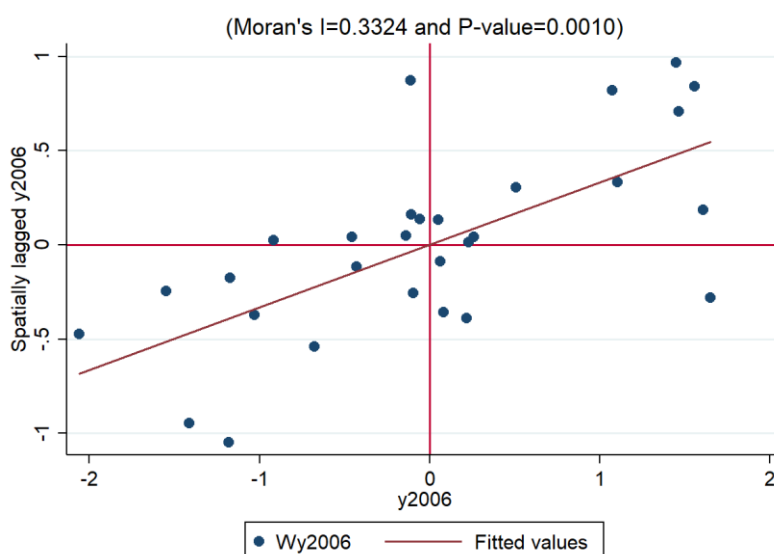


Figure 1. Moran scatter plot of industrial green transformation in 2006.

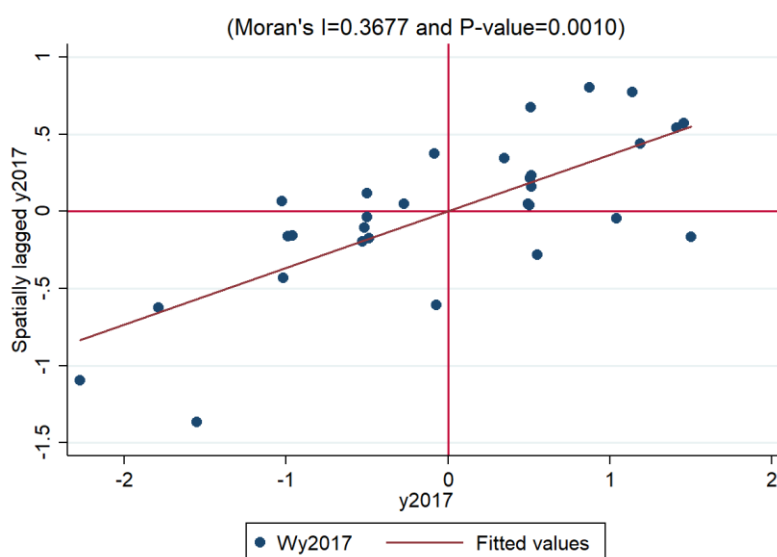


Figure 2. Moran scatter plot of industrial green transformation in 2017.

4.1.2. The estimated results of the direct effect

To ensure the robustness of the regression results, this paper also reports the estimation results of non-spatial panel model OLS, RE, System-GMM and Differential-GMM. According to the regression results in Table 5, AR (2) results show that there is no sequence correlation in the model; Hansen test results show that the selection of instrument variable is effective.

Table 5 shows that the coefficient of digital economy (DE) is significantly positive at the level of 1%. It shows that the DE can significantly promote the regional IGT, which to some extent supports the research conclusion of Zia (2016). The reasons include: With the vigorous development of the digital economy, the accelerated integration of digital technology and the real economy continues to provide momentum for the transformation and upgrading of traditional industries, and many new services, new business models and new modes have emerged. On the one hand, the digital economy, with its special technological attributes and strong network effect, can produce technological spillover effects on traditional industries and suppress the negative effects of technological impact, thus promoting the transformation and upgrading of traditional industries. Digital upgrading and transformation of traditional industries. At the same time, the continuous and in-depth integration of digital technology and traditional economy greatly improves the utilization rate of capital, energy and other factors, reduces the intensity of resource and energy consumption, promotes energy conservation and emission reduction, and promotes the green transformation of industry. On the other hand, relying on information technology innovation, the digital economy has given rise to new models such as sharing economy and experience economy, which promote effective integration of various information flows and realize efficient connection between supply and demand.

Table 5. The regression results of direct effects of the DE on IGT.

Variable	OLS	RE	SYS-GMM	DIF-GMM
DE	3.217*** (19.157)	1.001*** (2.926)	1.060*** (3.409)	3.210*** (6.573)
URB		0.690** (2.057)	-1.168*** (-3.964)	2.304*** (6.646)
FDI		1.284*** (3.311)	0.065 (0.202)	1.078* (1.956)

RD		19.743*** (4.772)	30.245*** (4.390)	-27.458*** (-2.964)
RDP		0.025*** (7.115)	0.000 (0.095)	-0.008*** (-5.320)
OPEN		-0.017 (-0.113)	-0.245*** (-2.994)	-0.869*** (-5.817)
L.DE			0.648*** (24.390)	-0.237*** (-4.854)
_CON	2.384*** (55.910)	1.930*** (13.720)	1.123*** (10.428)	
AR(2)			1.48 [0.140]	1.20 [0.231]
Hansen			28.26 [0.296]	28.46 [0.493]
Wald test			54507.49	2837.16
N	360	360	360	360

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

In geographic weight matrix, ρ is significantly positive at 1% confidence level. It shows that there is a significant spatial interaction between the DE and IGT, that is, digital economy and IGT are affected not only by their own factors, but also by regions with similar geographical region. In addition, although the panel model of spatial factors and the panel model of non-spatial factors are used for regression, the coefficients and significance of the core variables (DE) are very close. From the estimated results in Table 6, the spatial autoregressive coefficient of industrial green transformation is significantly positive at the 1% level, indicating that the spillover effect of industrial green transformation is significant. The estimated parameters of both direct and indirect effects of digital economy development on industrial green transformation are significantly positive, indicating that digital economy not only helps to promote industrial green transformation in the region, but also promotes industrial green transformation in the neighboring regions. That is, there is a significant spatial spillover effect of digital economy on the industrial green transformation of neighboring regions.

Table 6. The regression results of direct effects of the DE on IGT.

Variable	OLS	RE	SYS-GMM	DIF-GMM		
DE	2.679*** (16.347)	2.256*** (11.591)	2.293*** (10.891)	2.055*** (8.598)	0.748*** (2.676)	1.565*** (4.108)
URB		1.014*** (4.000)	0.911*** (3.154)	0.335 (1.014)	0.573* (1.857)	1.341*** (3.599)
FDI			0.300 (0.694)	0.351 (0.830)	0.187 (0.462)	0.291 (0.683)
RD				11.851*** (2.897)	22.808*** (5.627)	21.589*** (5.060)
RDP					0.027*** (7.410)	0.023*** (6.089)
OPEN						-0.571*** (-3.620)
W*DE	1.663*** (3.583)	1.396*** (2.813)	1.372*** (2.578)	0.897 (1.465)	1.938*** (2.809)	2.869*** (2.687)
W*URB		-0.317 (-0.992)	-0.136 (-0.376)	-0.664* (-1.752)	-0.595 (-1.336)	-0.839* (-1.762)
W*FDI			-1.151 (-0.590)	-0.310 (-0.159)	-0.729 (-0.407)	1.031 (0.421)
W*RD				18.441** (2.347)	-4.146 (-0.532)	-3.234 (-0.393)
W*RDP					-0.011	-0.010

					(-1.425)	(-1.227)
W*OPEN						-0.407
						(-1.051)
Spatial rho	0.282	0.226	0.358***	0.311**	0.300***	0.328***
	(1.202)	(0.822)	(3.037)	(2.388)	(3.148)	(2.723)
sigma2_e	0.218***	0.171***	0.169***	0.162***	0.131***	0.145***
	(11.154)	(13.051)	(13.161)	(12.968)	(12.671)	(10.557)
N	360	360	360	360	360	360

4.2. The estimation results of mediation effect

How does the DE reduce industrial green transformation? What is the specific process? The following is an empirical analysis of the transmission mechanism of DE to industrial green transformation from three aspects: human capital accumulation, and green technology innovation.

Table 7 presents the results of the mediating effect estimates. The model (1) and model (2) are the estimation results with human capital accumulation as the intermediary variable. The estimation coefficient of DE on human capital accumulation is positive, indicating that digital economy has a positive impact on human capital accumulation level. The regression coefficient of human capital accumulation to IGT is 0.103, which is significant at the level of 10%. It shows that the DE can indirectly promote the reduction of IGT through the accumulation of human capital. The general improvement of social human capital promotes technology R&D, thus improving the total factor productivity of enterprises and reducing industrial green transformation.

Model (3) and model (4) are estimates of green technology innovation (GTI) as mediate variables. We find that the impact coefficient of DE on GTI is significantly positive (2.378), and the impact coefficient of GTI on the IGT is 0.169, indicating that the DE indirectly promotes IGT by promoting green technology. The reason is that digital economy can promote technological innovation by reducing innovation costs and improving innovation efficiency. First, relying on digital technology development, the digital economy reduces the cost of data-based technological innovation activities. Second, digital economy development facilitates information flow and reduces information asymmetry in the market. At the same time, it can also blur the space and time boundaries of technological innovation activities. Enterprises can use digital technologies such as big data to analyze consumer behavior and target innovation, which improves the efficiency of technological innovation. On the other hand, technological innovation affects industrial structure upgrading. Technological innovation drives product innovation and process innovation, transforming traditional industries and fostering new industries. Technological innovation may lead to the emergence of new materials and products, change the demand structure of production and consumption, and push the industrial structure will transform to a higher level. Technological innovation can update and improve production processes or internal processes, reduce production costs and increase productivity. At the same time, it also changes the input ratios of production factors, prompting the flow of production factors.

Table 7. The regression results of the mediation effect of the DE on IGT.

Variable	(1)	(2)	(3)	(4)
	HUM	IGT	GTI	IGT
DE	0.712** (2.231)	1.074*** (3.129)	2.378*** (3.398)	0.598* (1.832)
URB	6.600*** (21.082)	1.370*** (2.729)	4.964*** (7.236)	-0.150 (-0.445)
FDI	-0.070 (-0.193)	1.277*** (3.303)	-2.589*** (-3.263)	1.722*** (4.658)
RD	23.209*** (6.007)	22.137*** (5.114)	59.361*** (7.012)	9.699** (2.338)

RDP	-0.013*** (-3.785)	0.024*** (6.639)	0.068*** (9.351)	0.014*** (3.695)
OPEN	-0.955*** (-6.942)	-0.115 (-0.736)	-1.837*** (-6.095)	0.294** (2.022)
HUM		0.103* (1.816)		
GTI				0.169*** (6.925)
CON	5.173*** (39.371)	2.464*** (7.567)	1.514*** (5.261)	1.674*** (12.196)
N	360	360	360	360

4.3. The estimation results of threshold effect

Furthermore, with the accumulation of environmental regulation, intellectual property protection and financial development, will the role of digital economy in industrial green transformation gradually increase? Therefore, this paper draws on the threshold regression model proposed by Hansen (1999), using environmental regulation, intellectual property protection and financial development as threshold variables to verify the non-linear relationship between DE and regional industrial green transformation.

Before the threshold effect analysis, it is necessary to test whether the threshold effect of the model exists and the number of possible thresholds. In this paper, the threshold effect is tested by bootstrap method. Table 8 shows that environmental regulation has passed the double threshold test, and intellectual property protection and financial development have passed the single threshold test, indicating that the DE has a non-linear relationship with IGT.

The results of Table 8 show that, in terms of environmental regulation, with the regional environmental regulation successively crosses the thresholds values, the positive impact of the DE on industrial green transformation gradually increases. It shows that the high level of environmental regulation is more conducive to promoting the IGT of the DE. Environmental regulation is an important way to address environmental pollution caused by market failures and other problems. When the intensity of environmental regulation is low, polluting enterprises face less stringent environmental standards and invest less in green technology research and development to meet the environmental standards set by the government. In this case, the investment in energy saving and emission reduction technology research and development is less than the cost caused by environmental pollution, which leads to the flow of factors of production to industries with inefficient use of resources. However, when the intensity of environmental regulations gradually increases, enterprises will face higher standards and stricter penalties for environmental pollution. Under the tendency of profit maximization firms may choose to engage in green technological innovation, which accelerates for the process of industrial green transformation.

In terms of financial development, when the regional financial development level successively crosses the threshold value of 1.473 and 2.365, the influence coefficient of DE on IGT changes from -0.800 to -1.158. It shows that the regional financial development can not only alleviate the investment and financing constraints of local enterprises, but also provide good external financing conditions for innovation activities of enterprises. By strengthening the integration of DE and financial development, it is conducive to technology research and innovation spillover of enterprises, thus improving the speed of industrial transformation IGT. The digital economy improves the efficiency of matching between financial supply and demand and reduces financial transaction costs. In fact, due to the existence of market frictions, information asymmetry in the financial market breaks the balance of interests between the two sides of financial transactions and affects the efficiency of financial resource allocation in industrial transformation. The development of digital economy, however, effectively reduces the degree of information asymmetry between the two sides of financial transactions, improves financial efficiency, and enhances

the process of industrial greening. Thus, the digital economy increases the effectiveness of financial market information. The technological advantage of the digital economy transforms cumbersome data into usable transaction information, reduces the information gap between financial institutions and the real business sector, and improves the efficiency of financial resource allocation. It enables financial institutions to better serve real enterprises and promote their technological research and development by easing financial constraints.

As far as intellectual property protection is concerned, the threshold effect of DE on regional IGT has changed from 0.414 to 1.715. It shows that the high levels intellectual property protection not only improves the allocation of production factors of traditional industries, but also accelerates the integration of networking and low-carbon industries, thus further reducing the IGT. Digital technology is an indispensable tool for modern enterprise innovation, which can help enterprises greatly improve innovation efficiency. Intellectual property protection can effectively reduce intellectual property disputes in collaborative innovation, and enhance the willingness of enterprises to increase investment in collaborative innovation. In addition, intellectual property protection can reduce the external spillover effect of innovation, improve the innovation income of enterprises, and accelerate the digitalization and service-oriented transformation of enterprises.

Table 8. The regression results of threshold model.

variable	ER	IPP	FD
URB	0.330538 (1.11)	1.228*** (4.73)	1.840*** (6.75)
FDI	0.11974 (0.55)	0.615*** (2.74)	0.822*** (3.47)
RD	43.7759*** (8.20)	20.20*** (5.72)	13.56*** (3.45)
RDP	-0.00251 (-0.81)	0.000741 (0.23)	0.00652** (2.30)
OPEN	0.26462*** 2.78	0.488*** (4.96)	0.452*** (4.77)
DE_1	0.30437 (1.06)	0.943*** (4.05)	0.474** (1.97)
DE_2	1.20362*** (4.50)	3.414*** (4.29)	1.715*** (5.31)
DE_3	3.65413*** (6.70)		
Cons	2.054*** (18.39)	1.987*** (17.85)	1.519*** (12.89)
N	360	360	360

4.4. Robustness test

In order to ensure the reliability of the spatial econometric regression results, this paper uses a regression analysis by means of a spatial weight matrix based on the empirical study of Ren et al (2020). In this paper, the econometric weight matrix regression is used, and the test results are shown in Table 9. where, model (1) does not include any control variables, and models (2)-(6) sequentially include multiple control variables. The estimated coefficient of the core explanatory variable (DE) is 2.612 when no control variables are included, and it passes the test at 1% significance level. meanwhile, in models (2 The regression parameters of digital economy on industrial green transformation are all significantly positive when control variables are added sequentially in models (2)-(6), indicating that the development of digital economy has a significant positive contribution to industrial green transformation during the period under investigation. each 1% increase in digital economy increases industrial green transformation by 0.929%. It can be seen that the above results are relatively robust.

Table 9. Empirical results of digital economy to IGT.

variable	Economic weight matrix					
DE	2.612*** (17.466)	2.125*** (11.761)	3.102*** (13.897)	2.734*** (11.873)	1.321*** (4.656)	0.929*** (3.147)
URB		1.111*** (4.603)	0.218 (0.707)	-0.486 (-1.452)	-0.167 (-0.526)	1.005*** (2.898)
FDI			0.063 (0.169)	0.115 (0.307)	-0.015 (-0.042)	0.870** (2.549)
RD				18.097*** (4.415)	25.576*** (6.203)	16.022*** (4.458)
RDP					0.025*** (7.611)	0.027*** (8.508)
OPEN						-0.233 (-1.630)
Spatial rho	0.639*** (11.892)	0.556*** (9.338)	0.436*** (5.727)	0.385*** (4.833)	0.385*** (4.718)	0.478*** (8.155)
sigma2_e	0.193*** (12.892)	0.185*** (12.945)	0.163*** (13.057)	0.152*** (13.287)	0.131*** (13.287)	0.146*** (13.174)
Direct effect	2.894*** (18.517)	2.293*** (11.502)	3.538*** (13.308)	3.134*** (11.695)	1.692*** (5.304)	0.987*** (3.089)
Indirect effect	4.432*** (4.462)	2.653*** (4.122)	7.992*** (5.304)	7.843*** (5.446)	7.368*** (5.484)	0.837** (2.339)
Total effect	7.326*** (7.019)	4.946*** (6.552)	11.530*** (6.839)	10.977*** (6.835)	9.060*** (5.949)	1.824*** (2.825)
N	360	360	360	360	360	360

5. Conclusion and policy recommendations

This paper estimates the comprehensive development and IGT of China's DE. Then, we analyze the influence mechanism of DE on IGT from three aspects: direct effect, mediation effect and threshold effect. The main conclusions are as follows: the DE has significantly reduced the IGT. The DE can indirectly improve the IGT through human capital accumulation, financial development and industrial upgrading. When they exceed the threshold value, the role of energy conservation and emission reduction of DE comprehensive development is gradually strengthened. There is regional heterogeneity in the reduction of China's IGT due to the DE. To enable the DE to play its role and reduce its IGT, this paper proposes some policy implications.

(1) First, increase the construction of digital infrastructure. Specifically, the government should introduce relevant policies and regulations to promote 5G commercialization and improve the coverage and application level of 5G network infrastructure. Second, it is necessary to accelerate the development of digital industries and improve the competitiveness of core industries. Moreover, policy makers should guide the development of information technology software and hardware products toward industrialization and scale, and improve the R&D innovation and supply capacity of key software technologies. It is necessary to improve the innovation capability and integration application level of new generation information technology and vigorously cultivate new digital industries. Finally, accelerate the degree of application of the digital economy. From the industrial viewpoint, enterprises should improve traditional industries from various production links through new technologies such as the Internet, improve the level of integration and application of industrial Internet, and use networked collaboration to cultivate a new production model of personalized customization. Enterprises need to be guided to strengthen digital thinking, promote business transformation in R&D, production, operation and sales in a comprehensive and systematic manner, and facilitate the full use of Internet resources for development.

(2) Each region should formulate relevant development strategies based on the foundation of regional

economic development. For the eastern region, it should strengthen the development advantages of the digital economy and continue to play a good role as a model leader in building a digital economy. Specifically, the eastern region should give full play to its advantages in innovation, industry, and resources, accelerate the introduction of digital talents, technology and other key factors of production, and form an effective model for developing a digital economy. For the central region, it should give full play to the digital economy's role in upgrading the industrial chain and supply chain. Specifically, it is necessary to accelerate the application of digital technology in various fields and improve the control of industrial chains and supply chains. For the western region, it should strengthen the construction of digital infrastructure and establish a comprehensive digital economy planning and policy system. Specifically, because of the low level of economic development, the degree of digital infrastructure construction in the western region at this stage still needs to be improved. Therefore, local governments should increase investment in traditional as well as new digital infrastructure. In addition, the western region should focus on building digital talent training platforms and bases to cultivate various types of professionals with digital capabilities.

The research is based on the provincial regional level, and does not involve the empirical analysis of micro innovation subjects such as cities or enterprises. This is mainly because the data of micro subjects in the use of the DE is difficult to obtain for a while. With the continuous improvement of micro data, the research on the impact of digital economy on the IGT of enterprises and its micro mechanism deserves attention. Although this paper establishes the index system of digital economy, it is not comprehensive enough. Therefore, future scholars can further enrich the digital economy index system, so as to more accurately reflect the comprehensive development of regional digital economy.

Funding Statement

This research received no external funding.

Declaration of Competing Interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

References

- Dahlman, C., Mealy, S., & Wermelinger, M. (2016). Harnessing the digital economy for developing countries. <https://doi.org/10.1787/4adffb24-en>
- Deng, H., Bai, G., Shen, Z., & Xia, L. (2022). Digital economy and its spatial effect on green productivity gains in manufacturing: Evidence from China. *Journal of Cleaner Production*, 378, 134539. <https://doi.org/10.1016/j.jclepro.2022.134539>
- Ding, C., Liu, C., Zheng, C., & Li, F. (2021). Digital economy, technological innovation and high-quality economic development: Based on spatial effect and mediation effect. *Sustainability*, 14(1), 216. <https://doi.org/10.3390/su14010216>
- Dong, F., Hu, M., Gao, Y., Liu, Y., Zhu, J., & Pan, Y. (2022). How does digital economy affect carbon emissions? Evidence from global 60 countries. *Science of The Total Environment*, 852, 158401. <https://doi.org/10.1016/j.scitotenv.2022.158401>
- Du, M., Hou, Y., Zhou, Q., & Ren, S. (2022). Going green in China: How does digital finance affect environmental pollution? Mechanism discussion and empirical test, *Environmental Science and Pollution Research*, 7(1):1–15. <https://doi.org/10.1007/s11356-022-21909-0>
- Feng, Z., & Chen, W. (2018). Environmental regulation, green innovation, and industrial green development: An empirical analysis based on the Spatial Durbin model. *Sustainability*, 10(1), 223. <https://doi.org/10.3390/su10010223>
- Fu, J., Xiao, G., Guo, L., & Wu, C. (2018). Measuring the dynamic efficiency of regional industrial green transformation in China. *Sustainability*, 10(3), 628. <https://doi.org/10.3390/su10030628>

- Han, D., Li, T., Feng, S., & Shi, Z. (2020). Does renewable energy consumption successfully promote the green transformation of China's industry?. *Energies*, 13(1), 229. <https://doi.org/10.3390/en13010229>
- Hao, X., Li, Y., Ren, S., Wu, H., & Hao, Y. (2023). The role of digitalization on green economic growth: Does industrial structure optimization and green innovation matter?. *Journal of Environmental Management*, 325, 116504. <https://doi.org/10.1016/j.jenvman.2022.116504>
- Hao, Y., Huang, J., Guo, Y., Wu, H., & Ren, S. (2022). Does the legacy of state planning put pressure on ecological efficiency? Evidence from China. *Business Strategy and the Environment*, 31:403–424. <https://doi.org/10.1002/bse.3066>
- Hou, J., Teo, T. S., Zhou, F., Lim, M. K., & Chen, H. (2018). Does industrial green transformation successfully facilitate a decrease in carbon intensity in China? An environmental regulation perspective. *Journal of cleaner production*, 184, 1060-1071. <https://doi.org/10.1016/j.jclepro.2018.02.311>
- Jin, G., Shen, K., & Li, J. (2020). Interjurisdiction political competition and green total factor productivity in China: An inverted-U relationship. *China Economic Review*, 61, 101224. <https://doi.org/10.1016/j.chieco.2018.09.005>
- Kumbhakar, S. C., & Tsionas, E. G. (2006). Estimation of stochastic frontier production functions with input-oriented technical efficiency. *Journal of Econometrics*, 133(1), 71-96. <https://doi.org/10.1016/j.jeconom.2005.03.010>
- Lange, S., Pohl, J., & Santarius, T. (2020). Digitalization and energy consumption. Does ICT reduce energy demand?. *Ecological Economics*, 176, 106760. <https://doi.org/10.1016/j.ecolecon.2020.106760>
- Li, K., & Lin, B. (2017). Economic growth model, structural transformation, and green productivity in China. *Applied Energy*, 187, 489-500. <https://doi.org/10.1016/j.apenergy.2016.11.075>
- Li, K., Kim, D. J., Lang, K. R., Kauffman, R. J., & Naldi, M. (2020). How should we understand the digital economy in Asia? Critical assessment and research agenda. *Electronic commerce research and applications*, 44, 101004. <https://doi.org/10.1016/j.eelerap.2020.101004>
- Liu, D., Wang, G., Sun, C., Majeed, M. T., & Andlib, Z. (2022a). An analysis of the effects of human capital on green growth: effects and transmission channels. *Environmental Science and Pollution Research*, 1-8. <https://doi.org/10.1007/s11356-022-22587-8>
- Liu, P., Zhao, Y., Zhu, J., & Yang, C. (2022b). Technological industry agglomeration, green innovation efficiency, and development quality of city cluster. *Green Finance*, 4(4), 411-435. <https://doi.org/10.3934/gf.2022020>
- Luo, K., Liu, Y., Chen, P. F., & Zeng, M. (2022). Assessing the impact of digital economy on green development efficiency in the Yangtze River Economic Belt. *Energy Economics*, 112, 106127. <https://doi.org/10.1016/j.eneco.2022.106127>
- Luo, Y., Salman, M., & Lu, Z. (2021). Heterogeneous impacts of environmental regulations and foreign direct investment on green innovation across different regions in China. *Science of the total environment*, 759, 143744
- Mao, W., Wang, W., & Sun, H. (2019). Driving patterns of industrial green transformation: A multiple regions case learning from China. *Science of The Total Environment*, 697, 134134. <https://doi.org/10.1016/j.scitotenv.2020.143744>
- Meng, F., & Zhao, Y. (2022). How does digital economy affect green total factor productivity at the industry level in China: From a perspective of global value chain. *Environmental Science and Pollution Research*, 29(52), 79497-79515. <https://doi.org/10.1007/s11356-022-21434-0>
- Meng, Y., Liu, L., Xu, Z., Gong, W., & Yan, G. (2022). Research on the Heterogeneity of Green Biased Technology Progress in Chinese Industries—Decomposition Index Analysis Based on the Slacks-based measure integrating (SBM). *Journal of Economic Analysis*, 1(2), 17-34. <https://doi.org/10.58567/jea01020002>
- Mergel, I., Edelmann, N., & Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government information quarterly*, 36(4), 101385. <https://doi.org/10.1016/j.giq.2019.06.002>
- Murthy, K. B., Kalsie, A., & Shankar, R. (2021). Digital economy in a global perspective: is there a digital divide?. *Transnational Corporations Review*, 13(1), 1-15. <https://doi.org/10.1080/19186444.2020.1871257>
- Nadal, M., Marquès, M., Mari, M., & Domingo, J. L. (2015). Climate change and environmental concentrations of POPs: A review. *Environmental research*, 143, 177-185. <https://doi.org/10.1016/j.envres.2015.10.012>
- Pan, W., Xie, T., Wang, Z., & Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. *Journal of Business Research*, 139, 303-311. <https://doi.org/10.1016/j.jbusres.2021.09.061>
- Qi, Y., Zou, X., & Xu, M. (2022). Impact of Chinese fiscal decentralization on industrial green transformation: From the perspective of environmental fiscal policy. *Frontiers in Environmental Science*, 10, 2046. <https://doi.org/10.3389/fenvs.2022.1006274>

- Ren, S., Hao, Y., & Wu, H. (2022a). Digitalization and environment governance: does internet development reduce environmental pollution?. *Journal of Environmental Planning and Management*, 1-30. <https://doi.org/10.1080/09640568.2022.2033959>
- Ren, S., Hao, Y., Xu, L., Wu, H., & Ba, N. (2021). Digitalization and energy: How does internet development affect China's energy consumption?. *Energy Economics*, 98, 105220. <https://doi.org/10.1016/j.eneco.2021.105220>
- Ren, S., Liu, Z., Zhanbayev, R., & Du, M. (2022b). Does the internet development put pressure on energy-saving potential for environmental sustainability? Evidence from China. *Journal of Economic Analysis*, 1(1), 50-65. <https://doi.org/10.58567/jea01010004>
- Rogers, D. L. (2016). *The digital transformation playbook: Rethink your business for the digital age*. Columbia University Press. <https://doi.org/10.7312/roge17544>
- Rouse, M. (2016). *Digital economy*. Techtarget, Newton, MA. <https://doi.org/10.1787/5jlwnkm2fc9x-en>
- Scoones, I., Leach, M., & Newell, P. (2015). *The politics of green transformations* (p. 238). Taylor & Francis. <https://doi.org/10.4324/9781315747378>
- Sorescu, A., & Schreier, M. (2021). Innovation in the digital economy: a broader view of its scope, antecedents, and consequences. *Journal of the Academy of Marketing Science*, 49(4), 627-631. <https://doi.org/10.1007/s11747-021-00793-z>
- Sulemana, I. (2016). Are happier people more willing to make income sacrifices to protect the environment?. *Social Indicators Research*, 127(1), 447-467. <https://doi.org/10.1007/s11205-015-0960-3>
- Teece, D. J. (2018). Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. *Research policy*, 47(8), 1367-1387. <https://doi.org/10.1016/j.respol.2017.01.015>
- Tian, C., Li, X., Xiao, L., & Zhu, B. (2022). Exploring the impact of green credit policy on green transformation of heavy polluting industries. *Journal of Cleaner Production*, 335, 130257. <https://doi.org/10.1016/j.jclepro.2021.130257>
- Ustundag, A., & Cevikcan, E. (2017). *Industry 4.0: managing the digital transformation*. Springer. <https://doi.org/10.1007/978-3-319-57870-5>
- Wang, M., Xu, M., & Ma, S. (2021). The effect of the spatial heterogeneity of human capital structure on regional green total factor productivity. *Structural Change and Economic Dynamics*, 59, 427-441. <https://doi.org/10.1016/j.strueco.2021.09.018>
- Wang, W., Yang, X., Cao, J., Bu, W., Adebayo, T. S., Dilanchiev, A., & Ren, S. (2022). Energy internet, digital economy, and green economic growth: Evidence from China. *Innovation and Green Development*, 1(2), 100011. <https://doi.org/10.1016/j.igd.2022.100011>
- Wu, H., Ba, N., Ren, S., Xu, L., Chai, J., Irfan, M., ... & Lu, Z. N. (2022). The impact of internet development on the health of Chinese residents: Transmission mechanisms and empirical tests. *Socio-Economic Planning Sciences*, 81, 101178. <https://doi.org/10.1016/j.seps.2021.101178>
- Wu, H., Hao, Y., Ren, S., Yang, X., & Xie, G. (2021a). Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy*, 153, 112247. <https://doi.org/10.1016/j.enpol.2021.112247>
- Wu, H., Xue, Y., Hao, Y., & Ren, S. (2021b). How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Economics*, 103, 105577. <https://doi.org/10.1016/j.eneco.2021.105577>
- Xu, S., Yang, C., Huang, Z., & Failler, P. (2022). Interaction between Digital Economy and Environmental Pollution: New Evidence from a Spatial Perspective. *International Journal of Environmental Research and Public Health*, 19(9), 5074. <https://doi.org/10.3390/ijerph19095074>
- Yang, X., Wang, W., Su, X., Ren, S., Ran, Q., Wang, J., & Cao, J. (2022). Analysis of the influence of land finance on haze pollution: An empirical study based on 269 prefecture-level cities in China. *Growth and Change*, 4, 1-29. <https://doi.org/10.1111/grow.12638>
- Yang, X., Wu, H., Ren, S., Ran, Q., & Zhang, J. (2021). Does the development of the internet contribute to air pollution control in China? Mechanism discussion and empirical test. *Structural Change and Economic Dynamics*, 56, 207-224. <https://doi.org/10.1016/j.strueco.2020.12.001>
- Zandalinas, S. I., Fritschi, F. B., & Mittler, R. (2021). Global warming, climate change, and environmental pollution: recipe for a multifactorial stress combination disaster. *Trends in Plant Science*, 26(6), 588-599. <https://doi.org/10.1016/j.tplants.2021.02.011>
- Zhai, X., & An, Y. (2020). Analyzing influencing factors of green transformation in China's manufacturing industry under environmental regulation: A structural equation model. *Journal of Cleaner Production*, 251, 119760. <https://doi.org/10.1016/j.jclepro.2019.119760>

- Zhai, X., & An, Y. (2021). The relationship between technological innovation and green transformation efficiency in China: An empirical analysis using spatial panel data. *Technology in Society*, 64, 101498. <https://doi.org/10.1016/j.techsoc.2020.101498>
- Zhao, X., Ding, X., & Li, L. (2021). Research on environmental regulation, technological innovation and green transformation of manufacturing industry in the Yangtze River Economic Belt. *Sustainability*, 13(18), 10005. <https://doi.org/10.3390/su131810005>
- Zhou, Q., Du, M., & Ren, S. (2022). How government corruption and market segmentation affect green total factor energy efficiency in the post-COVID-19 era: Evidence from China. *Frontiers in Energy Research*, 10, 1-15. <https://doi.org/10.3389/fenrg.2022.878065>