

Does Digital Economy Matter the Green Transformation of Manufacturing Industry?

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Abstract

In the context of the dual carbon target and the evolving green development stage, the digital economy emerges as a crucial catalyst for the green transformation of the manufacturing industry. This paper meticulously investigates the impact of the digital economy on the green transformation of manufacturing, employing panel data sourced from 263 Chinese cities spanning the period from 2011 to 2019. The key findings are as follows: (1) The digital economy significantly propels the green transformation of the manufacturing industry. Importantly, after a series of robustness tests, the conclusion remains significant. (2) Through spatial spillover effects, the digital economy plays a pivotal role in fostering the green transformation of manufacturing in neighbouring regions. (3) The positive impact of the digital economy on the green transformation of the manufacturing industry is particularly pronounced in non-resource cities, central cities, and pilot cities of big data pilot zones. (4) Financial development exhibits a negative moderating effect on the green transformation of the manufacturing industry, whereas urban innovation potential demonstrates a positive moderating effect. Our findings offer empirical insights that contribute to a deeper understanding of how the manufacturing industry navigates the path of green transformation in the wake of the digital economy's development.

Keywords: digital economy; manufacturing; green transformation

1.0 Introduction

Amidst the escalating global environmental challenges, there is a growing emphasis on sustainable economic development (Zhang et al., 2023). The 2022 Global Environmental Performance Index (EPI) Report reveals that China holds the 160th position out of 180 countries or regions participating in the environmental performance evaluation. This underscores the imperative for a profound green transformation within the Chinese economy. As the predominant force in the Chinese economic landscape, the manufacturing industry significantly contributes to the nation's overall economic advancement. The trajectory of China's economic green transformation is intricately linked to the corresponding evolution within the manufacturing sector. Effectively addressing the inherent contradiction between economic development and environmental preservation has emerged as a paramount mission for the manufacturing industry. In 2020, the added value of the Chinese manufacturing industry reached an impressive \$3.854 trillion, constituting 26.29% of the GDP. However, this achievement is shadowed by the fact that the energy consumption attributed to the manufacturing sector accounts for a substantial 56.12% of the total energy consumption. The developmental path of the manufacturing industry is notably characterized by elevated levels of energy consumption, significant pollution, and a pronounced lack of efficiency, thereby giving rise to a multitude of environmental challenges. Consequently, the prevailing extensive economic development model within the Chinese manufacturing sector remains a formidable

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obstacle to achieving a genuinely green and sustainable trajectory for the broader Chinese economy. Given its profound implications for both global economic development and environmental governance, the manufacturing industry stands at a critical juncture, necessitating a decisive embrace of green transformation. The endeavour to transition the manufacturing sector into a more environmentally sustainable entity is a multifaceted and systematic challenge. This undertaking involves the intricate interplay of a multi-domain technology index and the considerable costs associated with the conversion process (Huang et al., 2019). The pursuit of green transformation within the manufacturing industry demands substantial commitments to research and development, requiring a continuous and stable influx of capital investment. This financial dedication is crucial to navigating the complexities of adopting green technologies and practices that are essential for long-term sustainability. Furthermore, heightened environmental regulations add an additional layer of pressure on the manufacturing sector. Stringent regulatory frameworks, as noted by Jaffe et al. (1995), prompt manufacturing enterprises to recalibrate their product mix, management strategies, and technical approaches. This adjustment is geared towards enhancing green production efficiency and aligning with evolving environmental standards, reflecting a proactive response to the imperative of sustainable practices. The transformative journey of the manufacturing industry towards sustainability is further propelled by advancements in digital technologies. The burgeoning development of the digital economy has accelerated the widespread application of digital technologies (Guan and Ma, 2003). This technological integration has notably contributed to the improvement of the green total factor productivity within the manufacturing industry. The symbiosis between the digital economy and the tangible economic landscape plays a pivotal role in driving the green transformation of the manufacturing industry. Consequently, a thorough examination of the impact resulting from this green transformation becomes imperative. Such an analysis will shed light on the far-reaching effects on the economy and society, ultimately fostering the progression towards a greener and more sustainable future.

The relentless advancement of digital technologies, including big data, blockchain, artificial intelligence, and the Internet of Things, has positioned the digital economy as a crucial catalyst for global economic growth. Remarkably, despite a late start, China has rapidly emerged as a frontrunner in the development of the digital economy. By the close of 2022, the scale of China's digital economy reached RMB 50.2 trillion, exhibiting a nominal annual growth rate of 10.3%. Notably, the digital economy in China has consistently outpaced nominal GDP growth for 11 consecutive years, underscoring its robust and sustained development (Clifton et al., 2019). Recognized for its substantial development potential, the digital economy has become a focal point for economic growth in China (Abanyie et al., 2023). Beyond its economic contributions, the digital economy's integration into energy consumption and environmental protection has the potential to mitigate global environmental challenges and address issues of energy scarcity. The digital economy's high technology content and comparatively low environmental costs position it as a pivotal driver for overcoming technical bottlenecks in the green transformation of the manufacturing industry. Despite the inherent reluctance of the manufacturing industry to engage in green transformation due to high risks and positive externalities, the burgeoning digital economy offers a transformative influence. As digital technologies permeate environmental regulation, they significantly enhance the efficiency of regulatory efforts by policymakers. The proactive role of environmental regulations, coupled with increased attention from analysts and the media, intensifies environmental pressures on the manufacturing industry. In response, manufacturing enterprises are incentivized to undertake green transformation activities, aligning with the evolving environmental conservation landscape. Consequently, the digital economy plays a pivotal role

in enhancing the green production efficiency of the manufacturing industry. As digital information technology continues to advance at a rapid pace, the influence of the digital economy in steering the green transformation of the manufacturing industry becomes increasingly pronounced.

Despite the recent surge in attention towards the digital economy, current research predominantly emphasizes its positive influences on technological innovation, industrial structure, and overall economic development (Ma and Zhu, 2022). In parallel, some studies have delved into the digital economy's impact on enhancing urban green economic benefits, improving regional investment quality, and reducing carbon emission intensity at the urban level. While these aspects shed light on the broader ramifications of the digital economy, there is a notable gap in understanding the intrinsic factors influencing the green transformation within the manufacturing industry. The dearth of evidence on the driving forces behind the green transformation in manufacturing is a critical knowledge gap, particularly concerning the formulation of effective policy measures aimed at fostering sustainability initiatives and ecological equilibrium. Current studies have predominantly focused on the constraining impact of environmental regulations (Liu, Chen & Zhang, 2021), leaving the role of the digital economy largely unexplored as a key player in shaping resource allocation. While the impact of the digital economy on economic development has garnered substantial academic attention, its specific contribution to the green transformation of the manufacturing industry remains obscured and warrants closer examination. Clarifying this relationship is pivotal for a comprehensive understanding of how digital advancements can be strategically harnessed to drive sustainability within the manufacturing sector.

In recent years, the evolution of digital technology has given rise to the digital economy, presenting a promising avenue for economic expansion without compromising environmental quality. The growing emphasis on advocating green and sustainable development in national economies has sparked considerable scholarly interest in understanding the intricate relationship between the digital economy and the green transformation of manufacturing. However, despite numerous studies, there remains a lack of consensus on the impact, with divergent findings based on various research methods and data sources. On one hand, proponents argue that the digital economy holds the potential to significantly enhance manufacturing's green transformation (Bressanelli et al., 2018). In the digital age, the digital economy serves as a practical tool to advance clean technology, addressing critical technological barriers. The widespread adoption of clean technology forms the foundation for elevating the green transformation of the manufacturing industry. This transformation acts as a catalyst for improving product quality, leading to the displacement of traditional manufacturing industries characterized by excess production capacity and structural imbalances. The digital economy further accelerates continuous improvement and upgrading of production modes through green technology research and development, contributing substantially to the green transformation of manufacturing industries. Consequently, the digital economy emerges as a significant driving force for the environmentally-friendly development of the economy and society. On the other hand, detractors argue that the digital economy has led to a substantial increase in energy consumption, posing a hindrance to the green transformation of the manufacturing industry. From a resource perspective, the development and application of digital technologies are seen as endogenous determinants influencing resource availability (Litvinenko, 2020). This, in turn, results in elevated energy consumption and pollution emissions. Additionally, the expansion of digital infrastructure and the ubiquity of the Internet contribute to heightened resource consumption and environmental pollution. In summary, while existing academic research has yielded fruitful insights, there remains a need

for further exploration. The relationship between the green transformation of the manufacturing industry and the digital economy is characterized by uncertainty and ambiguity. The question of whether the digital economy can facilitate intelligent, high-end, and green production, serving as a decisive factor in the green transformation of the manufacturing industry, is still subject to ongoing discussion. To address these uncertainties, our research aims to provide specific solutions and identify the potential connections between the digital economy and the green transformation of the manufacturing industry.

This study makes several notable contributions to the existing literature on the green transformation of the manufacturing industry. First and foremost, building on the research methodologies of Zhong et al. (2021) and Fang et al. (2021), we employ the Slacks-Based Measure (SBM) model and Global Malmquist-Luenberger (GML) index to gauge the green total factor productivity (GTFP) of the manufacturing industry. Diverging from previous studies primarily focused on the provincial level, our quantitative analysis is conducted at the city level, offering a more granular and substantive perspective. Secondly, unlike prior research that predominantly explores the direct impact of the digital economy on improving the green transformation of manufacturing industries, we extend the literature by delving into the spatial spillover effect of the digital economy, both theoretically and empirically. Our findings unequivocally support the positive influence of the digital economy on the green transformation of manufacturing industries. Thirdly, we enhance the analytical framework by incorporating financial development and urban innovation potential into the study of the digital economy and the green transformation of the manufacturing industry. This addition provides a diversified mechanism and empirical basis for understanding how the digital economy contributes to green economic growth. Our results offer robust evidence of the impact of finance and innovation on the green transformation of manufacturing industries at the city level, elucidating the pivotal role of these factors in the relationship between environmental considerations and sustainable development. Lastly, adopting a perspective of heterogeneous effects, this paper investigates the impact of the digital economy on the green development of the manufacturing industry in cities with varying resource endowments, different developmental levels, and distinct policy strengths. The findings provide valuable reference and guidance for tailoring green transformation policies to local circumstances. In a period marked by a crucial economic structural adjustment and transformation, this study contributes to understanding the intricate mechanisms through which the digital economy influences the green transformation of manufacturing industries, offering actionable insights for decision-makers steering towards environmentally friendly economic development.

This study is structured as follows. Literature review and theoretical analysis are provided in Section 2. Section 3 introduces the methodology, including the model setting, data organization, and variable description. The empirical results are discussed in Section 4. Section 5 further analyses possible moderating effects. Section 6 conducts robustness tests on the benchmark regression results. In the last step, conclusions and policy recommendations are provided.

2.0 Theoretical Analysis and Research Hypotheses

2.1 The direct effect of the digital economy on the green transformation of manufacturing industry

The digital economy, with digital technology at its core, plays a pivotal role in enhancing the efficiency of pollution prevention and control by optimizing resource allocation structures (Thompson et al., 2013). It encourages the adoption of green technologies and improves the

management efficiency of industrial and supply chains (Agrawal et al., 2018). This multifaceted influence of the digital economy is instrumental in shaping the green transformation of the manufacturing industry. On one hand, the digitized knowledge and information provided by the digital economy offer crucial technical support for advancements in energy conservation and emission reduction, thereby expediting the green transformation of the manufacturing industry. On the other hand, data, as an emerging production factor, generates a "digital dividend," creating opportunities for manufacturing industries to enhance the efficiency of energy utilization. Furthermore, the digital economy accelerates the entire production process within the manufacturing industry, emerging as a vital breakthrough in reconciling the contradiction between resource scarcity and economic development. This acceleration contributes to efficient input allocation involving natural resources and leads to an increase in green total factor productivity. Therefore, based on these premises, we formulate the following hypothesis:

H1: The digital economy significantly contributes to the green transformation of the manufacturing industry.

2.2 The spatial spillover effect of the digital economy on the green transformation of the manufacturing industry

Propelled by information transmission and knowledge sharing, the burgeoning digital economy is revolutionizing traditional modes of production and daily life. As we enter the era of the digital economy, the cost-effective dissemination and rapid diffusion of data manifest substantial geographical spillover effects. Additionally, functioning as a technology spillover, the digital economy transcends the constraints of time and space in information transfer, thereby expanding the scope and depth of inter-regional connections in production activities. The pervasive innovation, robust penetration, and extensive coverage of the digital economy contribute to enhancing the interdependence of spatial connections between various regions, facilitated by convenient and efficient information transmission. These connections may, in turn, generate spatial spillover effects on the green transformation of manufacturing industries, expediting the eco-friendly evolution of manufacturing in neighboring areas. Furthermore, the digital economy has the capacity to stimulate the specialization of the manufacturing technology innovation chain in adjacent regions by augmenting technological innovation density, thereby catalyzing the overall development of the manufacturing industry. The concentration of the manufacturing industry and the dynamic interaction within regional network spaces foster a deepening integration and division of manufacturing factors. In summary, the growth of the digital economy and the improvement of Green Total Factor Productivity (GTFP) in manufacturing within a particular region may wield a substantial impact on the green transformation of the manufacturing industry in areas characterized by close geographical proximity or similar levels of economic development. Building on the aforementioned analysis, this paper posits the following hypothesis:

H2: The digital economy plays a significant role in the green transformation of the manufacturing industry through spatial spillover effects.

2.3 Heterogeneity of urban resource endowments

Resource-based cities, benefiting from favorable energy prices due to their abundant resources, are often chosen as preferred locations for manufacturing enterprises. Despite their resource abundance, these cities face challenges related to the unsustainable development and utilization

of resources, potentially leading to a detrimental "resource curse" effect. Consequently, the cost of transforming into environmentally sustainable hubs rises significantly for resource-based cities. Conversely, the digital economy presents a promising avenue for driving the green transformation of the manufacturing industry in these cities. In recent years, the digital economy has demonstrated enhanced efficiency in resource development and utilization within these resource-based cities. Cities with limited resources can strategically leverage the advantages offered by the digital economy to stimulate and facilitate the green transformation of manufacturing. Therefore, we propose the following hypothesis.

H3: In resource-exhausted cities, the digital economy makes a bigger contribution to the green transformation of the manufacturing industry.

2.4 Heterogeneity of the urban hierarchy

Central cities, as the focal points of economic development and national strategic planning, often experience advanced agglomeration of production factors, including top talents and high-end elements. The active digital economy in central cities may result in economies of scale and agglomeration effects, creating digital inequality and a digital divide between central and peripheral cities (Lyu et al., 2023). Consequently, peripheral cities may exhibit weaker digital infrastructure and less developed digital regulation and governance. Furthermore, peripheral cities, compared to central cities, are more likely to bear the manufacturing links associated with high pollution and emissions, indicating a more extended path for the green transformation of their manufacturing industries. Lastly, central cities may attract a variety of production factors, leading to a siphoning effect from peripheral cities. This dynamic could hinder the development and application of low-carbon and green technologies in peripheral cities. In light of these considerations, we propose the following hypothesis.

H4: In central cities, the digital economy plays a more significant role in driving the green transformation of the manufacturing industry.

2.5 Heterogeneity of urban policy intensity

In its role as a pivotal driver for the green transformation of the manufacturing industry, the development of the digital economy is significantly influenced by the support and guidance of national policies. Policies focused on digital infrastructure construction contribute to the enhancement of the innovation system for digital technology. Consequently, in cities characterized by high levels of policy intensity, the mechanisms for digital governance become more robust. This, in turn, leads to a higher level of development in the digital economy within these cities. The heightened development of the digital economy, in this context, plays a more substantial role in influencing the green total factor productivity of the manufacturing industry. Therefore, this paper puts forward the following hypothesis.

H5: In cities with high levels of policy intensity, the digital economy has a more substantial impact on the green transformation of the manufacturing industry.

3.Data and methodology

3.1 Variable selections

3.1.1 Dependent variable

The dependent variable in this study is the green transformation of the manufacturing industry, measured by green total factor productivity (GTFP). To account for energy consumption and environmental pollution within the analytical framework, the Slack-Based Measure (SBM) model is employed. This model addresses the limitations of the traditional Data Envelopment Analysis (DEA) by considering undesirable output. The SBM model compensates for DEA deficiencies, offering the advantage of comparing valid decision units while incorporating undesirable output.

GTFP is assessed using a set of input and output indicators. Capital, labor, and energy are considered equally crucial input indicators. The capital input is determined by the total fixed assets of industrial enterprises, employing the perpetual inventory method. With 2011 as the base period, an asset depreciation rate of 10.96% is applied for measurement. Labor input is gauged by the number of urban manufacturing employment at the end of each year. Energy input is quantified by the industrial water and electricity consumption. Concerning output indicators, this paper takes a comprehensive approach, considering economic development and environmental impact. Desirable output is represented by the total output value of industrial enterprises. The undesirable output is measured by a comprehensive index calculated using industrial wastewater, sulfur dioxide emissions, and smoke (dust) emissions.

3.1.2 Independent variable

The independent variable in this study is the digital economy (De). Prior studies on constructing digital economy indicator systems have primarily concentrated on the provincial level, lacking a unified standard for measuring the digital economy at the prefecture level. Drawing inspiration from Zhao (2021), this paper gauges the digital economy at the prefecture level, considering two dimensions: Internet development and digital inclusive finance. Table 1 provides a detailed breakdown of the digital economy measurement. The indicators are subsequently standardized and dimensionalized using the entropy evaluation method to derive the urban digital economy.

Table 1: Components of the digital economy index

The development of the digital economy	The development of the Internet	The number of internet and mobile phone users per 100 people
		Percentage of employment information service and software industry in the total number of employees
		The per capita telecommunications business
	The development of digital financial	The number of mobile phone users per 100 people
		The breadth of coverage
		The depth of usage
		The degree of digitization

3.1.3 Moderating variables

For a more in-depth exploration of the moderating mechanism of the digital economy on the green transformation of the manufacturing industry, we introduce financial development (Fin) and urban innovation potential (Inno) as moderating variables. Financial development (Fin) is measured by the ratio of the deposit balance to GDP. Urban innovation potential (Inno) is defined as the ratio of science and technology expenditure and education expenditure to the general public budget expenditure.

3.1.4 Control variables

To capture the potential influence of economic development and environmental conditions, this study incorporates a set of control variables that might impact the green transformation of the manufacturing industry. These variables encompass population density (Pop), quantified as the ratio of the total urban population to the administrative area. Human capital level (Human) is estimated by the years of schooling per capita. Industrial structure (Str) is considered, denoted by the ratio of the tertiary industry to the total output value of the secondary sector. Additionally, the level of urban income (Wage) is included, defined as the average wage of each city. Foreign direct investment (Fdi) is introduced as well, measured as the proportion of foreign investment to GDP. Lastly, the marketization degree (Mk) is incorporated, represented by the proportion of employment in non-public enterprises.

3.2 Baseline model

Based on the theoretical work, the baseline model is designed to evaluate the green transformation of the manufacturing industry in the development process of the digital economy.

$$GTFP_{it} = \alpha_0 + \alpha_1 De_{it} + \alpha_2 Control_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (10)$$

Where subscripts i and t denote the time and the individual respectively. $GTFP_{it}$ for the dependent variable, represented by the green transformation of the manufacturing industry. De is the level of the digital economy. u_i and λ_t captures time-invariant and time-invariant omissions, respectively. The estimated parameter α_1 , estimated through balanced panel data, indicates the average (homogeneous) response of the green transformation of the manufacturing industry to changes in the digital economy. Control is the vector set of control variables. Random error ε_{it} is also considered at the tail of the formula.

3.3 Spatial econometric model

Furthermore, we investigate the spatial spillover effect between the digital economy and the green transformation of the manufacturing industry. The spatial econometric model is constructed as follows.

$$GTFP_{it} = \rho W * GTFP + \phi_1 De_{it} + \theta_1 W * De_{it} + \phi_2 Control_{it} + \theta_2 W * Control_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (11)$$

Where ρ is the spatial auto-regressive coefficient, and W is the spatial weight matrix. θ_1 represents the coefficient of spatial lag explanatory variables. $\theta_1 W * De_{it}$ denotes the exogenous interactive relationships.

The proper selection of the spatial weight matrix is crucial for spatial analysis, as it allows the capturing of various spillover effect mechanisms (Lesage and Fischer, 2008). The spatial adjacency matrix (W1) is constructed based on whether two regions are adjacent to each other. Furthermore, considering the specific characteristics of environmental pollution and energy consumption, this study incorporates the economic-geography nested matrix (W2) to provide a more accurate depiction of spatial spillover effects between regions. To sum up, this paper constructs both the spatial adjacency matrix (W1) and the economic-geography nested matrix (W2).

3.4 Data sources

This study quantifies the impact of the digital economy on the green transformation of the manufacturing industry using data from 263 cities spanning the years 2011 to 2019. The sample period is defined as such due to changes in the statistical caliber of the China City Statistical Yearbook in 2020, which would have affected the measurement of GTFP. GTFP indicator data are sourced from the Chinese City Statistical Yearbook (CCSY), while data on control variables and various indicators of the digital economy are also obtained from CCSY. Data on the development of digital inclusive finance come from the Peking University Digital Finance Research Center. For missing data, linear interpolation is applied, and certain variables are log-transformed to smooth the data and reduce heteroskedasticity. Descriptive statistics of the variables are presented in Table 2.

Variable	Mean	Std. Dev.	Min	Max	Observations
GTFP	1.267	0.5160	0.1620	4.9870	2367
De	0.1370	0.0767	0.0200	0.6440	2367
Fin	1.418	0.619	0.290	7.200	2367
Inno	0.194	0.0415	0.0100	0.370	2367
Pop	5.7630	0.9110	1.6300	7.8800	2367
Fdi	0.0172	0.0177	0.0001	0.1990	2367
Wage	10.8700	0.3170	8.5090	12.6800	2367
Mk	0.5070	0.1330	0.0500	0.9400	2367
Human	8.8660	0.9450	7.0000	13.0900	2367
Str	0.9880	0.6630	0.1100	19.2100	2367

4.0 Empirical results and discussion

4.1 Baseline regression results

Table 3 presents the baseline regression results for the digital economy and the green transformation of the manufacturing industry. In both columns (1) and (2), the coefficient of De is statistically significant, whether control variables are included or not. This signifies that

the digital economy positively influences the green transformation of the manufacturing industry. Moreover, the estimated coefficient of De passes the significance test at the 1% level, indicating that the model effectively assesses the direction and magnitude of the relationship between the digital economy and the green transformation of the manufacturing industry. Thus, H1 is preliminarily verified.

Table 3: The baseline regression results

Variables	(1) GTFP	(2) GTFP
De	1.250*** (2.71)	1.209*** (2.63)
Pop		-0.033 (-0.16)
Fdi		3.270*** (4.04)
Wage		0.173** (2.10)
Mk		0.493*** (4.86)
Human		0.007 (0.19)
Str		-0.052*** (-2.82)
Constant term	0.907*** (22.01)	-1.031 (-0.70)
Year FE	Yes	Yes
Region FE	Yes	Yes
N	2367	2367
R ²	0.221	0.242

***, **, and * denote significance at the 1, 5, and 10 % levels, respectively.

4.2 Spatial Econometric Regression Results

Before proceeding with parameter estimation, we conduct several spatial model tests, encompassing the Lagrange Multiplier (LM) test, Likelihood Ratio (LR) test, and Hausman test. As shown in Table 4, the Spatial Durbin Model (SDM) incorporating time and individual fixed effects is considered the optimal model for estimating spatial spillover effects in this study.

Table 4: Spatial model tests

significance test	Null hypothesis	W1	W2
Hausman test	The time-fixed effect association was not significant.	1471.3160** *	1471.3160** *
	The spatial fixed effect association was not significant.	(0.0000)	(0.0000)
LM test		58.0910*** (0.0000)	58.0910*** (0.0000)
	LM test no spatial lag	188.3585***	7.4017***

		(0.000)	(0.007)
	robust LM test no spatial lag	5.8772** (0.015)	0.4136 (0.520)
	LM test no spatial error	188.3356*** (0.000)	12.8238*** (0.000)
	robust LM test no spatial error	5.8543** (0.016)	5.8357** (0.016)
LR test	SDM model can be degraded to the SAR model	37.80*** (0.0000)	14.17** (0.0482)
	SDM model can be degraded to the SEM model	45.83*** (0.0000)	16.57** (0.0204)
	SDM model can be degraded to the SAR model	37.94*** (0.0000)	14.20** (0.0477)
Wald test	SDM model can be degraded to the SEM model	45.87*** (0.0000)	16.58** (0.0203)
	The individual effect is more significant than the double fixed effect.	29.63*** (0.0002)	32.72*** (0.0001)
LR test	The time effect is more significant than the double fixed effect.	1475.56*** (0.0000)	1484.91*** (0.0000)

***, **, and * denote significance at the 1, 5, and 10 % levels, respectively.

Table 5 presents the estimation results of the impact of the digital economy on the green transformation of the manufacturing industry using the time and individual fixed effect SDM models. In Table 5, W1 refers to the adjacency matrix, while W2 represents the economic-geography nested matrix. The regression results for these two matrices are displayed in columns (1) to (4) of Table 5. The spatial autoregressive coefficients are both positive at the 1% significance level, indicating that the digital economy contributes to the GTFP of the manufacturing industry. In other words, regions with an active digital economy may experience greater progress in the green development of the manufacturing industry. However, the spatial dependence based on the economic-geography nested matrix is smaller than that based on the adjacency matrix. This finding may be attributed to the fact that the production process of the manufacturing industry exhibits obvious spatial dependence. Furthermore, the coefficient of W*De is positive at the 5% significance level under the economic-geography nested matrix, while it is not significant under the adjacency matrix. These results suggest that the GTFP of the manufacturing industry is highly correlated with the level of regional economic development. Therefore, H2 is verified.

Table 5: Results of spatial Durbin models

Variables	W1 (1)	W2 (2)	W1 (3)	W2 (4)
	GTFP	GTFP	Spatial interaction items	Spatial interaction items
De	0.982** (0.02)	0.782* (0.08)	0.626 (0.41)	3.325** (0.02)
Pop	-0.403** (0.04)	-0.215 (0.27)	0.906*** (0.01)	0.693 (0.15)

Fdi	1.510*	3.136***	3.013**	1.442
	(0.05)	(0.00)	(0.01)	(0.42)
Wage	0.042	0.164**	0.534***	0.128
	(0.57)	(0.03)	(0.00)	(0.30)
Mk	0.438***	0.486***	-0.034	0.028
	(0.00)	(0.00)	(0.85)	(0.91)
Human	0.023	0.023	0.015	0.101
	(0.50)	(0.53)	(0.81)	(0.33)
Str	-0.031*	-0.043**	-0.049	-0.051
	(0.06)	(0.01)	(0.11)	(0.46)
rho	0.304***	0.129***		
	(0.00)	(0.00)		
sigma2_e	0.106***	0.116***		
	(0.00)	(0.00)		
Observations	2367	2367		
R ²	0.067	0.044		

Economic exchanges between different regions have become increasingly interconnected. As a result, the empirical results of the spatial autoregressive coefficient are not optimally demonstrated in the SDM with global effect settings. To address this, we employed the partial differential methods introduced by Lesage and Pace (2009) to dissect the total effect into direct and indirect (spillover) effects. The empirical results, as presented in Table 6, indicate a significantly positive total effect of the digital economy under both spatial weight matrices. This suggests that the digital economy has a substantial impact on the green transformation of the manufacturing industry. The flourishing digital economy in one region radiates the development of digital technology in adjacent regions, consequently enhancing the efficiency of pollution prevention and control. Notably, the indirect effect based on the economic-geography nested matrix is positive at the 1% significance level, whereas it is not significant under the adjacency matrix. This empirical finding strongly supports the idea that the digital economy in economically similar regions significantly facilitates the green transformation of the manufacturing industry. Furthermore, the coefficient of the digital economy in column (2) is smaller than that in column (5), indicating that the indirect effect is more significant under the economic-geography nested matrix. As the digital economy develops, the improvement in the transmission efficiency of the digital economy contributes to increasingly closer economic exchanges between regions. Through the technology spillover effect, the spatial dependence of technological Research and Development (R&D) activities intensifies, potentially exerting a crucial impact on the GTFP of the manufacturing industry in adjacent regions.

In comparing different models, it is evident that the indirect effect under the economic-geography nested matrix is significantly stronger than the direct effect. The difference in the coefficient of the total effect of the digital economy is 2.384 under the two spatial weight matrices. With the implementation of Chinese regional economic development policies, scientific and technological cooperation between regions is becoming more frequent, playing an essential role in the green transformation of the manufacturing industry in adjacent regions. Moreover, active regions with a digital economy are more likely to attract top talents and investment from surrounding regions, thereby exhibiting a "demonstration effect." Additionally, the development of the digital economy shows a similar trend to GDP. It is noteworthy that considering economic factors in the spatial weight matrix provides a more accurate measurement of the impact of the digital economy on the GTFP of the manufacturing industry.

This emphasizes the importance of accounting for economic interactions when assessing the influence of the digital economy on regional green transformation.

Table 6: Decomposition results of spatial effects

	W1			W2		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
De	1.046** (0.01)	1.081 (0.23)	2.127* (0.05)	0.840* (0.06)	3.671*** (0.01)	4.511*** (0.00)
Pop	-0.362** (0.02)	1.061*** (0.01)	0.699 (0.11)	-0.224 (0.17)	0.757 (0.12)	0.533 (0.28)
Fdi	1.839** (0.03)	4.704*** (0.00)	6.544*** (0.00)	3.226*** (0.00)	2.106 (0.33)	5.332** (0.02)
Wage	0.092 (0.26)	0.755*** (0.00)	0.847*** (0.00)	0.173** (0.04)	0.179 (0.26)	0.352* (0.06)
Mk	0.428*** (0.00)	0.132 (0.61)	0.560* (0.06)	0.469*** (0.00)	0.104 (0.74)	0.573* (0.09)
Human	0.026 (0.44)	0.022 (0.77)	0.048 (0.58)	0.026 (0.45)	0.105 (0.33)	0.132 (0.27)
Str	-0.035** (0.03)	-0.075** (0.05)	-0.110** (0.01)	-0.043** (0.01)	-0.057 (0.43)	-0.100 (0.17)

***, **, and * denote significance at the 1, 5, and 10 % levels, respectively.

4.3 Heterogeneity analysis

4.3.1 Heterogeneous effect across urban resource endowments

We categorized our original sample into two groups based on the "National Sustainable Development Plan for Resource-based Cities (2013-2020)." Subsequently, we separately discussed the economic effects of the De on the GTFP within these subsamples. The results presented in columns (1) and (2) of Table 7 illustrate that the coefficient of De is not significant, regardless of whether control variables are added. However, the results in columns (3) and (4) suggest that this effect is statistically significant in cities with limited natural resources. The reason may be that the convenience and availability of natural resources in resource-based cities lead to less consideration of improving energy efficiency. In contrast, cities with limited natural resources prioritize the development of advanced digital technologies, helping further improve the marginal productivity of various resources. Based on the above analysis, H3 is supported.

Table 7: Results of natural resource heterogeneity

Variables	Resource-based cities		Non-resource-based cities	
	(1)	(2)	(3)	(4)
De	1.718 (1.21)	0.556 (0.39)	1.161** (2.43)	1.368*** (2.91)
Constant	0.906*** (10.41)	-4.843** (-1.99)	0.898*** (17.81)	2.228 (1.20)
Control variables	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes

Observations	945	945	1422	1422
R ²	0.197	0.222	0.247	0.291

***, **, and * denote significance at the 1, 5, and 10 % levels, respectively.

4.3.2 Heterogeneous effect across urban hierarchy

To investigate potential variations in the impact of De on the GTFP of the manufacturing industry, we distinguished between central cities and peripheral cities. Municipalities directly under the Central Government and sub-provincial cities, as well as provincial capital cities, were classified as central cities, while other cities were regarded as peripheral cities. As presented in columns (1) to (4) of Table 8, the digital economy plays a more significant role in stimulating the green transformation of the manufacturing industry, whether control variables are added. However, this impact is less pronounced in peripheral cities after incorporating control variables. Theoretically, robust economic growth and relatively developed information technology infrastructure in central cities provide favorable opportunities for the improvement of GTFP in the manufacturing industry. Based on the above analysis, H4 is verified.

Table 8: Results of hierarchical heterogeneity

Variables	Peripheral Cities		Central cities	
	(1)	(2)	(3)	(4)
De	1.506*	1.107	1.647***	1.229**
	(1.94)	(1.43)	(2.62)	(2.09)
Constant	0.907***	-1.053	0.728***	-10.337**
	(16.88)	(-0.64)	(6.16)	(-2.01)
Control variables	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	2070	2070	297	297
R ²	0.216	0.237	0.286	0.406

***, **, and * denote significance at the 1, 5, and 10 % levels, respectively.

4.3.3 Heterogeneous effect across urban policy intensity

The urban category is divided into two subsamples based on the "Action Outline for Promoting the Development of Big Data" issued by The State Council in 2015. Therefore, we established two subsamples, including pilot cities and non-pilot cities. As displayed in Table 9, the digital economy plays a significant role in facilitating the green transformation of the manufacturing industry in pilot cities. These findings may be attributed to the presence of well-established digital infrastructure and robust policy support in these cities, often resulting in a more dynamic digital economy. However, this relationship is not significant in non-pilot cities. The positive impact of the digital economy is inseparable from the support of national policy. The development of the digital economy in pilot cities has been significantly improved, thereby enabling the green transformation of the local manufacturing industry. In conclusion, H5 is supported.

Table 9: Regression results of policy intensity heterogeneity

Variables	Non-pilot cities		Pilot cities	
	(1)	(2)	(3)	(4)
De	0.982 (1.54)	0.904 (1.40)	1.513** (2.15)	1.721** (2.54)
Constant	0.936*** (18.97)	2.551 (1.43)	0.855*** (10.45)	-10.337** (-2.01)
Control variables	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	1674	1674	693	693
R2	0.235	0.253	0.205	0.293

***, **, and * denote significance at the 1, 5, and 10 % levels, respectively.

5.0 Further analysis: moderating effects

The green transformation of the manufacturing industry relies heavily on strong support from urban financial development. Sufficient financial backing not only serves to stimulate green technological innovation in manufacturing enterprises but also expedites the overall upgrade of the manufacturing industry. Additionally, urban innovation potential stands out as a crucial driver in the green transformation of the manufacturing industry. Traditional manufacturing industries often grapple with issues such as high environmental costs and low energy utilization efficiency. Urban innovation potential can assist traditional manufacturing enterprises in achieving resource conservation and recycling, reducing reliance on limited resources, and adopting more environmentally friendly and energy-efficient modes of production and operation. To further test the moderating effects of urban financial development and innovation potential on the green transformation of the manufacturing industry, this paper introduces interaction terms involving the digital economy, urban financial development, and urban innovation potential, respectively. The results are presented in Table 10.

The green innovation activities of cities stand to benefit from robust urban financial development. In areas with well-established financial systems, enterprises exhibit heightened awareness and enthusiasm to engage in green transformation activities. Moreover, improved urban financial development can streamline channels for enterprises to secure ample investment, leading to the expansion of enterprise scales. However, this expansion may trigger a range of adverse effects on environmental conservation, such as increased energy consumption and pollution emissions. To analyze the moderating effect of urban financial development on the green transformation of the manufacturing industry, this study introduces the interaction term of the digital economy and urban financial development to the baseline regression model. The results in column (1) of Table 10 demonstrate that urban financial development plays a significantly negative role in moderating the relationship between the digital economy and the green transformation of the manufacturing industry. In other words, the enhancement of urban financial development evidently weakens the impact of the digital economy on the green transformation of the manufacturing industry.

Positioned as the fundamental breakthrough for overcoming the sustained economic growth dilemma, technological innovation has gradually emerged as a pivotal enabler for the green transformation and upgrading of industries. In the present context, the green transformation of

the Chinese manufacturing industry faces a bottleneck period, where technological innovation serves as the indispensable catalyst for progress. In essence, technological innovation bears significant potential for enhancing green total factor productivity in the manufacturing industry. To explore the potential moderating effect of urban innovation potential, we introduce the interaction term of the digital economy and urban innovation potential to the baseline regression model. As evident in column (2) of Table 10, the positive impact of urban innovation potential on the green transformation of the manufacturing industry is statistically significant at the 1% level. In other words, our findings substantiate the crucial role of urban innovation potential in moderating the association between the digital economy and the green transformation of the manufacturing industry. The underlying rationale for these results lies in the fact that improved urban innovation potential enhances the efficiency of resource allocation in the manufacturing industry, thereby motivating manufacturing enterprises to undertake green transformation activities.

Variables	(1) GTFP	(2) GTFP
De	1.651*** (3.21)	1.101** (2.38)
Fin	-0.233*** (-5.78)	
De*Fin	-0.606*** (-2.82)	
Inno		0.584 (1.40)
De*Inno		11.953*** (3.22)
Constant	-0.024 (-0.02)	-0.221 (-0.15)
Year FE	Yes	Yes
Region FE	Yes	Yes
Observations	2367	2367
R ²	0.260	0.246

***, **, and * denote significance at the 1, 5, and 10 % levels, respectively.

6.0 Robustness tests

To ensure the robustness of our findings, we employ the following methods for robustness testing. First, we include a crucial control variable in the regression analysis. Second, we use the digital inclusive financial comprehensive index as a proxy for the digital economy. Lastly, to mitigate the impact of outliers, we apply winsorization to all control variables, limiting them to the 1% level.

6.1 Addition of control variables

Specifically, two sets of regression results need to be considered. The first set is the result of the baseline regression model, while the second set is the result after adding environmental regulations. These results are presented in columns (1) and (2) of Table 11. After adding

environmental regulations, the change in the regression coefficient of De is only 0.004. Importantly, the significance and directionality remain consistent with the baseline regression, highlighting the robustness of the benchmark outcomes.

6.2 Substitution of the core independent variable

We replace De by using the digital inclusive financial comprehensive index. Subsequently, the baseline model is re-estimated, as shown in column (3) of Table 11. The statistical analysis demonstrates that the digital economy can advance the green transformation of the manufacturing industry at 5% level of significance. The results coincide with the findings shown in Table 4.

6.3 Tail shrinkage test

To overcome the interference of randomness on model estimation, this paper applies the tail shrinkage test. Column (4) of Table 11 shows that after removing extreme values, the estimated coefficient for De remains significant. The results further confirm the feasibility of the baseline outcomes. Overall, the results in this section provide enough robustness check to our baseline regression result.

Table 11: Regression results of robustness test

Variables	(1) GTFP	(2) GTFP	(3) GTFP	(4) GTFP
De	1.209*** (2.63)	1.213*** (2.63)	1.048** (2.39)	1.253*** (2.75)
Constant	-1.031 (-0.70)	-1.043 (-0.71)	-0.978 (-0.66)	-3.208** (-2.00)
Er	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	2367	2367	2359	2367
R2	0.242	0.242	0.242	0.259

***, **, and * denote significance at the 1, 5, and 10 % levels, respectively.

7.0 Conclusions and Policy Implication

The prosperity and development of the digital economy significantly contribute to the green transformation of the manufacturing industry. Our research provides specific insights into the relationship between De and GTFP in the Chinese manufacturing industry. Empirical analyses were conducted using fixed-effect models, the spatial Durbin model, and the moderating effect model, examining prefecture-level panel data from 2011 to 2019. This paper aims to maximize the transformative impact of the digital economy on improving the GTFP of the manufacturing industry. Additionally, empirical findings on urban heterogeneity offer a comprehensive understanding of this relationship, providing essential insights for policymakers grappling with the challenges of sustainable societal and economic development. The conclusions and policy implications are discussed as follows.

- (1) The digital economy significantly improves the green transformation of the manufacturing industry. This conclusion remains robust even after a series of tests.
- (2) Through spatial spillover effects, the digital economy also possesses an essential effect on the green transformation of the manufacturing industry of geographically close or economically similar areas.
- (3) The positive effects of the digital economy are more pronounced on the green transformation of the manufacturing industry in resource-exhausted cities, in central cities, and in cities with greater policy intensity.
- (4) The moderating effect of financial development on the green transformation of the manufacturing industry is negative, while the urban innovation potential has a positive moderating effect.

Based on the main conclusions, this paper suggests several policy implications. Firstly, it is imperative to prioritize the potential influence of the digital economy to facilitate green and sustainable development across society. In this regard, the government is recommended to expedite research and development efforts focused on clean and low-carbon technologies. To support this, policymakers should consider fostering comprehensive industry-university-research platforms that drive the integration of digital and low-carbon technologies into manufacturing, thereby enhancing the fundamental capabilities of digital research and development. Additionally, proactive policy measures are essential, encouraging the manufacturing industry to establish a robust pollution regulation system and expedite the green transformation of manufacturing practices.

Second, the Chinese authorities are advised to focus on addressing the "resource curse." The abundance of natural resources often leads to a "path dependence" development model in resource-based cities. Policymakers should prioritize investments and enhance digital infrastructure to reduce dependence on traditional resources. Additionally, policies can be formulated to optimize the structure of production factors, with a specific focus on stimulating green and sustainable development in the manufacturing industry. Such policies can help minimize the environmental impact of manufacturing production.

Third, considering the relatively weak impact of the digital economy on the green transformation of the manufacturing industry in peripheral cities, policymakers should prioritize increased investment in infrastructure construction in these areas. Accelerating the green transformation of the manufacturing industry in peripheral cities is crucial, and policies should encompass various aspects, including measures to attract advanced technical talents and support research and development of clean technologies. Furthermore, by facilitating regional cooperation and economic exchanges between different areas, policymakers can enhance the green total factor productivity of the manufacturing industry.

Finally, policymakers should fully leverage the enabling role of digital policies, recognizing their significant positive impact. Policymakers are encouraged to actively promote the flourishing of the digital economy, addressing barriers to the flow of all types of production factors. This approach can minimize resource consumption and improve resource utilization efficiency. Moreover, Chinese authorities should commit to fostering the widespread adoption of digital policies in manufacturing production processes, leading a green revolution across the entire production process of the manufacturing industry.

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