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Empirical Analysis of the Impact of Green Finance and Technological Progress on Total Factor Productivity in China's Industrial Sector

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Abstract: The enhancement of industrial green total factor productivity is pivotal for achieving high-quality and sustainable economic development. This study assesses China's performance using the SBM-GML model, employing province-level panel data spanning from 2004 to 2020. Furthermore, we examine the influence of green finance and technological progress on industrial green total factor productivity using a spatial econometric model. The findings uncover that the relationship between the level of green financial development and industrial green total factor productivity follows a U-shaped curve. Initially, low levels of green financial development exert a suppressive effect on industrial green total factor productivity, proving ineffective in the short term. However, with the progression of green finance development, a positive and significant long-term impact on industrial green total factor productivity emerges. Moreover, technological progress demonstrates a noteworthy promotional effect on industrial green total factor productivity. The analysis delves deeper into revealing that industrial structure and environmental regulation intensity exhibit a significant negative relationship with industrial green total factor productivity. In contrast, both energy structure and education level showcase a substantial positive relationship with industrial green total factor productivity.

Keywords: Industrial green total factor productivity; Green finance; Technological progress

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1. Introduction

The 20th Party Congress report advocates for expediting the construction of a modernized economic system with a primary focus on enhancing total factor productivity. The industrial sector, being instrumental in national economic development, plays a pivotal role in fostering high-quality economic progress. Despite the remarkable advancements in the industry over the past forty years of reform and opening, China's manufacturing value added has consistently ranked first globally for over a decade. However, the conventional rugged industrial development model has resulted in excessive energy consumption and environmental pollution.

Between 2012 and 2021, China's industrial value-added consumed nearly 70% of its energy, emitting almost 80% of sulfur dioxide and 60% of nitrogen oxides [1]. To propel high-quality and sustainable economic development, an imperative shift toward green and low-carbon transformation in the industry is crucial. Traditional total factor productivity (TFP), not accounting for environmental pollution and resource consumption [2], necessitates the introduction of industrial green TFP. By incorporating environmental and resource measures [3], this framework accurately portrays the current state of China's industrial economic development in the new era.

Therefore, optimizing China's industrial green total factor productivity emerges as the key strategy to advance high-quality and sustainable economic development in the industrial sector. This optimization is integral to realizing the green and low-carbon transformation imperative for the industrial sector's future.

2. Literature review

In our research context, existing literature has delved into various factors influencing China's industrial green total factor productivity. These factors encompass environmental regulation, forward direct investment (FDI), outward foreign direct investment (OFDI), land resource mismatch, financial aggregation, industrial agglomeration, and financial mismatch, among others. Taking a perspective rooted in green finance, Ziju Yin *et al*. employed a spatial Durbin model and concluded that the level of green finance development exhibits a U-shaped relationship with green total factor productivity [4]. Notably, both showcase a distribution pattern of being "high in the east," "flat in the middle," and "low in the west." Research conducted by Chong Wang and Lei Wang reveals that green credit influences green total factor productivity through two distinct pathways: industrial structure upgrading and green innovation [5]. Yanwei Lyu posits that digital finance indirectly fosters the enhancement of industrial green total factor productivity by driving technological innovation, facilitating industrial upgrading, and invigorating entrepreneurial vitality [6]. Baolong Yuan and Chen Li contend that innovation in invention patents serves as a pivotal driver for achieving green growth in the Chinese industry [7]. Empirical evidence provided by Haibo Sun [8], utilizing Tobit and Panel Smooth Transition Regression (PSTR) models, substantiates the positive impact of technological innovation on industrial green total factor productivity. The collective insights from these studies contribute to a comprehensive understanding of the multifaceted dynamics shaping China's industrial green total factor productivity.

3. Model construction, data source, and variable measurement

The objective of this paper is to explore the influence of green finance and technological progress on industrial green total factor productivity, along with their respective impact paths. Consequently, the independent variables in focus are green finance and technological progress, while the dependent variable is industrial green total factor productivity. To assess their impact and pathways, this study adopts spatial econometric models as proposed by the spatial econometric theory of Cliff and Ord [9], specifically the spatial lag model (SLM), spatial error model (SEM), and spatial autoregressive model introduced by Anselin [10]. The following equation represents the model constructed in this study:

In the equation, represents industrial green total factor productivity. The variables include and (error terms for spatial and temporal fixed effects), (green finance), (the square term of GF), (technological progress), (industrial structure), (energy structure), (educational attainment), and (environmental regulation intensity). is a random disturbance term, denotes the 30 individual provinces and cities, and represents time. is a vector of independent variable coefficients, and is a spatial lag coefficient of the error term .

This study encompasses data from 30 provinces in China spanning from 2004 to 2020, with Tibet, Hong Kong, Macao, and Taiwan regions excluded due to data availability and completeness constraints.

4. Empirical results and explanations

4.1. Estimation results of panel data model and spatial correlation test

To assess the suitability of the spatial econometric model for the study's content, this paper employs the widely used panel data analysis method. Subsequently, a spatial autocorrelation test is conducted on the residuals. **Table 1** presents the estimation results of the four models, with model selection guided by a comparison of statistical indicators.

Table 1. Estimates and test results of panel data models

Variables	Mixture	Space fixed effect	Time fixed effect	Two-way fixed effects
GF	8.792***	16.1445***	-4.6744	-4.6744
	(3.1931)	(7.0141)	(-1.6418)	(-1.6418)
AGF	-27.6575***	-23.4576***	-3.979	-3.979
	(-4.4883)	(-5.3464)	(-0.655)	(-0.655)
TP	-0.5938	0.8343	-1.253***	-1.253***
	(-1.1515)	(1.1465)	(-2.6751)	(-2.6751)
IS	0.6306***	-0.6601***	0.4374***	0.4374***
	(3.6888)	(-2.6293)	-2.7983	(2.7983)
ES	-0.5924	-1.0788*	-0.9142**	-0.9142**
	(-1.2526)	(-1.665)	(-2.1416)	(-2.1416)
EDU	0.6738***	1.3083***	0.5728***	0.5728***
	(2.7607)	(2.5909)	-2.6134	(2.6134)
ERI	-33.6729*	-49.8931***	-7.5553	-7.5553
	(-1.8305)	(-3.4346)	(-0.4345)	(-0.4345)
R-squared	0.1005	0.6663	0.2769	0.7305
Log-L	-792.3294	-539.4621	-736.6702	-484.9882
DW	1.9166	1.8886	2.1555	2.1444
LM-sar	1.2548	1.2039	14.1047***	12.8824***
Robust LM-sar	52.5763***	31.2807***	0.0088	11.024***
LM-err	0.3389	0.7615	14.7412***	18.7697***
Robust LM-err	51.6604***	30.8382***	0.6453	16.9113***

Note: *, **, and *** denotes significance levels at 10%, 5% and 1%, respectively

Table 1 reveals that the two-way fixed effect model boasts the highest coefficient of determination (0.7305) and the most favorable fitting effect, as indicated by the "Log-L" statistic (-484.9882). In contrast, the mixed model registers the lowest coefficient of determination (0.1005) and the least satisfactory fitting effect, reflected in a "Log-L" statistic of -792.3294. Therefore, the two-way fixed effects model emerges as the most suitable for the research objectives outlined in this paper.

4.2. Estimation results of the spatial panel data model

Building on the analysis of the impact of green finance on industrial green TFP, **Table 2** demonstrates that the coefficient of green finance (GF) is negative, while its quadratic (AGF) coefficient is positive. Both coefficients are statistically significant at the 1% and 5% significance levels, respectively. This further validates Hypothesis 1, with the U-shaped inflection point value identified as 0.5727.

Table 2. Estimation results of spatial panel data model (two-way fixed effect model)

Variables	SEM	SLM
GF	-11.7947***	-9.7508***
	(-3.2109)	(-2.7137)
AGF	13.5085**	10.5325*
	(2.3569)	(1.8644)
TP	1.1883*	1.1697*
	(1.6632)	(1.7114)
IS	-1.1171***	-1.0585***
	(-4.4883)	(-4.0864)
ES	1.2833**	0.8195
	(2.031)	(1.2948)
EDU	0.8845*	0.6868
	(1.8593)	(1.4323)
ERI	-22.9589*	-24.3655*
	(-1.6492)	(-1.6642)
W*dep.var.		-0.2072***
		(-3.3386)
spat.aut.	-0.2622***	
	(-4.1298)	
R-squared	0.7296	0.7409
Log-L	-473.39124	-477.4345

Note: *, **, and *** denotes significance levels at 10%, 5% and 1%, respectively

Regarding the technological progress variable, this paper explores its influence on industrial green TFP. The results indicate that the coefficient of technological progress (TP) is positive and significant, confirming Hypothesis 2. This underscores the crucial role of technological progress in realizing green and sustainable development within the industrial production environment, thereby facilitating the transformation and upgrading of industrial development.

To ensure the robustness of the impact of green finance and technological progress on industrial green TFP, this paper introduces the economic spatial weight matrix for a robustness test, replacing the adjacency matrix. While the robustness test yields results somewhat different from the initial empirical analysis, the influence direction and coefficient size of the core variables – green finance, its quadratic term, and technological progress – remain largely consistent. This indicates the credibility and robustness of the conclusions drawn regarding the impact of green finance and technological progress on industrial green TFP.

5. Conclusions

This paper employs the SBM-GML model to measure the industrial green TFP across 30 provinces from 2004 to 2020. Additionally, it establishes a spatial econometric model to investigate how green finance and technological progress impact industrial green TFP. The key conclusions are outlined below:

Firstly, industrial green TFP exhibits a U-shaped trend with the progression of green finance levels. The underdevelopment of green finance hampers the enhancement of industrial green TFP. However, as green finance develops, there is an optimization of industrial green TFP. Technological progress significantly promotes industrial green TFP.

Secondly, in practical terms, industrial green TFP is influenced by other factors. Notably, industrial structure and the intensity of environmental regulation have a substantial negative impact, while energy structure and education level demonstrate a significant positive influence.

The prolonged reliance on the "Extensive type" growth model within input-intensive industries has resulted in a rapid surge in energy consumption and carbon emissions. This unsustainable development model curtails the potential and competitiveness of the economy. Consequently, China must expedite the green transformation of its industry, transitioning to a low-carbon, clean, and efficient production mode. This shift should prioritize fostering a mutually beneficial relationship between the economy and the environment.

To achieve these goals, it is imperative to enhance the green financial system and bolster the capacity of green finance. This involves establishing government-led, market-oriented green finance rooted in enterprise needs and infrastructure. Leveraging the synergy between green finance professional institutions and talents, the establishment of specialized green finance service institutions and talent training becomes crucial. Simultaneously, playing an open role in green financial trading platforms, setting environmental performance thresholds, disclosing enterprise environmental information, and utilizing diverse means such as green credit and green bonds will help mobilize idle financial capital in society, fostering the development of green finance. This comprehensive approach is essential for steering China toward a sustainable, environmentally friendly economic trajectory.

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