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Original Paper

How FinTech Influences Green Industry Development: A Causal Inference Study Based on Double Machine Learning

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Abstract

This study employs panel data from 30 provinces between 2011 and 2023 to conduct an empirical analysis on the impact of tech finance on green industry development using a double machine learning model. The findings demonstrate that the advancement of tech finance contributes positively to the growth of green industries. The regression results remain consistent after a series of robustness tests. Mechanism analysis indicates that tech finance fosters green industry development by promoting the agglomeration of technological talent and facilitating industrial structure upgrading. Heterogeneity tests reveal that tech finance has a significant promoting effect on green industry development in eastern and central regions, while its impact is not statistically significant in the western region.

Keywords

tech finance, green industry development, double machine learning, impact effects

1. Introduction

The importance and urgency of thoroughly implementing the sustainable development strategy have become a broad consensus. The comprehensive green transformation of economic and social development serves as a core manifestation of practicing the concept of sustainable development. Among these efforts, the green transformation of production modes and lifestyles will ultimately be realized through the development of green industries. Promoting the green and low-carbon transition of the economy and society is widely regarded as a crucial link in achieving high-quality development.

In the current landscape of financial development, "building a strong financial nation" has emerged as a strategic objective for the industry. In 2023, the focus within the sector has widely centered on five key areas: technology finance, green finance, inclusive finance, pension finance, and digital finance. Among these, technology finance is regarded as a core driver for technological innovation and economic growth. Against this backdrop, exploring the role of technology finance in promoting the development of green industries and analyzing its underlying mechanisms will not only help clarify its practical effects in fostering green transformation but also provide valuable insights for advancing related fields.

2. Literature Review and Research Question

Academic research on technology finance has a well-established history. Some scholars trace the origin of the term "technology finance" to the establishment of the China Association for Promotion of Science and Technology Finance in 1992, indicating its distinct Chinese characteristics. Fang (2015) conceptualizes the essence of technology finance as aiming to cultivate high value-added industries, create high-wage employment, and enhance overall economic competitiveness by fostering deep integration and convergence of innovative elements such as technological capital, innovation capital, and entrepreneurial capital.

From an empirical perspective, Lei et al. (2024) employed the Dagum Gini coefficient to analyze the development level of technology finance across China's eight major economic regions and used kernel density estimation to examine its dynamic evolution. Other scholars have investigated the impact of technology finance from various angles, including the agglomeration of scientific and technological talent (Xie, 2022), the quality of firms' export products (Huang & Zhang, 2022), green technological innovation (Zhou & Wang, 2023), urban carbon emission performance (Jiang & Jia, 2024), and the high-quality development of the real economy (Zou & Zhou, 2024).

Regarding the concept of "green industry," some academics suggest it originated from the term "Green Plan" proposed by the Canadian Minister of the Environment in 1989, which for the first time integrated environmental considerations with overall socio-economic development at a macro level. Existing research on green industries is predominantly policy-oriented, focusing on development strategies for specific regions such as Western China, Jiangxi Province, and the Wuyi Shan Mountain area. Empirical studies on green industries remain relatively limited. Notable examples include Ye et al. (2022), who analyzed the impact of financial agglomeration on green industry development, and Zhang and Yao (2024), who explored the effects of green credit on the development of green industries in agriculture and rural areas.

Therefore, while academic research on technology finance is substantial, empirical studies on green industry development remain relatively scarce, and research specifically exploring the impact of technology finance on green industry development is notably lacking. Furthermore, existing studies predominantly rely on traditional econometric models, with limited application of machine learning algorithms. To address these gaps, this study utilizes panel data from 30 Chinese provinces spanning 2011 to 2023 and employs a double machine learning model to analyze the impact effects and underlying mechanisms of technology finance on green industry development. The potential marginal contributions of this paper are as follows: (1) It integrates technology finance and green industry development within a unified analytical framework, thereby enriching the research findings on green industry development. (2) It adopts a machine learning algorithm, which offers the distinct advantage of potentially overcoming the "curse of dimensionality." (3) It investigates the potential mechanisms through which technology finance development influences green industry development, thereby contributing to the empirical evidence regarding this relationship.

3. Research Hypotheses

3.1 Direct Impact of Technology Finance on Green Industry Development

Technology finance can directly influence green industry development through three primary channels: alleviating financing constraints, promoting green production, and stimulating green consumption. First, many green enterprises are in the early stages of technological R&D and innovation. They often face challenges such as unstable business models, inconsistent definitions of "green" among financial institutions, and insufficient support for the green economy, leading to difficulties in securing affordable financing. Technology finance can address this by directing financial resources—through instruments like non-reimbursable grants, repayable funding, loan interest subsidies, and post-project subsidies—towards major national technological innovation initiatives. By prioritizing the allocation of resources to ecological protection and sustainable development projects (Fu & Wang, 2025), technology finance helps mitigate the financing constraints faced by green industries. Second, technology finance provides crucial funding for corporate energy-saving and emission-reduction initiatives. This financial support encourages firms to integrate ecological considerations into their production processes, thereby fostering green production. Furthermore, providers of technology finance can raise lending standards for high-pollution enterprises by tightening financing requirements and shortening debt maturities, which stimulates these firms to improve their production technologies (Li & Cai, 2024). Finally, the development of technology finance facilitates financing for emerging industries, such as small and medium-sized technology enterprises in their start-up and growth phases, as well as specialized "little giant" firms. This support helps build a pipeline for future green product development and manufacturing (Liu, Xu, & Song, 2024). Additionally, through its ecological awareness effect, technology finance can enhance public environmental consciousness, thus promoting the growth of green consumption.

3.2 Analysis of Impact Mechanisms: Technology Finance on Green Industry Development

To further elucidate the relationship between technology finance development and green industry development, this paper examines the transmission mechanisms through two pathways: the agglomeration of scientific and technological talent, and financial agglomeration.

First, technology finance affects green industry development through the talent agglomeration channel. Specifically, technology finance generates a talent concentration effect. It provides tailored financial services for technology enterprises, particularly SMEs, alleviating their financing constraints. With adequate innovation funding, firms demonstrate greater initiative in pursuing advanced innovation, consequently generating substantial demand for scientific talent and creating numerous employment opportunities (Li & Zhang, 2025). Moreover, the development of technology finance is accompanied by policy measures such as increased fiscal subsidies for innovation and enhanced insurance coverage for technical personnel. These supports attract significant talent concentration (Yang, 2025). Additionally, cities with advanced technology finance systems typically implement comprehensive incentive packages, including housing support, residency permits, education, and healthcare benefits, to retain skilled professionals (Xie, 2022) thereby fostering high-level talent agglomeration. The agglomeration of scientific and technological talent subsequently promotes green industry development through multiple channels. Technologically skilled workers attract green enterprises to specific regions, facilitating the formation of green industrial clusters and supporting the development of optimized green industry chains. Such cluster development enhances resource utilization efficiency, reduces production costs, increases collaboration frequency among firms, and ultimately drives innovation in green production technologies (Wang, Feng, Li et al., 2025). Furthermore, higher-income groups, typically associated with talent agglomeration areas, generally exhibit stronger preferences and willingness for green consumption compared to lower-income groups (Shi & Yi, 2020). This expands local green market scale and stimulates green innovation activities within industries. Simultaneously, green consumption generates demonstration effects that encourage wider adoption of environmentally friendly consumption patterns among residents (Bao, Yin, & Yang, 2025). Based on this analysis, we propose the following research hypothesis:

Hypothesis H2a: Technology finance development promotes green industry development by facilitating the agglomeration of scientific and technological talent.

Second, technology finance influences green industry development through the channel of industrial structure upgrading. On one hand, technology finance promotes industrial structure upgrading by optimizing resource allocation efficiency. First, it provides a favorable financial environment for technology enterprises, effectively alleviates financing constraints, facilitates capital accumulation, and enables better allocation of production factors, thereby driving industrial transformation. Second, the development of technology finance fosters effective integration of financial resources and directs them toward high-efficiency production sectors, consequently improving the allocation efficiency of resource elements. Simultaneously, by facilitating access to financial support for technology entrepreneurs, it enhances entrepreneurial efficiency and further accelerates industrial structure upgrading (Zhang & Wang, 2023). Third, technology finance reduces financial risks in innovation activities, effectively improving regional technological progress efficiency (Li & Liu, 2021). The widespread application of new technologies accelerates the phase-out of obsolete enterprises while supporting competitive emerging firms, thus speeding up industrial transformation. On the other hand, industrial structure upgrading contributes to green industry development through multiple channels (Lun & Liu, 2022). First, it facilitates the elimination of backward polluting enterprises while strengthening support for new green businesses. Second, from the perspective of upper and middle industrial chains, industrial upgrading drives rapid iteration in product development and production technologies, accelerating the development of new green industries. Third, industrial structure upgrading enhances diversification competition in industries and products, promotes the transformation of manufacturing services, and strengthens green industry innovation capacity (Huang, H., Huang, H., Xiao, Y. et al., 2024). Based on this analysis, we propose the following research hypothesis:

Hypothesis H2b: Technology finance development promotes green industry development by facilitating industrial structure upgrading.

4. Research Design

4.1 Econometric Model

4.1.1 Model Specification

This study employs the Double Machine Learning approach to identify the impact of technology finance development on green industry development. The following double machine learning model is constructed:

$$GL_{it+1} = \theta_0 TF_{it} + g(X_{it}) + U_{it} \tag{1}$$

$$E(U_{it} | TF_{it}, X_{it}) = 0 \tag{2}$$

In the equations: i denotes the city; t denotes the year; GL_{it+1} represents the level of green industry development; TF_{it} indicates the level of technology finance development; θ_0 denotes the coefficient of technology finance development, which is the primary focus of this study; X_{it} refers to the control variables, with the functional form $\hat{g}(X_{it})$ to be estimated using machine learning algorithms; U_{it} represents the error term.

Direct estimation of Equation (1) and Equation (2) may yield biased results. This bias arises because, in high-dimensional or complex model settings, machine learning models must incorporate regularization terms to reduce dimensionality. While this approach mitigates excessive variance in the estimators, it introduces regularization bias, preventing $\hat{\theta}$ from converging to the true parameter θ_0. To address this issue, the following auxiliary regression is constructed:

$$TF_{it} = m(X_{it}) + V_{it} \tag{3}$$

$$E(V_{it} | X_{it}) = 0 \tag{4}$$

In the equations: $m(X_{it})$ represents the regression function of the treatment variable on the high-dimensional control variables, with its functional form $\hat{m}(X_{it})$ to be estimated using machine learning algorithms. The specific procedure is as follows: First, a machine learning model is employed to estimate $m(X_{it})$, obtaining the estimator $\hat{m}(X_{it})$. Next, the residual term V_{it} is calculated as $\hat{V}_{it} = TF_{it} - \hat{m}(X_{it})$. This residual $\hat{V}_{it}$ is then used as an instrumental variable for TF_{it} in the estimation process. Finally, machine learning algorithms are applied again to estimate the function $g(X_{it})$, yielding the estimator $\hat{g}(X_{it})$, and thereby obtaining an unbiased estimate of the parameter of interest

$$\hat{\theta}_0 = \left(\frac{1}{n} \sum_{i \in I, t \in T} \hat{V}_{it} TF_{it} \right)^{-1} \frac{1}{n} \sum_{i \in I, t \in T} \hat{V}_{it} \left(GL_{it+1} - \hat{g}\left(X_{it} \right) \right).$$

4.1.2 Variable Selection

This study selects the following four categories of variables.

(1) Dependent Variable

Green Industry Development Level (GL). This study constructs a comprehensive evaluation system for green industry development, comprising three systemic layers and twenty two specific indicators, as detailed in Table 1. Subsequently, all indicators are standardized through mean normalization to eliminate dimensional influences. Finally, the entropy method is applied to determine indicator weights, and the green industry development level is measured using a weighted aggregation approach.

Table 1. Comprehensive Evaluation Index System of Green Industry Development

System Level	Indicator Level	Indicator Attribute	Unit
Green Production	Electricity consumption per 10,000 yuan of GDP	Negative	10,000 kWh/ 10,000 yuan
	Industrial water consumption per 10,000 yuan of GDP	Negative	Cubic meters/10,000 yuan
	Comprehensive utilization rate of general industrial solid waste	Positive	%
	Proportion of output value of tertiary industry and agriculture, forestry, animal husbandry and fishery services in primary industry in GDP	Positive	%
	GDP per unit of land	Positive	100 million yuan/square kilometer
	Proportion of environmental protection expenditure in fiscal expenditure	Positive	%
	Proportion of completed investment in industrial pollution control in fiscal expenditure	Positive	%

System Level	Indicator Level	Indicator Attribute	Unit
	Number of authorized domestic patent applications per 10,000 people	Positive	Items/10,000 people
	Average transaction volume per technology market contract	Positive	10,000 yuan/ contract
Green Consumption	Urban sewage treatment rate	Positive	%
	Harmless treatment rate of domestic waste	Positive	%
	Number of public transport vehicles per 10,000 people	Positive	Standard veh icles/10,000 people
	Proportion of water-saving irrigation in agricultural land	Positive	%
	Chemical fertilizer usage per unit area of agricultural land	Negative	Tons/10,000 hectares
	Pesticide usage per unit area of agricultural land	Negative	Tons/10,000 hectares
	Urban gas penetration rate	Positive	%
Green Environment	Forest coverage rate	Positive	%
	Proportion of wetland area in the jurisdiction area	Positive	%
	Proportion of artificial afforestation area in the jurisdiction area	Positive	%
	Proportion of nature reserve area in the jurisdiction area	Positive	%
	Chemical oxygen demand (COD) emissions	Negative	10,000 tons
	Number of civil motor vehicles per 10,000 people	Negative	Vehicles/10,0

(2) Independent Variable

Technology Finance (TF). Following the methodology established in prior literature (Fang, Guo, & Xia, 2023), a comprehensive evaluation index system for technology finance is constructed. This system comprises two primary dimensions and a total of ten specific indicators, as presented in Table 2. The entropy method is then employed to calculate the comprehensive technology finance index (TF) for each province and each year.

Table 2. Comprehensive Evaluation Index System of Technology Finance

System Level	Indicator Level	Indicator Explanation	Indicator Attribute	Unit
Public Technology Finance	Number of scientific and technological activity personnel	Ratio of R&D personnel in high-tech enterprises to total employees	Positive	-
	R&D institution resources	Ratio of number of R&D institutions in high-tech industry to total number of enterprises	Positive	-
	Per capita fiscal expenditure on science and technology	Fiscal expenditure on science and technology/total population	Positive	Yuan
	Intensity of fiscal expenditure on science and technology	Fiscal expenditure on science and technology/GDP	Positive	-
	Per capita government funds for R&D expenditure	Government R&D expenditure/total population	Positive	Yuan
Market Technology Finance	Per capita enterprise funds for R&D expenditure	Non-government R&D expenditure/total population	Positive	Yuan
	Financing capacity of financial institutions	Loan amount of financial institutions/GDP	Positive	-
	Scientific research level	Number of scientific and technological papers	Positive	Papers
	Innovation level	Number of authorized patent applications of high-tech enterprises/internal R&D expenditure of high-tech	Positive	-

System Level	Indicator Level	Indicator Explanation	Indicator Attribute	Unit
		enterprises		
	Maturity of technology market	Transaction volume of technology market	Positive	10,000 yuan

(3) Control Variables

This study selects the following indicators as control variables. The urbanization rate (URB) is measured by the proportion of urban population to the total resident population at year-end. The state-owned sector share (SOE) is represented by the proportion of state-owned industrial enterprises among all industrial enterprises above a designated size. The level of openness (OPEN) is expressed as the ratio of total import and export value to GDP. Labor input (LAB) is measured by the logarithm of the total employed population.

(4) Mechanism Variables

The agglomeration of scientific and technological talent (TAG) is measured by the number of scientific and technical personnel per 10,000 employed persons in the region. Industrial structure upgrading (IND) is assessed using the ratio of the value-added of the tertiary industry to that of the secondary industry.

4.2 Data Description

This study utilizes panel data from 30 provincial-level regions spanning the period 2011-2023. Tibet Autonomous Region was excluded from the sample due to significant data unavailability. The data were compiled from various official statistical yearbooks, including the China Statistical Yearbook, China Population and Employment Statistical Yearbook, China Statistical Yearbook on Science and Technology, China Financial Yearbook, China Torch Statistical Yearbook, and China Statistical Yearbook on Environment, supplemented by provincial statistical yearbooks. Missing values were addressed using linear interpolation. Table 3 presents the descriptive statistics for all variables.

Table 3. Variable Description and Descriptive Statistics

Variable Category	Variable Name	Abbreviation	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Dependent Variable	Green Industry Development	GL	390	0.218	0.075	0.123	0.600
Independent Variable	Technology Finance	TF	390	0.085	0.084	0.014	0.554
Control Variables	Population Urbanization Rate	URB	390	0.603	0.121	0.344	0.942
	Degree of	SOE	390	0.108	0.076	0.017	0.351

Variable Category	Variable Name	Abbreviation	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
	Nationalization Level of Opening-up	OPEN	390	0.264	0.282	0.008	1.548
	Labor Input	lnLAB	390	7.578	0.782	5.545	8.864
Mechanism Variables	Agglomeration of Scientific and Technological Talent	TAG	390	0.884	0.868	0.139	6.609
	Industrial Structure Upgrading	IND	390	1.308	0.723	0.549	5.690

5. Analysis of Empirical Results

5.1 Benchmark Regression Results

Following the operational approach of Zhou (2024), this study adopts a 1:4 data splitting ratio for the double machine learning method. The Random Forest algorithm is employed for prediction, and a generic interactive model is utilized for computation. The test results regarding the impact of technology finance on green industry development are presented in Table 4. Column (I) reports results without fixed effects, Column (II) includes time fixed effects, Column (III) incorporates spatial fixed effects, and Column (IV) controls both time and spatial fixed effects. The results demonstrate that the estimated coefficients for technology finance remain significantly positive at the 1% level across all specifications, indicating that technology finance development effectively promotes green industry development. This positive relationship can be attributed to several mechanisms. Technology finance alleviates financing constraints for green industries through diverse financial instruments, thereby supporting their development. It also fosters the growth of emerging enterprises, creating a pipeline for future green industry expansion. Simultaneously, technology finance encourages high-pollution firms to improve their production processes by tightening lending standards. Furthermore, technology finance development enhances public environmental awareness, thereby expanding the market for green consumption. These empirical findings are consistent with the theoretical analysis presented earlier, thus validating Hypothesis H1.

Table 4. Regression Results of the Impact of Technology Finance on Green Industry Development

Variable	(I)	(II)	(III)	(IV)
	GL	GL	GL	GL
TF	0.232^{***}	0.284^{***}	0.216^{***}	0.273^{***}

	(0.072)	(0.077)	(0.060)	(0.065)
_cons	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Control Variables	Yes	Yes	Yes	Yes
Machine Learning Model	Random Forest Algorithm	Random Forest Algorithm	Random Forest Algorithm	Random Forest Algorithm
Time Fixed Effects	No	No	No	Yes
City Fixed Effects	No	No	Yes	Yes
Sample Size	390	390	390	390

5.2 Robustness Tests

To ensure the reliability of the regression results, this study conducted the following procedures. First, all continuous variables were winsorized at the 1st and 99th percentiles, and the regression was re-estimated to mitigate the influence of outliers. Second, the Random Forest algorithm was replaced with the Lasso algorithm for re-estimation. Third, the sample splitting ratio was adjusted to 1:7 and 1:3, respectively, to test whether a smaller ratio reduces model learning capacity or a larger ratio leads to overfitting. Finally, to address potential biased estimates caused by reverse causality between technology finance and green industry development, the instrumental variable approach was employed for endogeneity treatment, using the one-period lagged value of the explanatory variable as the instrument. Following the study by Zhou et al. (2024), an instrumental variable model based on double machine learning was constructed. The regression results, shown in Column (V) of Table 5, indicate a significantly positive coefficient for technology finance, confirming that the results pass the endogeneity test. The results from all the above tests are presented in Columns (I) to (V) of Table 5. The coefficients for technology finance remain significantly positive across all specifications, collectively demonstrating the robustness of the findings.

Table 5. Robustness Test Results

Variable	(I)	(II)	(III)	(IV)	(V)
	Outlier Handling	Changing Machine Learning Method	Adjusting Cross-validation Ratio		Instrumental Variable Method
TF	0.295***	0.126**	0.232***	0.246***	0.423***
	(0.067)	(0.050)	(0.076)	(0.067)	(0.104)
Control	Yes	Yes	Yes	Yes	Yes

Variables					
Machine Learning Method	Random Forest Algorithm	Lasso Algorithm	Random Forest Algorithm	Random Forest Algorithm	Random Forest Algorithm
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes
Sample Size	390	390	390	390	360

5.3 Mechanism Test

The theoretical analysis section posits that technology finance influences green industry development through two channels: facilitating the agglomeration of scientific and technological talent and promoting industrial structure upgrading. To empirically verify these mechanisms, this study examines the impact of technology finance on the respective mechanism variables. Table 6 presents the mechanism test results. Columns (I) and (II) report the results with the agglomeration of scientific and technological talent (TAG) and industrial structure upgrading (IND) as the dependent variables, respectively, and technology finance development (TF) as the independent variable. The results in Column (I) show a significantly positive coefficient for technology finance, indicating that its development promotes talent agglomeration. This can be attributed to two primary reasons. First, technology finance alleviates financing constraints for corporate innovation activities, thereby increasing the demand for scientific and technological talent. Concurrently, its development is often accompanied by policy measures such as increased fiscal subsidies and residency benefits, whose attractive packages draw talent concentration. Second, this talent agglomeration fosters the cluster development of green industries in relevant regions, while the preference of skilled workers for green consumption further expands the market for green products, thus confirming Hypothesis H2a.The results in Column (II) also show a significantly positive coefficient for the independent variable, demonstrating that technology finance development drives industrial structure upgrading. This outcome stems from several factors. Technologically, it enhances the efficiency of financial resource allocation, reduces financing risks for innovation activities, and accelerates capital accumulation and optimal factor allocation in technology firms, thereby facilitating industrial transformation. Furthermore, by promoting technological innovation, it speeds up the phasing out of obsolete enterprises, thus accelerating the pace of industrial upgrading. This upgrading, in turn, supports the cultivation of green industries, intensifies diversification competition among industries and products, and enhances the innovation capacity of the green sector. These empirical findings align with the prior theoretical analysis, validating Hypothesis H2b.

Table 6. Mechanism Test Results of the Impact of Technology Finance on Green Industry Development

Variable	(I)	(II)
	TAG	IND
TF	3.265^{**}	4.308^{***}
	(1.389)	(1.491)
_cons	0.022	0.011
	(0.015)	(0.018)
Control Variables	Yes	Yes
Machine Learning Model	Random Forest Algorithm	Random Forest Algorithm
Time Fixed Effects	Yes	Yes
City Fixed Effects	Yes	Yes
Sample Size	390	390

5.4 Heterogeneity Analysis

To examine regional variations in the impact of technology finance on green industry development, the total sample was divided into eastern, central, and western regions for subgroup regression analysis.

As shown in Columns (I) to (III) of Table 7, the estimated coefficients for technology finance are significantly positive in both eastern and central regions, but statistically insignificant in the western region. These results suggest that technology finance effectively promotes green industry development in eastern and central China, while its effect remains limited in the western region. This regional disparity can be attributed to the underdeveloped institutional ecosystem for technology finance in western China, which features fewer specialized technology finance service providers, accounting firms, law firms, and property rights trading platforms[25]. This less mature infrastructure results in a lower overall level of technological finance development, insufficient financial support for enterprises, and consequently limited effectiveness in alleviating financing constraints for green industries. In contrast, the more advanced technology finance systems in eastern and central regions, supported by a greater concentration of financial institutions, are better equipped to address industrial financing needs and thereby demonstrate a more pronounced promoting effect on green industry development.

Table 7 Heterogeneity Test Results

Variable	(I)	(II)	(III)
	Eastern Region	Central Region	Western Region
TF	0.154***	0.173***	0.045
	(0.059)	(0.059)	(0.076)
Control Variables	Yes	Yes	Yes
Machine Learning Model	Random Forest Algorithm	Random Forest Algorithm	Random Forest Algorithm
Time Fixed Effects	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes
Sample Size	169	78	143

6. Research Conclusions and Policy Implications

This study empirically examines the impact of technology finance development on green industry development using panel data from 30 Chinese provinces spanning 2011 to 2023. The main conclusions and corresponding policy recommendations are as follows:

6.1 Research Findings

First, the Double Machine Learning results demonstrate that technology finance development significantly promotes green industry development, a finding that remains robust after a series of rigorous tests. Second, mechanism analysis reveals that technology finance fosters green industry development primarily by facilitating the agglomeration of scientific and technological talent and promoting industrial structure upgrading. Third, regional heterogeneity analysis indicates that technology finance exerts a significant positive effect on green industry development in eastern and central regions, whereas its impact in the western regions shows no statistically significant effect.

6.2 Policy Implications

First, the development of technology finance should be actively encouraged. On one hand, regarding public technology finance, government departments should enhance their role in guiding and coordinating capital allocation, with particular emphasis on supporting small and medium-sized technology enterprises to ensure their development despite financial constraints. Fiscal support should be strengthened to bolster technological innovation and improve financing accessibility for innovative firms. On the other hand, for market-oriented technology finance, monetary authorities should implement targeted policies to reduce policy uncertainty, thereby mitigating capital misallocation and lowering corporate financing costs.

Second, deliberate efforts should be made to guide the agglomeration of scientific and technological talent. Local governments can attract highly educated technical professionals through comprehensive packages including relocation allowances, housing subsidies, children's education, and healthcare services. Concurrently, based on actual industrial development needs, a new talent recruitment model emphasizing "industry-talent integration and mutual empowerment" should be established. While enhancing talent aggregation efficiency, equal attention should be paid to maintaining balanced distribution of talent within clusters. Throughout the entire process, from planning to implementation, the core objective of achieving precise alignment between talent resources and industrial requirements must be maintained. This approach fosters deep integration and efficient coordination among talent, technology, capital, and projects, fundamentally moving beyond quantitative-focused recruitment strategies that prioritize numbers over quality and acquisition over proper utilization. At the implementation level, a collaborative mechanism featuring "government facilitation and employer leadership" should be established, genuinely delegating recruitment decision-making and initiative to research institutions and enterprises. Specific pathways include: governments formulating forward-looking recruitment plans and dynamically updated catalogs of high-demand talents aligned with regional development strategies, with focused targeting of key technical specialists; research institutions and enterprises precisely identifying their required talent specifications—including specialized fields, skill levels, and quantity—based on their R&D directions and production needs; and establishing regular reporting and immediate feedback mechanisms to communicate precise recruitment requirements to government entities. This enables either government-coordinated talent matching or direct targeted recruitment by employers, achieving both precision in talent acquisition and avoidance of homogeneous competition, thereby maximizing talent resource allocation efficiency.

Finally, technology finance policies should be tailored to regional conditions, acknowledging the heterogeneous effects observed across different areas. Particularly for western regions, policies should be designed according to local development realities. Simultaneously, the cross-regional impact of technology finance development deserves attention. Sound inter-regional cooperation mechanisms should be established to ensure smooth cross-regional flow of capital elements, facilitating the exchange of talent, knowledge, and funds across regions. This enables technology finance to fully exert its cross-regional catalytic effect. Specifically, eastern and central regions should provide technological and talent support to western regions. Regions with successful policies should assist less developed areas, while latter can adapt and implement technology finance policies based on successful experiences and local conditions.

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