



Nonlinear Effects of Green Finance on Ecological Welfare Performance in Chinese Provinces

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Abstract

Background and Aim: China faces significant challenges balancing economic development with ecological sustainability. Green finance has emerged as a potential solution, yet previous research has insufficiently examined its nonlinear effects on ecological welfare performance and its interactive mechanisms with other policy instruments. This study addresses this gap by examining the nonlinear relationship between green finance development and ecological welfare performance in China, while investigating previously unexplored interactive effects with environmental regulation, openness, and innovation across different regional contexts.

Materials and Methods: Using provincial panel data from 30 Chinese provinces (2000-2021), we measured green finance development through the Entropy Weight Method, selected for its ability to objectively weight multiple financial indicators. We assessed ecological welfare performance via the Super Efficiency Slack-Based Measure (SBM) model with undesirable outputs, which effectively captures both resource utilization efficiency and environmental impact. Threshold regression and baseline regression models were employed to analyze nonlinear relationships and interaction effects.

Results: Our analysis reveals a significant double-threshold effect of green finance on ecological welfare performance, demonstrating a positive U-shaped nonlinear pattern. As green finance development increases, it progressively mitigates the negative impacts of environmental regulation and economic openness on ecological welfare. Additionally, while green finance amplifies the positive impact of innovation on ecological welfare performance, this synergistic effect gradually diminishes as green finance reaches higher levels. The influence of these relationships varies substantially across eastern, central, and western Chinese regions.

Conclusion: Green finance development demonstrates complex, nonlinear relationships with ecological welfare performance across China. These findings necessitate region-specific policy approaches tailored to different development stages. Policymakers should implement targeted green finance initiatives that account for regional economic structures, environmental constraints, and innovation capabilities to optimize ecological welfare outcomes, particularly in regions with varying levels of economic development and environmental challenges.

Keywords: Green Finance; Ecological Welfare Performance; Threshold Effect; Regional Disparities; Nonlinear Relationships

Introduction

Since the implementation of China's reform and opening-up policy in 1978, the country has experienced rapid GDP growth, which has been accompanied by the overconsumption of natural resources and severe environmental degradation. This economic-ecological dilemma has prompted the emergence of green finance as a mechanism to balance economic development with environmental sustainability. Green finance—the allocation of financial resources to environmentally sustainable projects and initiatives—represents a crucial shift in how China addresses the ecological costs of its development model. By channeling investment into green industries and technologies, green finance has become instrumental in China's transition from a growth model that prioritizes speed and scale toward a more ecologically friendly and low-carbon sustainable approach.

In response to these sustainability challenges, the Chinese government has introduced a comprehensive sustainable development strategy, implementing policies that promote economic sustainability while aligning with global frameworks such as the United Nations Sustainable Development Goals. These initiatives include the transformation of traditional industries, green technological innovation, and the development of new energy sectors, all designed to achieve sustainable growth while reducing resource consumption and environmental pollution. The effectiveness of these policy interventions can be





evaluated through the lens of ecological welfare performance, a metric that captures the complex relationship between economic development and environmental sustainability.

With the evolution of sustainable development theory and steady-state economics, Chinese scholars Zhu, D., & Qiu, S. (2008) introduced the innovative concept of "Ecological Welfare Performance" as a tool to measure and evaluate sustainable economic development potential. This concept uniquely captures the relationship between ecological resource consumption, economic growth, and social welfare improvement in an integrated manner. Unlike conventional economic indicators, ecological welfare performance accounts for environmental externalities and intergenerational equity concerns, making it particularly relevant for assessing the sustainability of China's development model. Building on this conceptual innovation, scholars such as Sun, R. (2022), Liu, N., Zhang, J., & Wang, X. (2021), and Xiao, L., & Ji, H. (2018) have demonstrated the wide applicability of this metric in analyzing China's sustainable development challenges.

Green finance plays a pivotal role in enhancing ecological welfare performance by facilitating the efficient and rational use of resources and energy (Wen et al, 2022; Chen et al, 2021). However, the relationship between green finance and ecological welfare performance is unlikely to be uniform across China's diverse regional landscapes. Economic structures, industrial composition, technological capabilities, and policy variations across provinces likely create nonlinear effects and regional disparities in how green finance impacts ecological outcomes. By attracting capital into green industries and environmental protection projects, green finance supports the green transition of production systems and lifestyles through various instruments, including green bonds, environmental risk assessment mechanisms, and specialized credit facilities. Moreover, green finance encourages businesses and financial institutions to incorporate Environmental, Social, and Governance (ESG) factors into investment decisions, steering capital flows toward sustainability and fostering long-term sustainable economic growth (Zhou, 2020).

This study examines the potentially nonlinear relationship between green finance development and ecological welfare performance across different Chinese provinces, investigating how this relationship is moderated by factors such as environmental regulation, economic openness, and innovation capabilities. Understanding these complex relationships is essential for developing targeted, region-specific policies that optimize the impact of green finance on sustainable development outcomes in China.

Objectives

This study examines the impact of green finance on China's sustainable economic development using ecological welfare performance as a key metric.

Literature review

1. Concept and measurement of ecological welfare performance

1) Concept of ecological-welfare performance

The concept of Ecological Welfare Performance originates from the steady-state economics proposed by Daly (1974). This theoretical foundation was enhanced by Costanza et al. (1997), who emphasized the interdependence between economic systems and ecological services. Few (1993) highlighted the symbiotic relationship between ecological resilience and economic welfare enhancement, arguing that sustainable development requires concurrent welfare improvements within ecological constraints.

Chinese scholars Zhu, D., & Qiu, S. (2008) advanced this framework by introducing "Ecological Welfare Performance," which seeks to maximize human welfare with minimal natural resource consumption. Their approach extends previous theories by focusing on two core transformations: converting natural resources into economic growth, then transforming this growth into human welfare. Unlike traditional growth models that prioritize output maximization, Ecological Welfare Performance emphasizes social welfare outcomes alongside resource efficiency, representing a significant evolution in sustainable development theory.





2) Indicator System for Measuring Ecological Welfare Performance

Daly's (1974) work established a foundational approach by calculating the ratio of service flow to throughput. Zhu, D., & Qiu, S. (2008) built on this by utilizing the ratio of natural resource inputs to social welfare outputs. For resource inputs, researchers like Deng et al (2020, 2021) have measured energy, water, and land resource consumption.

For social welfare measurement, the United Nations Development Programme (1990) introduced the Human Development Index (HDI), comprising health, education, and economic development dimensions. However, the HDI has limitations in capturing ecological sustainability as it doesn't account for environmental degradation, potentially overestimating welfare in resource-intensive economies. Alternative indices like the Genuine Progress Indicator (GPI) address some of these shortcomings by incorporating environmental costs.

Recent scholars such as Wang, Z., & Wang, Z. (2021) and Chen & Liu (2023) have developed more comprehensive approaches by incorporating environmental welfare into social welfare measurements. Additionally, Guo, B., and Li, C. (2021) argue that outputs should consider environmental pollution as an undesired outcome, acknowledging production externalities. This study will develop a measurement system for Ecological Welfare Performance incorporating these multi-dimensional perspectives on environmental impacts.

3) Method of ecological welfare performance measurement

Ecological Welfare Performance measurement methods include ratio methods, Stochastic Frontier Analysis (SFA), and Data Envelopment Analysis (DEA). DEA offers distinct advantages: it requires no specific production function, uses dimensionless indicators, and handles multiple inputs and outputs simultaneously - essential for capturing ecological welfare's multifaceted nature.

This study specifically adopts the super-efficiency DEA SBM model because it effectively distinguishes between desirable and undesirable outputs while accounting for slack variables, providing a more accurate assessment when environmental degradation is present. Recent applications by Zhang et al. (2022) in evaluating regional environmental performance demonstrate its effectiveness in capturing both environmental and economic dimensions. Additionally, the super-efficiency feature allows for ranking among efficient decision-making units, providing nuanced insights into relative performance across provinces. RetryClaude can make mistakes. Please double-check responses.

2. Concept and measurement of green finance

1) Concept of green finance

Green finance originated from environmental policy responses in the United States, particularly the Superfund Act and the "Love Canal" pollution incident. This concept has evolved significantly across different economic systems over time. According to Salazar (1998) and Cowan (1999), green finance initially referred to financial tools used by governments and financial institutions to promote ecological protection and sustainable economic development. More recently, Clark et al. (2018) have expanded this definition to encompass financial services that integrate environmental, social, and governance (ESG) criteria into investment decisions, reflecting the growing emphasis on sustainability in global financial markets.

Wang, F., & Wang, K. (2018) position green finance within the broader category of environmental policy instruments. Building on this, Wen et al (2022) and Chen & Liu (2023) note that while definitions may vary in focus, they converge on the concept of financial services aimed at economic sustainability through ecological protection, resource efficiency, and climate change mitigation.

In 2006, China established its national definition of green finance as a comprehensive financial service, including investment, financing, project operation, and risk management, aimed at promoting sustainable development through projects related to ecological protection, energy conservation, emission reduction, and climate change mitigation. This definition, while broadly aligned with international frameworks such as the EU Green Taxonomy, places distinctive emphasis on energy efficiency and ecological protection in the Chinese context. This study adopts this definition as its conceptual foundation.





2) Indicator System for Measuring Green Finance

The indicators used to measure green finance have evolved to include green credit, green securities, green insurance, and green investment (Yu, B., & Fan, C., 2022). These indicators were selected based on their ability to comprehensively capture the multifaceted nature of green finance activities across different sectors. As climate concerns have intensified, scholars have incorporated carbon finance (carbon emission intensity) into green finance measurement systems (Liu, D., Zhang, F., & Huang, Y., 2021; Zhou, B., & Li, Y., 2024).

Recent empirical studies have highlighted challenges in measuring green finance, particularly regarding the risk of greenwashing, where institutions may misrepresent conventional investments as environmentally beneficial. To address this concern, researchers such as Lin, M., & Xiao, Y. (2023) have emphasized the importance of including policy-driven indicators like government green support. Additionally, Xue, H., & Kan, L. (2024) and Li, J., & Liu, X. (2024) have incorporated green funds into measurement frameworks to better capture institutional investment flows toward sustainable activities.

This study will utilize seven specific indicators—green credit, green securities, green insurance, green investment, green funds, green support, and carbon finance—to measure green finance development, providing a comprehensive assessment that reflects both market-driven and policy-driven dimensions of China's green finance landscape.

3) Measurement Methods for Green Finance

The primary methods for measuring green finance are principal component analysis (PCA) and the entropy weighting method. While PCA excels at reducing dimensionality while preserving variance, comparative analyses by Liu et al. (2022) and Wang et al. (2010) demonstrate that the entropy weighting method offers particular advantages in the context of green finance measurement. The entropy method assigns weights based on the variation in indicator values, providing a more objective assessment that is less susceptible to subjective bias compared to other weighting approaches. Additionally, it preserves more information from the original indicators without assuming linear correlations, making it particularly suitable for the heterogeneous nature of green finance indicators. Accordingly, this study will employ the entropy weighting method to calculate a comprehensive index of green finance development. RetryClaude can make mistakes. Please double-check responses.

3. Influence relationship of green finance on ecological welfare performance

1) Impact of green finance on ecological welfare performance

Existing literature presents varied perspectives on how green finance influences ecological welfare performance. Liu, D., Zhang, F., & Huang, Y. (2021) used panel data (2007-2018) with a Tobit model to identify positive impacts at the provincial level, while Liu, X., & Zhuang, X. (2022) and Shi, J. (2023) confirmed similar positive relationships in different contexts.

However, Busch et al. (2021) highlight potential challenges, including resource misallocation and financialization risks, where financial innovation may outpace actual environmental benefits. These counterarguments emphasize the need for careful policy design.

Methodologically, previous studies predominantly employ Tobit panel regression models, which transform continuous ecological welfare variables into binary values, resulting in information loss. Our approach preserves the continuous nature of ecological welfare data, allowing for more nuanced analysis. Additionally, this study extends the timeframe to 2000-2021, encompassing multiple policy cycles and economic transitions, providing more robust findings across different developmental stages.

2) Non-linear impact of green finance on ecological welfare performance

Recent research has increasingly focused on non-linear relationships in sustainability studies. Li, S., et al. (2024) and Li, J., & Liu, X. (2024) demonstrated non-linear effects of green finance on industrial green development and common prosperity, respectively. In parallel research, Guo, B., & Lin, J. (2021) and Guo, B., & Feng, Y. (2023) found non-linear impacts of environmental regulation on ecological welfare performance, while Xu, W., & Li, L., et al. (2021) identified similar non-linear patterns with green innovation efficiency.



These findings collectively suggest that sustainability-oriented policies, including green finance, likely have varying effects across different development stages and regional contexts. However, there remains a notable gap in research specifically examining the non-linear relationship between green finance and ecological welfare performance. This study addresses this gap by employing threshold regression models to investigate potential non-linear impacts and threshold effects, providing insights for more targeted policy approaches.

Methodology

1. Model design

1) Panel-threshold regression model

Based on the research hypothesis, this study will first employ a panel threshold regression model to examine whether there are nonlinear threshold effects of green finance on ecological welfare performance. The following threshold regression model will be constructed:

$$\begin{aligned} \text{Instfl} = & \beta_0 + \beta_1 \text{Ingreenf} \cdot I(\text{Ingreenf} \leq \delta_1) \\ & + \beta_2 \text{Ingreenf} \cdot I(\delta_1 < \text{Ingreenf} \leq \delta_2) \\ & + \beta_3 \text{Ingreenf} \cdot I(\delta_1 < \text{Ingreenf}) + \sum_{j=1}^5 \gamma_j \text{control}_{j,i,t} + \varepsilon_{i,t} \end{aligned} \quad (1)$$

In the model, $I(\cdot)$ represents an indicator function, where, $I(\cdot)=1$, if the condition within the parentheses is true, and $I(\cdot)=0$, otherwise; δ_1 and δ_2 denotes the threshold value of green finance ; β_i ($i = 1,2,3$) represent the regression coefficients for the threshold variables in different intervals of green finance values. ; $\text{control}_{j,i,t}$ denotes the control variables.

To further investigate the nonlinear threshold effects of green finance in the context of how control variables impact ecological welfare performance, this study constructs the following panel threshold regression model, with green finance as the threshold variable and various control variables as independent variables.

$$\begin{aligned} \text{Instfl} = & \beta_0 + \beta_1 \text{control}_{i,t} \cdot I(\text{Ingreenf} \leq \delta_1) \\ & + \beta_2 \text{Ingreenf} \cdot I(\delta_1 < \text{Ingreenf} \leq \delta_2) \\ & + \beta_3 \text{Ingreenf} \cdot I(\delta_1 < \text{Ingreenf}) + \sum_{j=2}^3 \gamma_j \text{control}_{j,i,t} + \varepsilon_{i,t} \end{aligned} \quad (2)$$

1) Baseline Panel Regression Model

If a threshold effect exists in the impact of green finance on ecological welfare performance, to precisely characterize the specific nonlinear effects of green finance on ecological welfare performance, this study utilizes a baseline panel regression model. In the modeling process, the squared term of green finance, Ingreenf^2 is used to represent the specific impact of green finance. The following model is constructed to examine this relationship:

$$\text{Instfl}_{i,t} = \gamma + \gamma_1 \text{Ingreenf}_{i,t} + \gamma_2 \text{Ingreenf}^2_{i,t} + \sum_{j=3}^7 \gamma_j \text{control}_{j,i,t} + u_i + \mu_i + \varepsilon_{i,t} \quad (3)$$

In the model, $\text{Ingreenf}_{i,t}$ represents the level of green finance in province i at time t , $\text{Ingreenf}^2_{i,t}$ denotes the squared term of green finance in province i at time t , $\text{Instfl}_{i,t}$ indicates the level of ecological welfare performance , u_i denotes the individual fixed effects, μ_i denotes the random effects, $\varepsilon_{i,t}$ represents the error term.

2) Dynamic System GMM Regression Model

To ensure the reliability of the regression results and address potential endogeneity issues during the analysis, this study introduces a first-order lag of ecological welfare performance into a dynamic panel

model. The System GMM method is employed to analyze the impact of green finance on ecological welfare performance, facilitating the examination of endogeneity and robustness.

This study examines the dynamic effects of fiscal decentralization on ecological welfare performance, the dynamic effects of green finance on ecological welfare performance, and the combined temporal dynamic effects of fiscal decentralization and green finance on ecological welfare performance. To this end, the study first establishes the following dynamic panel models based on the System GMM method and further employs the Sargan test and Arellano-Bond autocorrelation test to validate the endogeneity and robustness of the regression results.

$$\ln stfl_{i,t} = \alpha + \beta \ln stfl_{i,t-1} + \gamma_1 \ln greenf_{i,t} + \gamma_2 \ln greenf_{i,t} + \sum_{j=3}^7 \gamma_j \text{control}_{j,i,t} \quad (4)$$

In the model, $\ln stfl_{i,t-1}$ represents the l -th order lag of ecological welfare performance.

2. Variable selection

1) Dependent variable

In this study, the dependent variable is ecological welfare performance. For the specific measurement indicators of ecological welfare performance, this research constructs an indicator system based on the work of scholars such as Long, L., & Wang, X. (2017), Fang, S., & Xiao, Q. (2019), Xu, Y. (2017), Deng et al (2020), Chen & Liu, (2023), Xiao, L., & Xiao, Q. (2021), Zhu, J., & Pang, W. (2022), and Sun, W., & Wang, Z. (2022). This indicator system is tailored to the ecological welfare performance relevant to this study (see Table 1).

Table 1 indicator system of ecological welfare performance

Primary Indicator	Secondary Indicator	Tertiary Indicator	Remarks
Resource Consumption	Energy Consumption	Per Capita Coal Usage (tons)	Long, L., & Wang, X. (2017)
	Water Resource Consumption	Per Capita Water Usage (cubic meters)	
	Land Resource Consumption	Per Capita Construction Land Area (square meters)	
Welfare Level	Economic Development Welfare	Urban-Rural Income Gap	Chen & Liu, (2023)
		Per Capita Disposable Income (Yuan)	Xiao, L., & Xiao, Q. (2021)
	Healthcare Welfare	Number of Health Personnel per 1,000 People	Zhu, J., & Pang, W. (2022)
Number of Medical and Health Institution Beds per 1,000 People		Wang, Z., & Wang, Z. (2021)	
Average Life Expectancy (years)		(2021)	
Environmental Welfare	Green Coverage Rate in Built-up Areas (%)	Sun, W., & Wang, Z. (2022)	
	Per Capita Park Green Space Area (square meters/person)		
Educational Welfare	Rate of Non-hazardous Treatment of Domestic Waste (%)	Long, L., & Wang, X. (2017)	
	Average Years of Education		



Primary Indicator	Secondary Indicator	Tertiary Indicator	Remarks
Environmental Pollution	Wastewater Discharge	Per Capita Sewage Discharge (tons)	Long, L., & Wang, X. (2017),
	Solid Waste Emission	Per Capita Solid Waste Discharge (tons)	
	Air Pollution	Per Capita Air Pollutant Emission (tons)	Wang, Z., & Wang, Z. (2021)
	Household Waste	Per Capita Household Waste (tons)	

2) Core explanatory variables

The core explanatory variable in this study is green finance. For the specific measurement indicators of green finance, this research constructs an indicator system based on the work of scholars such as Yu, B., & Fan, C. (2022), Lin, M., & Xiao, Y. (2023), and Xue, H., & Kan, L. (2024). This indicator system is tailored to the green finance relevant to this study. (see Table 2)

Table 2 indicator system of green finance

Primary Indicator	Secondary Indicator	Operational Definition of Secondary Indicator	Notes
Green Finance	Green Credit	Ratio of Environmental Project Loans to Total Loans	Environmental Project Loan Amount / Total Loan Amount Yu,B.,& Fan,C. (2022).
	Green Investment	Ratio of Environmental Pollution Control Investment to GDP	Environmental Pollution Control Investment / GDP. Yan,Z. (2023)
	Green Insurance	Extent of Promotion of Environmental Pollution Liability Insurance	Environmental Pollution Liability Revenue / Total Premium Income
	Green Bonds	Degree of Development of Green Bonds	Total Issued Green Bonds / Total Bond Issuance
	Green Support	Ratio of Fiscal Environmental Protection Expenditure to General Budget Expenditure	Fiscal Environmental Protection Expenditure / General Budget Expenditure (Lin,M.,& Xiao,Y.(2023))
	Green Funds	Ratio of Green Fund Market Value to Total Fund Market Value	Total Market Value of Green Funds / Total Market Value of All Funds Xue, H., & Kan, L. (2024)
	Carbon Finance	Carbon Emission Intensity	Carbon Emissions / GDP

3) Control variables

This study selects variables with significant impacts on ecological welfare performance as control variables. Drawing from the research of Fang, S., & Xiao, Q. (2019), Guo, B., & Tang, L. (2023), Gu & Chen, (2020), and Zhao, L., Zhang, H., & Li, M. (2024), this study includes openness, innovation level, industrial structure, and environmental regulation as control variables.

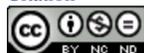




Table 3 Control Variables

Control Variable	Operational Definition	Notes
Degree of Openness	Foreign Direct Investment / GDP	Fang & Xiao (2019)
Level of Innovation	Number of Invention Patent Applications Accepted Annually	Guo & Tang (2023)
Industrial Structure	Value Added of the Tertiary Industry / Value Added of the Secondary Industry	Gu & Chen, (2020).
Environmental Regulation	Investment in Industrial Pollution Control / Industrial Value Added	Zhao, L., Zhang, H., & Li, M. (2024)

3. Data Sources and Descriptive Statistics

1) Data Sources

This study utilizes data from 2000 to 2021 for 30 provincial-level administrative regions in China, excluding Tibet, Taiwan, Macau, and Hong Kong. These regions were excluded due to significant data limitations and distinct economic-ecological characteristics that could introduce methodological inconsistencies. While this affects generalizability to unique regions like Tibet's high-altitude ecosystems or Hong Kong's specialized financial system, the 30 included provinces represent the vast majority of China's population, economic activity, and ecological diversity.

Data sources include: the China Energy Statistical Yearbook (energy consumption), China Statistical Yearbook (land/water resources, economic indicators, environmental welfare), China Health Statistical Yearbook and Population Employment Statistical Yearbook (health welfare), China Environmental Statistical Yearbook (pollution outputs, environmental regulation), China Financial Statistical Yearbook (green credit, bonds, funds), China Insurance Yearbook (green insurance), and CEADs China Carbon Accounting Database (carbon emissions).

To ensure data validity, Levin-Lin-Chu panel unit root tests confirmed stationarity after first-differencing for all variables, preventing spurious correlations in our analysis.

2) Descriptive statistics

Our analysis reveals that ecological welfare performance in China decreased initially from 2000, reaching its lowest point in 2006, before exhibiting a gradual annual increase through 2021. Significant regional disparities exist, with the eastern region showing the highest average performance (0.632), followed by central (0.514), western (0.475), and northeastern regions (0.421).

These regional variations suggest potential spatial dependencies in ecological performance. Moran's I tests confirm moderate spatial autocorrelation ($I=0.342$, $p<0.01$) across neighboring provinces, indicating that ecological outcomes in one province may be influenced by conditions in adjacent areas. To account for these spatial effects, we incorporate regional dummy variables in our econometric models, enhancing their explanatory power.

Table 4 Development level of ecological welfare performance

Year	Eastern region	Central region	Western region	Northeastern region	China
2000	0.533	0.668	0.511	0.292	0.528
2001	0.48	0.588	0.531	0.294	0.502
2002	0.533	0.483	0.53	0.291	0.498
2003	0.412	0.562	0.439	0.289	0.439
2004	0.404	0.475	0.397	0.288	0.404
2005	0.381	0.353	0.31	0.292	0.341
2006	0.369	0.316	0.248	0.272	0.304
2007	0.39	0.348	0.265	0.283	0.325
2008	0.404	0.374	0.315	0.287	0.354



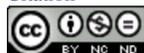


Year	Eastern region	Central region	Western region	Northeastern region	China
2009	0.434	0.411	0.343	0.29	0.382
2010	0.448	0.39	0.287	0.3	0.363
2011	0.489	0.474	0.341	0.32	0.415
2012	0.562	0.49	0.374	0.335	0.456
2013	0.62	0.521	0.396	0.331	0.489
2014	0.746	0.539	0.398	0.345	0.537
2015	0.662	0.584	0.421	0.355	0.527
2016	0.694	0.57	0.466	0.35	0.551
2017	0.757	0.588	0.502	0.362	0.59
2018	0.769	0.591	0.58	0.379	0.625
2019	0.802	0.681	0.661	0.405	0.686
2020	0.797	0.702	0.73	0.494	0.723
2021	0.866	0.827	0.802	0.548	0.803
Annual average	0.5705	0.5244	0.4476	0.3364	0.4928

The development levels of green finance in the eastern, central, western, and northeastern regions of China, as well as in China as a whole, from 2000 to 2021 are examined (see Table 5). Overall, green finance has exhibited a trend of annual increases since 2000. Regionally, the northeastern region has the highest average annual level of green finance, followed by the western region, then the eastern region, with the central region having the lowest level of green finance development. There are noticeable differences in the development levels of green finance among these regions.

Table 5 Development level of green finance

Year	Eastern region	Central region	Western region	Northeastern region	China
2000	0.0967	0.0930	0.0921	0.1231	0.0969
2001	0.1256	0.1272	0.1329	0.1301	0.1291
2002	0.1640	0.1604	0.1771	0.1636	0.1681
2003	0.2003	0.2023	0.2062	0.2190	0.2047
2004	0.2389	0.2459	0.2476	0.2312	0.2427
2005	0.2750	0.2955	0.2610	0.3099	0.2775
2006	0.3228	0.3168	0.3134	0.3256	0.3184
2007	0.3538	0.3329	0.3500	0.3482	0.3477
2008	0.3897	0.3813	0.3913	0.4105	0.3907
2009	0.4180	0.4339	0.4369	0.4530	0.4316
2010	0.4662	0.4412	0.4447	0.4952	0.4562
2011	0.4847	0.4815	0.4875	0.4842	0.4851
2012	0.5157	0.5274	0.5433	0.5357	0.5302
2013	0.5583	0.5665	0.5809	0.5937	0.5718
2014	0.6079	0.5938	0.6126	0.6080	0.6068
2015	0.6129	0.6239	0.6203	0.6658	0.6231





Year	Eastern region	Central region	Western region	Northeastern region	China
2016	0.6824	0.6682	0.6773	0.6291	0.6723
2017	0.7077	0.6915	0.7177	0.7559	0.7130
2018	0.7661	0.7329	0.7529	0.7537	0.7534
2019	0.7873	0.7987	0.7861	0.7937	0.7898
2020	0.8173	0.8128	0.7914	0.7993	0.8051
2021	0.8610	0.8474	0.8488	0.8935	0.8571
总计	0.4751	0.4716	0.4760	0.4874	0.4760

4. Empirical analysis

4.1 Modeling prerequisite testing

For modeling panel data with time series components, it is generally required that the variables exhibit significant correlations, that the series for each variable are stationary, and that there is cointegration among the variables. These conditions will be verified in this study. To enhance the stationarity of the data series, this research first applies a logarithmic transformation to each variable before proceeding with the subsequent analysis.

1) Correlation test

Table 6 shows that the correlation coefficient between the dependent variable ecological welfare performance (Instfl), and the explanatory variable, green finance (Ingreenf), is 0.250, which is significant at the 1% level. The correlation coefficients between ecological welfare performance and the control variables—environmental regulation (Inhjgz), industrial structure (Incyjg), innovation level (Incxsp), and openness (Indwkf)—are -0.321, 0.349, 0.595, and 0.110, respectively, all significant at the 1% level. These results indicate strong correlations among the variables, which forms the basis for constructing the econometric model.

Table 6 Pearson correlation test

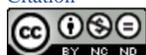
Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Instfl	1.000					
(2) Ingreenf	0.250	1.000				
(3) Inhjgz	-0.321	-0.416	1.000			
(4) Incyjg	0.349	0.342	-0.385	1.000		
(5) Incxsp	0.431	0.694	-0.520	0.316	1.000	
(6) Indwkf	0.110	-0.204	-0.151	-0.005	0.164	1.000

2) Stability test

The Fisher and LLC tests were used to examine the stationarity of each variable. The results indicate that the variables are non-stationary at their levels but become stationary after first differencing (see Table 7). This suggests that all variables exhibit significant first-order stationarity.

Table 7 Stationarity Test

variable	Test statistical indicators		Statistic	p-value	
D.Instfl		Inverse chi-squared(60)	P	354.4733	0.0000
	Fisher	Inverse normal	Z	-11.0818	0.0000
		Inverse logit t(154)	L*	-16.9422	0.0000
		Modified inv. chi-squared	Pm	26.8816	0.0000





variable	Test statistical indicators	Statistic	p-value
D.Ingree nf	Levin-Lin-Chu	Adjusted t*	-11.257 0.0000
	Inverse chi-squared(60)	P	639.4387 0.0000
	Fisher Inverse normal	Z	-21.2035 0.0000
	Inverse logit t(154)	L*	-32.2685 0.0000
	Modified inv. chi-squared	Pm	52.8953 0.0000
D.Inhjgz	Levin-Lin-Chu	Adjusted t*	-11.9977 0.0000
	Inverse chi-squared(60)	P	263.745 0.0000
	Fisher Inverse normal	Z	-10.8419 0.0000
	Inverse logit t(154)	L*	-12.8764 0.0000
	Modified inv. chi-squared	Pm	18.5993 0.0000
D.Incyjg	Levin-Lin-Chu	Adjusted t*	-2.8574 0.0021
	Inverse chi-squared(60)	P	131.5651 0.0000
	Fisher Inverse normal	Z	-5.297 0.0000
	Inverse logit t(154)	L*	-5.469 0.0000
	Modified inv. chi-squared	Pm	6.533 0.0000
D.Incxsp	Levin-Lin-Chu	Adjusted t*	-4.9121 0.0000
	Inverse chi-squared(60)	P	194.709 0.0000
	Fisher Inverse normal	Z	-8.0048 0.0000
	Inverse logit t(154)	L*	-9.0504 0.0000
	Modified inv. chi-squared	Pm	12.2972 0.0000
D.Inczhs P	Levin-Lin-Chu	Adjusted t*	-6.3822 0.0000
	Inverse chi-squared(60)	P	244.8391 0.0000
	Fisher Inverse normal	Z	-11.3688 0.0000
	Inverse logit t(154)	L*	-12.2605 0.0000
	Modified inv. chi-squared	Pm	16.8734 0.0000
D.Indwkwf	Levin-Lin-Chu	Adjusted t*	-10.3246 0.0000
	Inverse chi-squared(60)	P	245.8863 0.0000
	Fisher Inverse normal	Z	-9.285 0.0000
	Inverse logit t(154)	L*	-11.3392 0.0000
	Modified inv. chi-squared	Pm	16.969 0.0000
	Levin-Lin-Chu	Adjusted t*	-7.5173 0.0000

3) Cointegration test

First, the lag order of cointegration for the variables ecological welfare performance, green finance, environmental regulation, industrial structure, innovation level, and openness was determined based on information criteria. The output indicates that, according to the information criteria MBIC, MAIC, HQIC, and SBIC, the lag order of cointegration among the variables is one.

Table 8 Order of cointegration among the variables

lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	1.000	242.263	0.014	-967.799*	-149.737*	-471.299*
2	1.000	175.038	0.057	-732.509	-118.962	-360.134
3	1.000	117.635	0.086	-487.396	-78.365	-239.147
4	1.000	54.335	0.279	-248.181	-43.665	-124.056

*Represents the minimum value





To further investigate the cointegration among the variables, both Pedroni and Kao tests were conducted. The results reveal the presence of cointegration among the variables, indicating that there is a long-term equilibrium relationship among them.

Table 9 Pedroni and Kao cointegration test

Statistics of the cointegration test		Statistic	p-value
Pedroni	Modified Phillips–Perron t	5.3872	0.0000
	Phillips–Perron t	-3.3919	0.0003
	Augmented Dickey–Fuller t	-2.8954	0.0019
Kao	Modified Dickey–Fuller t	-3.1627	0.0008
	Dickey–Fuller t	-4.1051	0.0000
	Augmented Dickey–Fuller t	-2.317	0.0103
	Unadjusted modified Dickey–Fuller t	-7.3287	0.0000
	Unadjusted Dickey–Fuller t	-5.9265	0.0000

In summary, the variables—ecological welfare performance, green finance, environmental regulation, industrial structure, innovation level, and openness—exhibit first-order stationarity. Additionally, there are significant correlations among these variables, and they demonstrate notable first-order cointegration. These findings provide a foundation for the construction and analysis of econometric regression models.

Results

1) Threshold Regression Analysis

Firstly, a triple threshold regression model was established with ecological welfare performance as the dependent variable and green finance as the threshold variable. The threshold effect of green finance was then tested. The results indicate that, at the 5% confidence level, the dual threshold effect is significant. Further calculations reveal that the threshold values under the dual threshold regression model are -1.2571 and -1.7284. Firstly, a triple threshold regression model was established with ecological welfare performance as the dependent variable and green finance as the threshold variable. The threshold effect of green finance was then tested. The results indicate that, at the 5% confidence level, the dual threshold effect is significant. Further calculations reveal that the threshold values under the dual threshold regression model are -1.2571 and -1.7284.

Table 10 Self-sampling test results of the threshold effect of green Finance

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	72.165	0.1131	48.66	0.0000	19.5601	23.5773	33.3053
Double	68.4803	0.1073	34.33	0.0000	18.9718	22.3357	24.1941
Triple	67.1816	0.1053	12.33	0.3400	19.4674	23.6366	35.4199



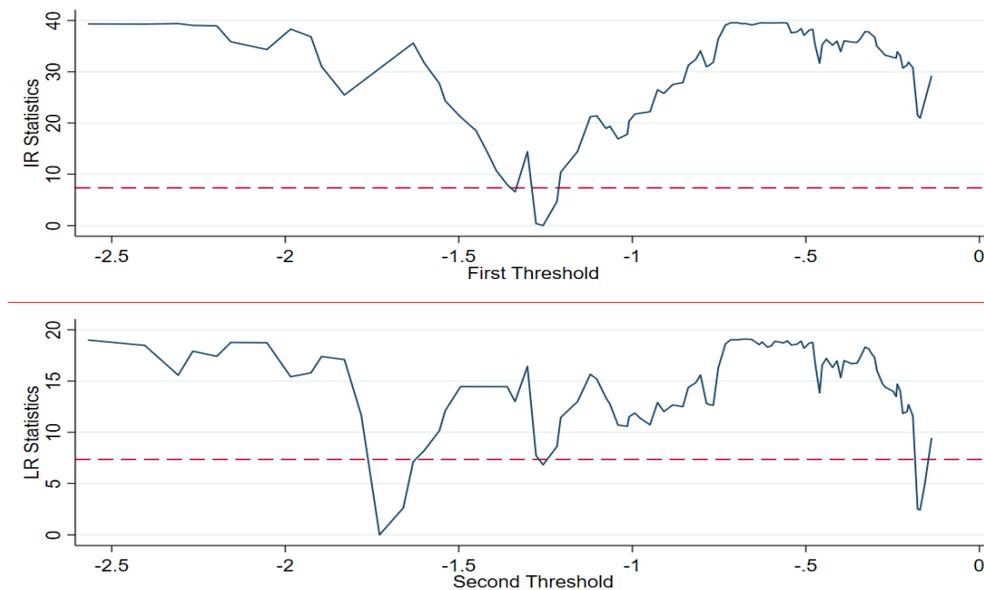


Figure 1 Estimate of the green Finance threshold

The results in Table 11 indicate that as the level of green finance increases, its nonlinear impact on ecological welfare performance becomes increasingly pronounced. Specifically, when green finance is below -1.7284, its effect on ecological welfare performance is minimal and not significant. However, when green finance ranges from -1.7284 to -1.2571, the impact coefficient on ecological welfare performance increases to 0.157, which is significant at the 10% level. Furthermore, when green finance exceeds -1.2571, the impact coefficient on ecological welfare performance further increases to 0.431, and this effect is significant at the 1% level.

Table 11 Estimation of the regression coefficient of the green finance threshold

	Coefficient	Std. err.	t	P>t
Lngreenf<-1.7284	-0.063	0.071	-0.890	0.372
-1.728<Lngreenf<-1.257	0.157*	0.090	1.730	0.083
Lngreenf>-1.257	0.431***	0.111	3.900	0.000

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In summary, there is a significant threshold effect in the impact of green finance on ecological welfare performance. The higher the level of green finance development, the stronger its positive effect on ecological welfare performance, displaying notable nonlinear characteristics. Based on these findings, this study will further develop a panel regression model to specifically characterize the nature of this nonlinear impact.

2) Baseline regression analysis

In this study, the square term of green finance (Lngreenf) is introduced into the regression models to specifically examine the nonlinear impact of green finance on ecological welfare performance. Several regression models are constructed, with green finance as the explanatory variable and ecological welfare performance as the dependent variable. Model a1 represents a mixed regression model without control variables, while model a2 includes control variables. Model a3 is a panel random effects regression model without control variables, and model a4 includes control variables. Model a5 is a panel fixed effects regression model without control variables, and model a6 includes control variables.

The results indicate that, across models a1 through a6, green finance has a significant positive effect on ecological welfare performance at the 1% significance level, with a pronounced nonlinear effect also observed. This confirms the robustness of the conclusion regarding the positive nonlinear impact of green finance on ecological welfare performance. The specific form of the nonlinear impact is a positive U-shape.

Table 12 Baseline regression model Estimation

	Mixed regression models		Random-effects regression model		Fixed-effects regression model	
	(a1)	(a2)	(a3)	(a4)	(a5)	(a6)
Ingrenf	1.3781*** (12.6194)	0.8927*** (6.6650)	1.3755*** (17.5043)	0.5575*** (3.7668)	1.3754*** (17.4823)	0.5838*** (3.4058)
Ingrenf2	0.4886*** (10.9941)	0.3848*** (8.1330)	0.4861*** (15.1888)	0.2932*** (6.7501)	0.4860*** (15.1670)	0.2964*** (6.2902)
lnhjgz		-0.0193 (-0.7569)		-0.0614*** (-2.7674)		-0.0605*** (-2.6694)
lncyjg		0.1833*** (3.3642)		0.2568*** (3.5297)		0.2484*** (3.0936)
lncxsp		0.7850*** (6.3370)		0.9377*** (4.5981)		0.8491*** (3.3602)
lndwkf		0.0436** (2.2876)		-0.0713** (-3.2802)		-0.0904*** (-3.8485)
_cons	-0.1990*** 1.3781***	-2.0854*** 0.8927***	-0.1983*** 1.3755***	-3.3213*** 0.5575***	-0.1983*** 1.3754***	-3.1901*** 0.5838***
N	660	660	660	660	660	660
adj. R2	0.208	0.313			0.348	0.361

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Further, the Hausman test is conducted for both the random effects model and the fixed effects model. The test results show that $\chi^2(7) = 10.77$ and $\text{Prob} > \chi^2 = 0.1487$, with a p-value greater than 0.05, indicating that there is no significant difference between the coefficients of the random effects model and the fixed effects model. Therefore, the random effects model is more efficient than the fixed effects model. Based on this, the study selects model a4 to describe the nonlinear impact of green finance on ecological welfare performance.

According to this model, the impact of green finance on ecological welfare performance shows a significant U-shaped nonlinear relationship: the coefficient for green finance is 0.5575, while the coefficient for the square term of green finance is -0.2932. This implies that as the level of green finance increases, it increasingly promotes the enhancement of ecological welfare performance.

It is also observed that, under the consideration of the U-shaped nonlinear effect of green finance, each control variable has a significant impact on ecological welfare performance: specifically, the industrial structure and innovation level have positive effects, with coefficients of 0.2568 and 0.9377, respectively. This indicates that a higher proportion of the tertiary industry and a higher level of technological innovation can better promote the improvement of ecological welfare performance. On the other hand, environmental regulation hurts ecological welfare performance, with a coefficient of -0.0614. This negative effect might be due to increased economic costs during the implementation of environmental regulations, insufficient policy enforcement, and inadequate corporate adaptability. Additionally, openness to foreign trade also exhibits a negative effect, with a coefficient of -0.0713. This phenomenon may arise from the fact that foreign direct investment prioritizes commercial economic benefits over environmental and social welfare concerns, leading to environmental degradation, regulatory challenges, and socio-economic inequalities.

3) Endogeneity and Robustness Analysis

Based on the system GMM dynamic panel model, with ecological welfare performance as the dependent variable and the one-period lagged term of ecological welfare performance as an instrumental variable, green finance is used as the explanatory variable. The model is fitted using a two-stage approach to establish model b1. Next, a squared term of green finance is added to model b1 to examine the nonlinear spatial convergence effect of green finance on ecological welfare performance, resulting in model b2. Finally, control variables are included to assess their impact on ecological welfare performance under the nonlinear influence of green finance, leading to model b3. The fitting results of each model are presented in Table 13.

The regression results of model b1 indicate that the coefficient for green finance is 0.3231 and is significant at the 1% level, suggesting a significant positive impact of green finance on ecological welfare performance, consistent with the previous conclusions. The results of model b2 show that the coefficient for the squared term of green finance is 0.4757 and is significant at the 1% level, indicating a significant positive U-shaped nonlinear effect of green finance on ecological welfare performance, which aligns with the previous conclusions. The results of model b3, which includes control variables, reveal that the nonlinear positive U-shaped effect of green finance and its squared term on ecological welfare performance remains significant, confirming the robustness of the conclusion that green finance has a positive U-shaped nonlinear impact on ecological welfare performance.

Table 13 Two-stage systematic GMM model estimation

	(b1)	(b2)	(b3)
L.lnstfl	0.4947*** (58.9426)	0.2451*** (14.8487)	0.2099*** (8.5571)
lngreenf	0.3231*** (28.1490)	1.3754*** (22.6207)	0.6336*** (6.8200)
lngreenf2		0.4757*** (19.7077)	0.3418*** (10.1799)
lnhjgz			-0.0424*** (-9.7968)
lncyjg			0.0367 (0.8952)
lncxsp			1.4648*** (14.7846)
lndwkf			-0.0628*** (-7.3415)
_cons	-0.1352*** (-7.8351)	0.0631*** (2.8299)	-4.0764*** (-17.5236)
<i>Wald</i>	4049.87	4201.04	4268.63
<i>Prob > chi2</i>	0.000	0.000	0.000

The Sargan test was employed to examine the validity of over-identification in the three models. The results (see Table 14) show that the p-values of the Sargan statistics for these models are 1.0000, which is well above the 0.05 significance level. This indicates that the instrumental variables used in these models are valid and appropriate, with no over-identification issues and no significant endogeneity.

Furthermore, the Arellano-Bond test for autocorrelation was conducted. If first-order autocorrelation is significant and second-order autocorrelation is not significant, it suggests that the model is correctly specified and effectively captures the dynamic features of the dependent variable, indicating that the model estimates are valid and robust. Conversely, if both first-order and second-order autocorrelation are significant, it implies that the model may be missing important variables, leading to potential estimation bias and reduced validity of the model.

The test results (see Table 14) reveal that for model b1, when examining the impact of green finance on ecological welfare performance alone, the Arellano-Bond test shows that the significance level of second-order autocorrelation is $0.03 < 0.05$, indicating possible model misspecification due to omitted variables, leading to estimation bias and reduced model validity. However, when the squared term of green finance is added to model b1, the second-order autocorrelation becomes non-significant (with a significance level of 0.0638, greater than 0.05), indicating that the model estimates become valid and robust. Both model b2 and model b3, which include the squared term of green finance, also show robust Arellano-Bond test results. This suggests that when examining the impact of green finance on ecological welfare performance, it is essential to consider the nonlinear effects of green finance, further confirming the significant nonlinear impact of green finance on ecological welfare performance.

In summary, based on the results from the threshold regression analysis, mixed regression analysis, benchmark regression analysis, and the Arellano-Bond and Sargan tests, all findings converge on a consistent result: green finance has a nonlinear effect on ecological welfare performance and its spatial convergence, and this conclusion is robust.

Table 14 Arellano-Bond and Sargan tests of the systematic GMM model

	Arellano-Bond test			Sargan test	
	Order	z	Prob > z	chi2(230)	Prob > chi2
Model (b1)	1	-2.6094	0.0091	27.97363	1
	2	2.1704	0.0300		
Model (b2)	1	-2.5437	0.0110	27.44862	1
	2	1.8537	0.0638		
Model (b3)	1	-2.4496	0.0143	28.49348	1
	2	1.8324	0.669		

4) Heterogeneity Analysis

According to the classification standards for geographic location and economic development level by the National Bureau of Statistics of China, the sample period is divided into four regions: Eastern, Central, Western, and Northeastern China. The nonlinear impact of green finance on ecological welfare performance across these regions is examined. The results of the regression analysis are presented in Table 15. The findings indicate that while green finance has a significant positive nonlinear effect on ecological welfare performance in all regions, the magnitude of this effect varies across different regions. Additionally, the impact of control variables on ecological performance also shows regional differences. This suggests that the positive nonlinear impact of green finance on ecological welfare performance exhibits regional heterogeneity.

Table 15 Regression estimates of heterogeneity tests

	D1	D2	D3	D4	D5
	Eastern region	Central region	Western region	Northeastern region	China
Ingreenf	0.9679*** (7.1396)	1.9885*** (4.5281)	0.6409** (2.2101)	0.4116** (2.0158)	0.5575*** (3.7668)
Ingreenf2	0.4249*** (9.3796)	0.6471*** (4.6846)	0.2791*** (3.2293)	0.2413*** (3.9243)	0.2932*** (6.7501)
Inhjgz	0.0062 (0.2741)	-0.0091 (-0.1192)	-0.0941* (-1.8445)	-0.0516** (-2.0344)	-0.0614*** (-2.7674)
Incyjg	0.2200*** (4.2286)	-0.1604 (-0.7313)	0.3999** (2.2517)	-0.1501** (-2.4091)	0.2568*** (3.5297)
Incxsp	1.3902*** (9.7882)	-0.6089 (-1.0101)	0.2674 (0.7294)	1.5097*** (4.1921)	0.9377*** (4.5981)
Indwkf	0.1253*** (3.2066)	-0.3051*** (-3.3791)	-0.0835** (-2.1596)	-0.0676** (-2.2526)	-0.0713*** (-3.2802)
_cons	-2.9280***	0.2104	-2.1844**	-4.8147***	-3.3213***



D1	D2	D3	D4	D5
Eastern region	Central region	Western region	Northeastern region	China
(-7.2454)	(0.1220)	(-2.3977)	(-4.9526)	(-6.1773)

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5) Expandability Analysis

As observed from the baseline regression analysis, environmental regulation, openness, innovation level, and industrial upgrading all exhibit significant impacts on ecological welfare performance when considering the influence of green finance. To further investigate the nonlinear mechanisms of green finance within the context of these control variables' effects on ecological welfare, a threshold regression model with green finance as the threshold variable is employed. The results of the threshold effect from the sample test are shown in Table 16.

The output indicates that green finance exhibits a threshold effect in the context of industrial upgrading's impact on ecological welfare performance. Moreover, significant dual threshold effects of green finance are observed in the contexts of environmental regulation, openness, and innovation level affecting ecological welfare performance. The first and second threshold values are consistently -1.7284 and -1.2775, respectively. Notably, the dual threshold effect of green finance on ecological welfare performance is observed with a first threshold value of -1.2784 and a second threshold value of -1.2571, which is close to -1.2775. This proximity suggests a degree of robustness in the threshold values for the nonlinear effects of green finance.

Table 16 Self-sampling tests for the threshold effects of the control variables

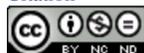
	Thresh old	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Environmental regulation	Single	73.1168	0.1146	90.81	0.000	40.6284	45.3821	57.2301
	Double	70.0473	0.1098	27.96	0.040	20.2734	23.5328	30.7525
Openness level	Single	73.1168	0.1146	90.81	0.000	40.6284	45.3821	57.2301
	Double	70.0473	0.1098	27.96	0.040	20.2734	23.5328	30.7525
Innovation level	Single	72.6595	0.1139	95.4	0.000	36.3749	44.4903	56.6788
	Double	70.1272	0.1099	23.04	0.0733	21.333	26.9207	33.1413

Dual threshold regression models are established with green finance as the threshold variable to examine its impact on ecological welfare performance, specifically in the contexts of environmental regulation, openness, and innovation level. The regression results are presented in Table 17.

The results in column c1 reveal that as the level of green finance increases, the negative constraint effect of environmental regulation on ecological welfare performance progressively diminishes. When green finance is below -1.7284, the negative impact of environmental regulation on ecological welfare performance is at its highest, with a coefficient of -0.1918, significant at the 1% level. When $-1.728 < \text{green finance} < -1.2775$, the negative impact of environmental regulation decreases to -0.1093, still significant at the 1% level. When green finance exceeds -1.2775, the negative impact of environmental regulation further diminishes to -0.0593, significant at the 1% level.

The results in column c2 indicate that as the level of green finance rises, the negative constraint effect of openness on ecological welfare performance also weakens. When green finance is below -1.7284, the negative impact of openness on ecological welfare performance is at its maximum, with a coefficient of -0.2055, significant at the 1% level. When $-1.728 < \text{green finance} < -1.2775$, the negative impact of openness decreases to -0.1112, significant at the 1% level. When green finance exceeds -1.2775, the negative impact of openness further reduces to -0.04527, significant at the 5% level.

The results in column c3 demonstrate that as the level of green finance increases, the positive promotion effect of innovation level on ecological welfare performance also declines. When green finance is below -1.7284, the positive impact of innovation level on ecological welfare performance is at its peak, with a coefficient of 1.7740, significant at the 1% level. When $-1.728 < \text{green finance} < -1.2775$, the positive



impact of innovation level decreases to 1.5466, significant at the 1% level. When green finance exceeds -1.2775, the positive impact of innovation level further weakens to 1.4215, significant at the 5% level.

Table 17 Threshold regression estimates of t control variables on EWP

	C1	C2	C3
	Environmental regulation	Openness level	Innovation level
$\text{Lngreenf} < -1.7284$	-0.1918*** (-8.11)	-0.2055*** (-8.27)	1.7740*** (10.73)
$-1.728 < \text{Lngreenf} < -1.2775$	-0.1093*** (-4.84)	-0.1112*** (-4.56)	1.5466*** (9.84)
$\text{Lngreenf} > -1.2775$	-0.0593*** (-2.8)	-0.04527** (-1.91)	1.4215*** (10.10)

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In summary, except industrial structure, green finance exerts a significant dual-threshold nonlinear impact on the effects of environmental regulation, openness, and innovation level on ecological welfare performance. Specifically, green finance mitigates the negative impact of environmental regulation and openness on ecological welfare performance, though this mitigating effect diminishes as the level of green finance increases. Conversely, green finance enhances the positive impact of innovation level on ecological welfare performance, yet this enhancement wanes as the level of green finance rises.

Conclusion

This study examines the nonlinear impact of green finance on ecological welfare performance, providing a novel perspective on this relationship. Utilizing provincial panel data from 2000 to 2021, we employed the entropy weight method and the non-desired output super-efficiency SBM model to measure green finance development and ecological welfare performance. We then established threshold regression models to explore nonlinear relationships, with a two-stage system GMM dynamic regression model verifying the robustness of our findings.

Our research reveals that green finance has a significant dual-threshold nonlinear impact on ecological welfare performance, following a U-shaped pattern. This finding aligns with environmental Kuznets curve theory but extends it to the financial sector, suggesting that green finance may initially require substantial investment before yielding positive ecological returns. The observed U-shaped relationship may reflect the time lag between financial allocation and tangible environmental improvements, as initial investments in green infrastructure and technologies require time to mature and yield ecological benefits.

The analysis of interaction effects reveals complex relationships between green finance and other economic factors. While industrial structure significantly promotes ecological welfare performance without evident threshold effects from green finance, innovation demonstrates a dual-threshold effect. As green finance levels rise, its enhancement of innovation's positive impact gradually diminishes, suggesting diminishing returns in the green finance-innovation nexus. This finding challenges conventional assumptions about the continuously increasing benefits of green innovation financing and calls for more strategic allocation of innovation resources at different development stages.

Environmental regulation and economic openness currently exhibit negative impacts on ecological welfare performance, but green finance demonstrates a mitigating effect on these negative influences. As green finance development increases, the adverse impacts of both factors progressively decrease, indicating green finance's potential to harmonize environmental policies with economic objectives. This finding supports the Porter Hypothesis (1995) that well-designed environmental policies, when complemented by appropriate financial mechanisms, can enhance rather than hinder competitiveness.

Regional analysis reveals significant heterogeneity in the development of green finance and ecological welfare performance across China. The eastern region demonstrates the highest levels of both indicators, followed by central, western, and northeastern regions. These disparities reflect variations in economic structures, institutional capacities, and policy implementation. While all regions exhibit a positive U-shaped relationship between green finance and ecological welfare performance, the threshold points and effect magnitudes vary considerably, suggesting the need for regionally tailored approaches.



These findings have important policy implications. First, policymakers should recognize that green finance benefits may not be immediate, necessitating sustained commitment beyond initial implementation phases. Second, regional governments should develop differentiated green finance strategies based on their specific development stages and ecological challenges. Third, financial institutions should design green financial products that complement existing environmental regulations while supporting industrial upgrading and technological innovation. Finally, coordinated policy frameworks that integrate green finance with environmental regulation, innovation promotion, and international economic cooperation would optimize ecological welfare outcomes.

Future research should explore several promising directions: the sector-specific impacts of green finance on ecological welfare; the role of green finance in carbon neutrality strategies; cross-national comparisons of green finance effectiveness; and the long-term dynamic relationship between green finance, economic growth, and ecological sustainability. Additionally, investigating the microeconomic mechanisms through which green finance influences firm-level environmental performance would further enhance our understanding of its practical implications.

Discussion

Green Finance's Nonlinear Impact on Ecological Welfare Performance

The results of our research found that green finance has a significant dual-threshold nonlinear impact on ecological welfare performance, demonstrating a positive U-shaped pattern. Specifically, green finance exhibits minimal effect below the first threshold value (-1.7284), begins to show positive significance between the thresholds (-1.7284 to -1.2571), and demonstrates the strongest positive impact above the second threshold (-1.2571).

This nonlinear relationship may be because in early stages of green finance development, financial institutions lack experience in evaluating environmental projects, resulting in inefficient resource allocation. As green finance matures beyond critical thresholds, improved assessment capabilities and regulatory frameworks enhance its ecological effectiveness.

These findings are consistent with Zhou et al. (2020), who observed that green finance requires capacity building before demonstrating significant environmental improvements, and Li et al. (2019), who found nonlinear threshold effects of green finance on industrial green development.

Interactive Effects with Environmental Factors

Our research reveals that environmental regulation and openness currently exert negative effects on ecological welfare performance, but green finance progressively mitigates these impacts. This mitigation effect may occur because green finance provides the necessary capital for businesses to adapt to environmental regulations through technological upgrades.

These findings align with the Porter Hypothesis (1995) discussed by Chen et al. (2021), who argued that appropriate financial mechanisms can transform environmental regulations into competitive advantages. Similarly, our results show that while green finance enhances innovation's positive impact on ecological welfare, this effect diminishes at higher green finance levels, consistent with Wen et al. (2022), who identified diminishing returns in the relationship between green finance and technological innovation.

Regional Heterogeneity

Our regional analysis revealed significant heterogeneity in green finance effects across Chinese regions. While all regions exhibit a positive U-shaped relationship, the eastern region demonstrates the strongest effect, followed by central, western, and northeastern regions.

This regional variation may exist because the eastern region possesses more mature financial markets and technological capabilities that enhance green finance effectiveness, while the northeastern region faces challenges from its legacy industrial structure.

These findings are consistent with Wang & Wang (2021), who observed significant spatial variations in ecological welfare performance across Chinese regions, and extend this understanding by demonstrating that these spatial patterns are intertwined with regional green finance development patterns.

Recommendation

Based on our findings regarding green finance's nonlinear impact on ecological welfare performance, we propose the following policy recommendations:

For different development stages, tailored policies are essential. In the early stages, the government should promote green finance through fiscal incentives and tax benefits for environmental enterprises.





During intermediate stages, improving market transparency and strengthening regulations will direct funds toward sustainable projects. At advanced stages, focus should shift to high-quality green projects to address diminishing returns.

Regional differences require specific approaches. Eastern regions should accelerate green finance internationalization and innovation. Central regions should prioritize the green transformation of traditional industries. Western and Northeastern regions need enhanced green finance infrastructure and targeted environmental investment.

To leverage the positive impact of industrial structure and innovation, policies should drive industrial upgrading toward service-oriented and low-carbon sectors, while encouraging financial institutions to support green technologies. Given the diminishing returns in innovation, precise investment in high-potential technologies should be prioritized over broad financial distribution.

To mitigate the negative impacts of environmental regulation and openness, policymakers should implement market-based mechanisms like carbon trading and align domestic green finance standards with international practices, helping transform regulatory challenges into sustainable development opportunities.

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