Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8, 1039-1068
2025
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v9i8.9542

How green finance drives innovation: An empirical analysis based on urban efficiency evaluation

Siyao Liu[1]*
[1]Beijing Foreign Studies University, Beijing 100089, China; Liusiyao_100089@163.com (S.L.).

Abstract: Based on balanced panel data of 284 prefecture-level cities in China from 2007 to 2021, this paper employs the SBM-DEA model, which is based on a two-stage value chain perspective, to measure green technology efficiency (GTE) and green result efficiency (GRE). The study utilizes fixed effect panel models (FE), dynamic threshold models, and spatial Durbin models (SDM) to explore the mechanisms and effects of green finance on GTE and GRE. The results indicate that green finance significantly improves both GTE and GRE: for every 1% increase in green finance, GTE and GRE increase by 0.203% and 0.258%, respectively. These findings remain robust under various tests for endogeneity and sensitivity. Green finance primarily enhances GTE by alleviating financing constraints and stimulating social consumption. Additionally, formal and informal environmental regulations significantly strengthen the impact of green finance on GTE and GRE. When using green finance as a threshold variable, the analysis reveals a nonlinear increasing effect on both GTE and GRE. Furthermore, green finance exhibits spatial spillover effects on GTE and GRE and demonstrates significant spatio-temporal heterogeneity. This study contributes to understanding and promoting the application of green finance in supporting rural revitalization and smart agricultural energy solutions.
Keywords: *Green innovation efficiency, Rural revitalization, Smart energy, Spatial spillover, Two-stage value chain.*

1. Introduction

Since the Industrial Revolution, the intensive use of fossil fuels has steadily increased global greenhouse-gas emissions, and climate change has become an urgent challenge for governments worldwide, exerting wide-ranging impacts on natural ecosystems and human living environment [1]. Compared with the pre-industrial baseline (1850–1900), the global mean surface temperature during 2011–2020 rose by 1.09 °C, and average warming is expected to exceed 1.5 °C within the next two decades [2]. Mounting evidence shows that the harmful consequences of climate change—manifested through air-pollution-related illnesses, epidemics, extreme weather events, forced displacement, foodinsecurity and mental-health stress—are undermining both human health and sustainable development [3, 4]. Although these effects are worldwide,emerging economies such as China face particular difficulties because of their intense demand for energy and resources.

As a result of fast economic expansion and crude urbanization, China is now the biggest worldwide energy consumer and CO_2 emitter [5]. The International Energy Agency (IEA) states that China became the world's top energy consumer in 2011. The BP Statistical Yearbook of World Energy 2022 shows that China's total primary energy consumption climbed from 16.65 EJ to 157.65 EJ between 1978 and 2021, and its proportion of global primary energy consumption increased from 6.11% to 26.5%. Furthermore, China's energy carbon emissions climbed from 1,419 million tons to 10,523 million tons, bringing its contribution to total global carbon emissions from less than 1/10 to nearly 1/3. So as to ensure green and sustainable growth, the Chinese government said that it is going to try to get peak carbon emissions by 2030 and proceed toward the goal of carbon neutrality by 2060 [6]. This is a critical requirement for attaining sustainable and high-quality development. Green industry

History: Received: 25 June 2025; Revised: 6 August 2025; Accepted: 12 August 2025; Published: 19 August 2025
* Correspondence: Liusiyao_100089@163.com

investments and green technology upgrades are needed to transform China's economy with the constraints of the "double carbon" goal [7]. Many scholars emphasize the function of green technology innovation [8, 9]. Green technical innovation has the potential to significantly improve industrial technology while also focusing on resource conservation and economic development. It is a key step toward achieving a coordinated development model for the environment and economy [10].

Yet green innovation typically entails large investment, high project risk, long payback periods and positive externalities [11]. Under fierce market competition, these factors dampen firms' motivation to engage in green R&D [12]. Enterprises,universities and research institutes—all primary sources of green innovation—must therefore rely on enhanced financial support [13, 14]. Because conventional finance is profit-oriented, it often fails to integrate with green technology. Building an effective green-innovation ecosystem consequently depends on the development of green finance (GF).

China 's 20th CPC National Congress called for an accelerated green transformation of the growth model and for improving fiscal, financial, investment, price and standard systems that support green development. Participation by green-finance institutions can supply critical funding for corporate R&D teams and mitigate market risk [15] GF is therefore vital for improving green-innovation efficiency (GIE).

At the policy level the Chinese government has issued multiple documents to foster GF.In 2017 eight pilot zones for green-finance reform and innovation were established in Zhejiang, Jiangxi, Guangdong, Guizhou and Xinjiang [16]. By 2020 these zones had amassed RMB 236.83 billion in outstanding green loans (15.1 % of all local lending—four percentage points above the national average) and RMB 135 billion in green bonds, up 66 % year-on-year [17]. A relatively complete service system—covering organisations, products and infrastructure—has therefore taken shape, and pilot zones have achieved notable success.

Existing studies mainly examine how specific green-credit policies affect the environment.Evidence suggests that green credit can ease financing constraints, boost innovation investment, optimise economic structure and raise regional green efficiency [18, 19]. However, little is known about (i) how green finance improves GIE, (ii) whether nonlinear or spatial characteristics exist in this relationship and (iii) the relevance of rural application scenarios.

To fill these gaps, this study adopts a two-stage value-chain perspective that divides GIE into green technology efficiency (GTE) and green result efficiency (GRE). Using balanced panel data for 284 prefecture-level Chinese cities (2007 –2021), this study:

First, investigated the characterization of the effect of GF on GIE using the panel two-fixed-effects model (FE). Second, we examine the path mechanism of GF for GIE enhancement from the standpoint of financial constraints (FIN) and social consumption (SOC) Then, investigate whether different forms of environmental regulations have distinct moderating effects in terms of formal environmental regulation (FER) and informal environmental regulation (LER). Third, used the dynamic threshold panel model to explore the threshold characteristics of GF on GIE. Finally, used the spatial Durbin model (SDM) to evaluate the spatial influence of GF on GIE.

The research design is the following (Fig. 1): First, this paper explains the current state, research gap, and research implications of GF and GIE. Second, Section 2 conducts a comprehensive evaluation of pertinent studies on the effects of GF on GIE and proposes research hypotheses. Third, Section 3 introduces SYS-GMM, the mediated effects model, the moderated effects model, the dynamic threshold model, SDM, and data sources. Fourth, Section 4 offers an in-depth examination of the effects of GF on GIE, including direct effects, mediating effects, moderating effects, dynamic threshold effects, and spatial effects. Finally, Section 5 summarizes the investigation findings and discusses the policy applications.

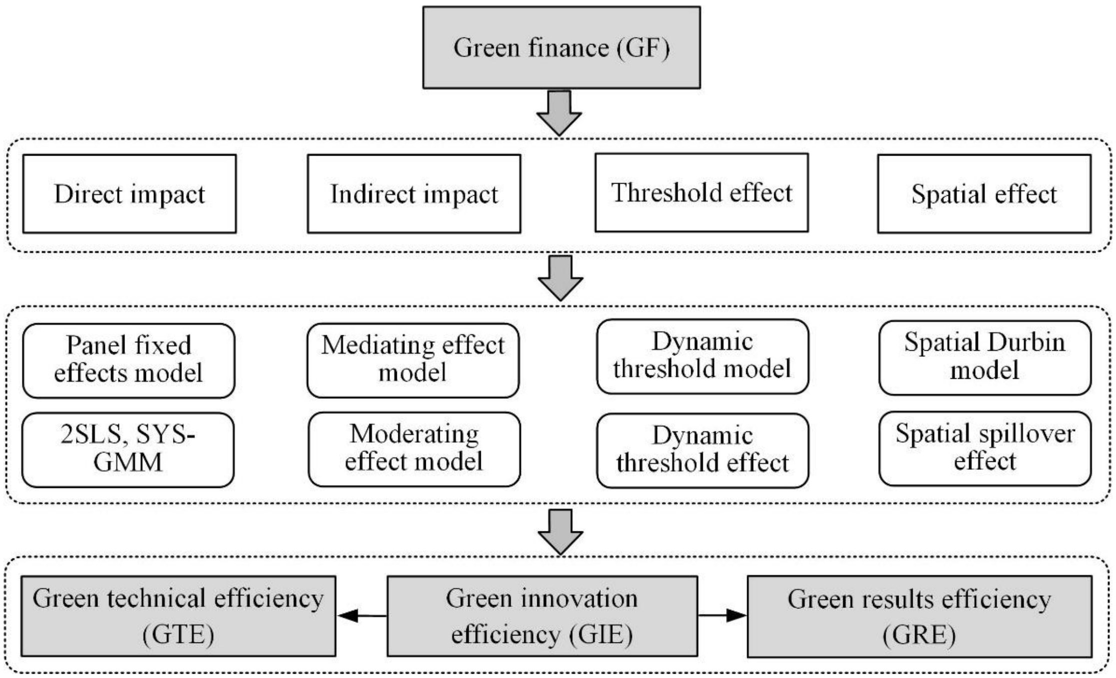

Figure 1.
Research framework of this paper.

2. Theoretical Analysis and Research Hypotheses

2.1. GF and GIE

The conclusion that financial sector development can promote economic efficiency has been confirmed by contemporary studies [20]. However, the characteristics of profit-seeking and agglomeration in finance itself lead to the fact that funds are often not invested in high-cost and high-risk green innovation industries. Second, GF operates by implementing differentiated standards that impose strict constraints on financing for highly polluting firms while reducing the economic burden on environmentally friendly enterprises. When evaluating financing requests, these institutions take into account environmental considerations and establish lending criteria based on a company's environmental credentials and sustainable development strategy [21]. This approach efficiently limits the scale of finance for highly polluting sectors while offering more favorable financing conditions for environmentally conscious enterprises, thereby enhancing their Green finance (GF) can effectively alleviate financial constraints on innovative green firms, enabling them to allocate more resources towards green innovation initiatives. First, GF offers customized financial services, such as green loans, green bonds, and green venture capital, tailored to meet the unique needs of innovative green businesses. These financial services align with firms' green projects and business strategies, facilitating the attainment of sustainable development goals [22].

Second, GF provides favorable financing conditions, including low-interest loans, preferential interest rates, and flexible repayment terms. These conditions not only reduce the financing costs for green and innovative companies but also enhance the efficiency of capital utilization [23]. Third, through the provision of risk management tools like green insurance and green guarantees, GF helps alleviate the innovation risks faced by environmentally friendly businesses. These tools primarily aim to safeguard the environment and promote sustainable growth, thereby increasing investor and financial institution confidence in these businesses and fostering their long-term development [24]. Finally, GF plays a pivotal role in enhancing corporate transparency and sustainability. It requires green enterprises to adhere to environmental, social, and governance (ESG) criteria, thereby improving their overall sustainability. This includes conducting environmental and social impact assessments, establishing disclosure and reporting standards, and enhancing their ESG image. These actions contribute to fostering investor trust and attracting greater capital inflows [25].

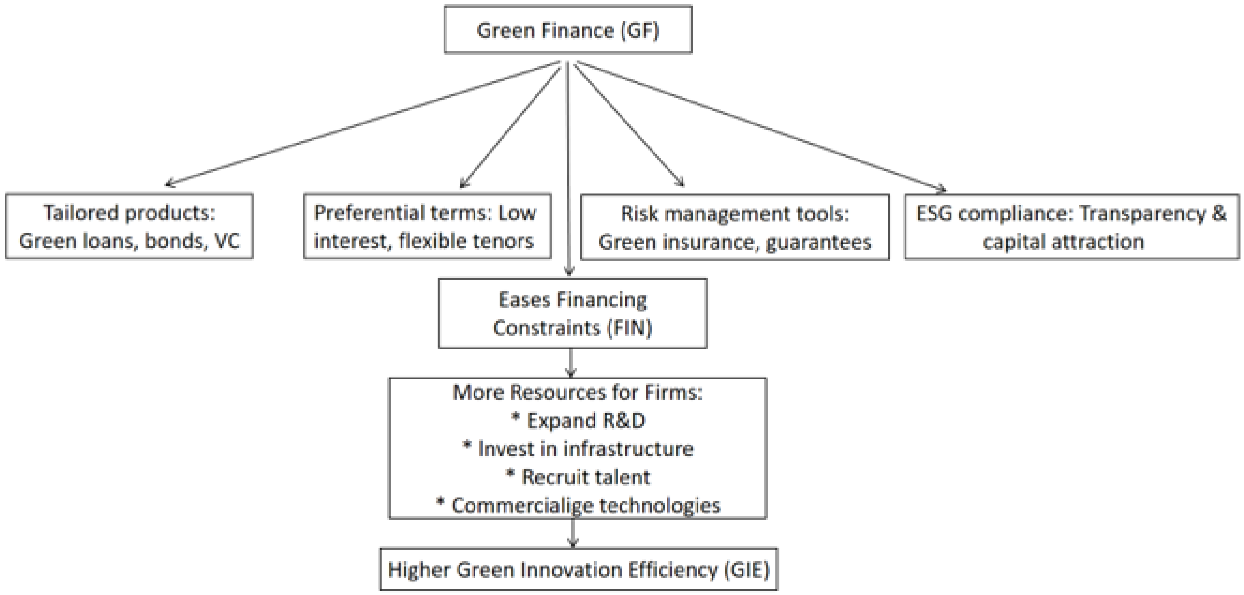

Figure 2.
Distribution of GF in 2007 and 2021.

Hypothesis 1: GF promotes GIE by alleviating FIN.

2.2. GF, FIN and GIE

When firms effectively mitigate financial constraints (FIN) through green finance (GF), it implies an increase in resource availability for firms' green innovation activities, which enhances green innovation efficiency (GIE). First, by mitigating FIN, firms gain access to sufficient funds to expand their investments in innovative research and development (R&D) beyond production activities, thereby enhancing their overall innovation capacity. Second, enterprises can attract and retain high-quality R&D talent, establish innovation teams and cooperation networks, and facilitate the rapid development of green innovation [26]. Second, the mitigation of FIN provides enterprises with a broader space and deeper exploration opportunities to pursue green innovation. Companies can proactively explore diverse green technologies and solutions, expanding into various industries and markets. This expanded scope of innovation allows firms to identify new opportunities and apply technologies effectively, thereby driving further green innovations [27]. Finally, the mitigation of FIN plays a crucial role in the commercialization of green innovations by enterprises. Companies can facilitate the commercialization of green innovation products and services by increasing investments in marketing, scaling up production, and constructing robust supply chains [28]. This not only improves the efficiency and competitiveness of enterprises but also promotes the long-term development of green innovation. Based on the aforementioned analysis, we propose hypothesis 2.

Hypothesis 2: GF can affect GIE by alleviating FIN.

2.3. GF, SOC and GIE

GF development will have a positive impact on SOC. First, from the supply side, GF could provide funding to environmentally friendly companies. The GF has prompted these companies to introduce more green products and solutions to meet consumer demand for sustainable and environmentally friendly products [29, 30]. Meanwhile, GF impacts the funding costs of pollution enterprises and reduces the financing expenses of environmentally friendly firms, forcing firms to innovate production technology to realize industrial structure upgrades and provide consumers with more green products and services [18]. Second, from the consumer side, consumers can choose to buy these products through green financial methods to express their support for environmental protection, which in turn promotes the popularization of sustainable consumption [31]. In addition, GF plays a guiding and educational role in SOC [32]. By publicizing and advocating the concept and practice of green finance, consumers can better understand the advantages of environmentally friendly products and enterprises, prompting them to consider the environmental performance and social impacts of products when making purchasing decisions. This will promote the growth of green consumption.

Increased SOC largely influences green innovation efficiency. First, consumer demand and purchasing behavior for environmentally friendly products directly affect the motivation and direction to pursue green innovation. When consumer demand for green products increases, companies are compelled to invest more resources in green innovation to meet market demand [33]. This market-driven force incentivizes companies to allocate more resources towards green inventions, thereby driving the advancement of green innovation efforts [34]. Second, the influence of SOC on the green innovation ecosystem is closely linked to firm behavior and market competition. In order to establish a leading position within their respective industries, companies must continuously innovate and introduce greener products and solutions. The pressure of market competition serves as a catalyst for firms to enhance their green innovation initiatives and strive for continuous improvement in green innovation efforts [35]. From a broader perspective, GF has an impact on the structure and behavior of social consumption by providing financial support to environmentally friendly enterprises and guiding consumers towards green consumption patterns [36]. The demand and behavior of social consumption directly influence the motivation and direction of green innovation initiatives within enterprises, thereby indirectly affecting the overall improvement of GIE. This reciprocal relationship demonstrates that GF can influence GIE through SOC. Based on the aforementioned analysis, we propose research hypothesis 3.

Hypothesis 3: GF can affect GIE through greater SOC.

2.4. GF, ER and GIE

GF is affected by the extent of regional environmental regulation (ER), which influences green innovation efficiency. ER is a rule established by the government for protecting the environment and a general requirement for imposing green restrictions on the manufacturing behavior of enterprises. First, as the degree of ER gets higher, firms face higher costs for pollution treatment at the end of the pipe. In order to enhance competitiveness in the market, companies have to eventually maximize long-term profitability by lowering pollution prevention and operating costs through innovative green technologies, products, and processes [37]. Second, stronger ER raises public awareness of environmental protection, and consumer preference for environmentally friendly firms increases, and such firms are more probable to receive support from the GF. To increase their customer base and acquire an edge over competitors across a range of industries, firms decide to implement green techniques to manufacture environmentally friendly goods to attract customers [38, 39]. Finally, as ER has increased, environmental indicators have been incorporated into the assessment criteria for encouraging officials in regions. According to the existing economic and financial structure, the government often formulates a series of environmental protection regulations that are customized to local situations. For instance, decreasing taxes or incentives can reduce the overall expenses of green innovation for enterprises, and GF and digital finance can solve the problem of challenging financing for enterprises [40]. In this paper, we argue that green finance provides strong financing support to industries in the context of increasingly stringent existing ER and that this support will increase access to funding sources for innovative activities. Accordingly, we formulate hypothesis 4.

Hypothesis 4: ER can effectively moderate the impact of the GF on the GIE.

ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

2.5. The Threshold Effect of GF on GIE

As a relatively new form of green financing, GF needs long-term support in terms of technology, capital, market, and policy to achieve its function in promoting GIE. During the beginning period of GF development, the technology is not mature enough, and financial institutions may have difficulties recognizing and evaluating complex or newer green projects [41]. Second, the size of the GF market and the availability of capital may be limited, resulting in green innovation firms facing certain constraints in accessing financial support [42]. Third, GF needs to consider market prospects and commercial viability when promoting green technological innovations, and the facilitating role of green finance may be limited if the market size is small or demand is insufficient [43]. Finally, the development of GF requires corresponding policy and regulatory support. If the relevant laws and regulations are not sound or the policy measures are not perfect, green technology finance may face compliance and policy risks, thus affecting the enhancement and development of GIE [44]. When GF develops to a certain extent, the diversification of financial products and services will satisfy the demands of diverse kinds of environmentally friendly businesses and green investors [24]. Second, the scale of the GF market is expanding, the supply of GF projects and products is sufficient, and market participants have higher recognition and acceptance of green finance [45]. In addition, technical means such as fintech improve the efficiency and convenience of GF [46]. Finally, environmental protection policies, financial regulatory policies, and tax policies are necessary to preserve the sustainability and stability of GF [47]. In summary, the process of GF promoting GIE is characterized by a threshold effect, i.e., as the level of GF rises, the promotion impact of GF on GIE will gradually increase. Accordingly, we formulate research hypothesis 5.

Hypothesis 5: There is a threshold effect in the process of GF influencing GIE with GF itself as the threshold variable.

2.6. The Spatial Effect of GF on GIE

With China's financial system and norms continuously improving, GF is gradually characterized by geographic clustering. However, due to the huge size of the country, the inter- regional green financial base and green financial resources show an uneven geographical distribution. First, according to the "information hinterland theory," local protectionism and administrative boundary delineation readily limit the spatial spillover effects of GF development, which continues to be strongly influenced by local preferences and policies [48]. With the expansion of GF in the region, financial infrastructure construction has also been consolidated, contributing to efforts to alleviate information imbalance. This can not only help green enterprises or projects in the region to reduce the financing cost and improve the efficiency of financing, but also have a radiating effect on the neighboring regions through the effective flow offactors of production. This will increase the GIE in the neighboring regions [49]. Second, the theory of "growth poles" suggests that regional imbalances in economic development necessitate intervention from the government to reestablish balance. The government could take advantage of the propagation and dispersion functions of growth poles to rationally allocate financial resources and narrow the regional development gap [50]. The government guides green finance and green technology to circulate among regions, which promotes the enhancement of local GIE and at the same time will lead to the growth of GIE in other regions [10]. Given that, this study shows the following research hypotheses:

Hypothesis 6: GF can improve GIE through spatial spillovers.

3. Methods and Data

3.1. Measurement of GF

GF is defined as financial services for environmental protection, energy conservation, and renewable energy to increase the efficiency of resource utilization and improve environmental governance. Its purpose is to transfer finances from polluted and energy-intensive industries to cleaner, higher-tech sectors. Currently, GF in China mostly includes green credit, green securities, green insurance, and green investment [51]. Therefore, we constructed the GF composite index from these four indicators [29, 52, 53]. Table 1 summarizes the indicator system.

The GF index is calculated using the following steps: First, each indicator is statistically transformed to get rid of problems with measurement that include discrepancies and disagreements between indicators. For this purpose, the indicators can be divided into positive and negative indicators and processed by using the formula for the extreme difference between groups. Second, the index values were calculated by the entropy method [29]. The detailed calculation process is described as following.

Data standardizing processes Processing. The data matrix consisting of n indicators for m cities was standardized by formula (1) for positive indications and formula (2) for negative indicators:

$$Z_{ij} = \left\{Y_{ij} - \min Y_{ij}\right\} \Big/ \left\{\max Y_{ij} - \min Y_{ij}\right\} \tag{1}$$

$$Z_{ij} = \left\{\max Y_{ij} - Y_{ij}\right\} \Big/ \left\{\max Y_{ij} - \min Y_{ij}\right\} \tag{2}$$

Indicator information entropy calculation. Calculate the entropy value of the jth indicator:

$$d_j = -\left(\frac{1}{\ln m}\right)\sum_{i=1}^{m}\left(Z_{ij} \Big/ \sum_{i=1}^{m} Z_{ij}\right)\ln\left(Z_{ij} \Big/ \sum_{i=1}^{m} Z_{ij}\right), \quad 1 \le j \le n \tag{3}$$

Indicator weight calculation. Calculate the weight value of the jth indicator:

$$W_j = \left(1 - d_j\right) \Big/ \sum_{j=1}^{n}\left(1 - d_j\right) \tag{4}$$

Comprehensive Evaluation Score Calculation. Calculate the composite evaluation score for the ith city:

$$GF_i = \sum_{j=1}^{n} W_j Z_{ij} \tag{5}$$

Based on the above methodology, we calculate the GF index of Chinese cities from 2007 to 2021, as shown in Figure 3.

Table 1.
GF development level evaluation indicator system.

First level indicator	Secondary indicators	Indicator description
Green finance	Green credit	Total bank loans to environmental protection enterprises as a proportion of total loans from financial institutions The proportion of interest expenditures in total industrial interest expenditures, except for the six major energy- consuming industrial industries
	Green investment	Investment in environmental pollution management as a proportion of GDP The proportion of overall fiscal expenditures in the energy conservation and environmental protection expenditures Environmental protection firms' A-share market value as a percentage of the overall A-share market value of listed corporations
	Green securities	Agricultural insurance spend as a percentage of overall insurance expenditure
	Green insurance	

ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

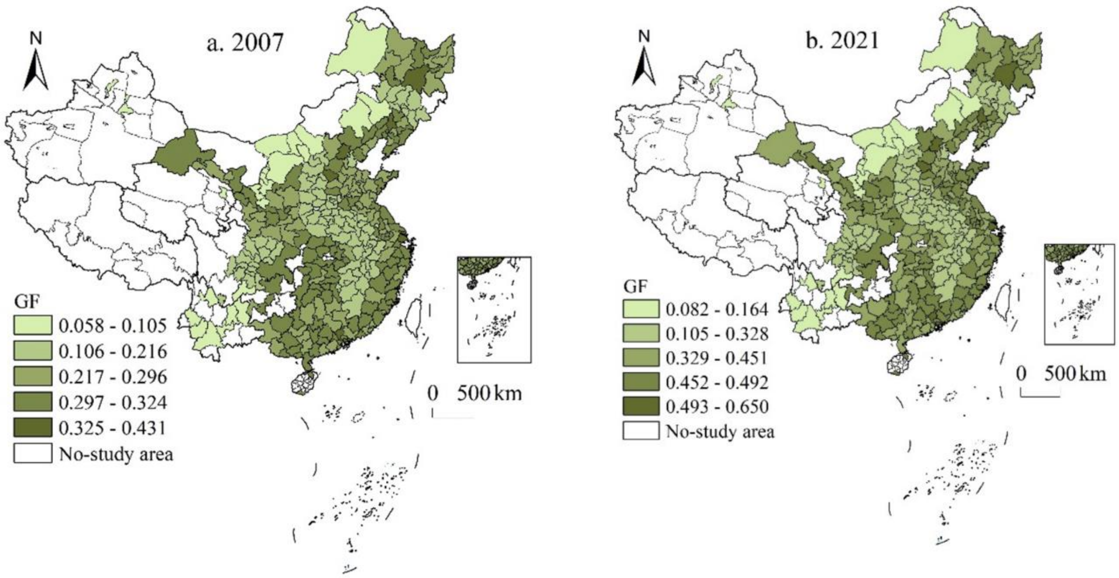

Figure 3.
Distribution of GF in 2007 and 2021.

3.2. Measurement of GIE

The DEA model is a method used in operations research to evaluate the production efficiency of the decision-making department. It provides a more efficient method for evaluating multiple input and output indicators, compares multiple inputs with multiple outputs to obtain an efficiency analysis, and has been widely used in performance evaluation [54]. However, such a method faces several limitations. For example, there are limitations in handling unanticipated outputs, and when input and output variables are slack, efficiency values may be overestimated. Therefore, based on the ideas of Tone and Tsutsui [55] the study uses the SBM-DEA model, adding undesirable outputs, to evaluate the two-stage GIE [56].

$$\rho = \min \frac{1-\frac{1}{E}\sum_{e=1}^{E} S_e^x / x_{k'e}^{t'}}{1+\frac{1}{D+1}\left(\sum_{d=1}^{D} s_d^y / y_{k'd}^{t'} + \sum_{i=1}^{I} s_i^b / b_{k'i}^{t'}\right)} \tag{6}$$

$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{kd}^t + s_e^x = x_{k'e}^{t'}, e = 1,2,\cdots,E \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{kd}^t - s_d^y = y_{k'e}^{t'}, d = 1,2,\cdots,D \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{ki}^t + s^b = b_{k'e}^{t'}, i = 1,2,\cdots,I \\ z_k^t \geq 0, s_e^x \geq 0, s_d^y \geq 0, k = 1,2,\cdots,K \end{cases} \tag{7}$$

Here, r represents the value of GIE; E , D , and I represent the quantities of inputs, desired outputs, and undesirable outputs, respectively, s_e^x , s_d^y , s_i^b represents the input-output slack vector, x

ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

${}^{t'}_{k'e}$, $y^{t'}_{k'e}$, $x^{t'}_{k'e}$ represents the input-output value of the region k in time t t , z_k represents the weight of the decision unit, and r accepts values within the range of [0.1].

Referring to the two-stage value chain perspective, we categorize green innovation actions into two processes: green technology research and development and green results transformation. Table 2 displays the evaluation index system of GIE. The green technology research and development stage is mainly the process of utilizing innovative resource inputs to realize innovative outputs. The green results transformation stage is the process of putting innovative outputs into the market to realize economic growth and environmental protection. The first stage is green technology research and development efficiency (GTE). The input indicators correspond to the research of Zhu, et al. [57] respectively: science and technology expenditures are selected as capital inputs, practitioners engaged in science and technology activities are selected as labor inputs, and the total amount of electricity supply is used as resource inputs. The second stage is green results transformation efficiency (GRE), which refers to the studies of Kiani Mavi, et al. [58] and Zhao, et al. [59] takes the output indicators of the green technology research and development stage as the input indicators of the outcome transformation stage. Among the output indicators, the gross regional product is chosen as the desired output, and industrial wastewater, industrial sulfur dioxide, and regional carbon dioxideemissions are used as the non-desired outputs [8] respectively. This is used to reflect both economic and environmental output throughout the achievement transformation stage. Fig. 3 shows the calculated GTE and GRE indices.

Table 2.
GIE development level evaluation indicator system.

GIE	**First level indicator**	**Secondary indicators**	**Indicator description**
GTE	Input Output	Capital input Labor input Resource input Technical output	Government expenditure on science and technology Number of persons engaged in scientific and technological activities Total electricity supply in the city Count of green patents granted
GRE	Input Output	Technical input Desired output Undesired output	Count of green patents granted Gross regional product (GDP) Industrial wastewater, industrial sulphur dioxide and carbon dioxide emissions

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

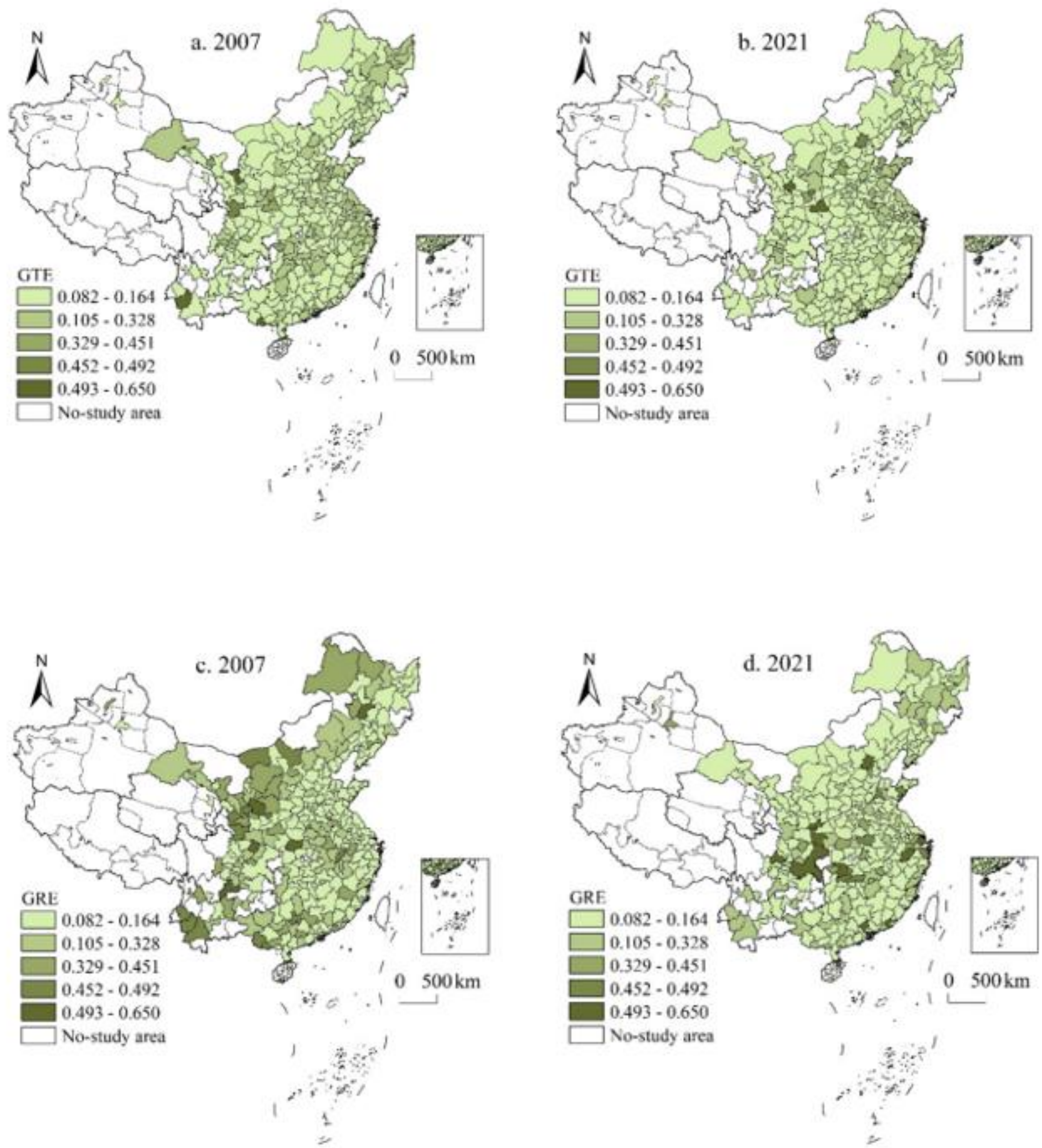

Figure 4.
Distribution of GTE and GRE in 2007 and 2021.

3.3. Mechanism variables
3.3.1. Mediating variables

Financing constraint (FIN). FIN is an important factor influencing green technology innovation activities [41]. Following on from the aforementioned theoretical research and the accessibility of municipal data, we use FIN as the mediating variable; it is defined as the per capita year-end loan balance of financial institutions [11] and the higher the per capita loan balance, the higher the level of financial development and the lower the degree of FIN.

Social consumption (SOC). According to the above theoretical analysis, SOC may play a mediating role between GF and GIE. Consumer demand pushes enterprises to invest in green technology innovation, while GF fosters it by encouraging financial resources for green technology. This cycle of interaction will promote the realization of an economy characterized by green and sustainable development [46]. In our study, the per capita year-end social consumption retail sales are used to estimate the urban social consumption level.

3.3.2. Moderation Variables

Environmental regulation (ER). ER represents a constraining force aimed at protecting the environment. It consists of mandatory measures implemented by local governments for the purpose of environmental governance, as well as the supervision and participation of environmental non-governmental organizations and the public. Formal environmental regulation (FER) reflects the government's comprehensive requirements for the environmental layer. In accordance with Yu, et al. [60] we use the total number of word frequencies of words related to "environmental protection" in the work reports of local governments as a substitute variable for the index ofFER.

In addition, ER is also inseparable from public regulation, and cities with a larger number of environmental management practitioners tend to have higher environmental regulation and environmental awareness and will devote more attention to the ecological environment [61]. Therefore, we quantify the degree of informal environmental regulation (LER) using the proportion of people engaged in water and environmental management in the city.

3.4. Control Variables

According to related studies Hsu, et al. [62] and Irfan, et al. [13] we have provided additional control variables that may affect the GIE. For example, the level of economic development (PGDP), the level of government intervention (GOV), transportation infrastructure (TRI), industrial structure upgrading (INS), and the level of educational development (EDU) are added to the econometric model. In addition, we give the statistical descriptions and data sources of all key variables in Table 3.

3.5. Econometric Model

3.5.1. Baseline Model

This paper refers to Ben Arfi, et al. [63] equation (1) includes the core independent variable, GF. To supplement additional critical factors that impact the GIE, we introduced further control variables [13, 62]. Here is the benchmark regression model.

$$GIE_{it} = a_0 + a_1 GF_{it} + a_2 X_{it} + \mu_i + n_t + e_{it} \quad (8)$$

Here, GIE_{it} is green innovation efficiency, including GTE_{it} and GRE_{it} ; GF_{it} is the green finance index; X_{it} is control variables; μ_i is the city fixed effect, and v_t is the time fixed effect; ε_{it} is the random error term.

We further add the lag term of GIE to equation (1) and establish a dynamic panel model (2) for estimation. To ensure the experimental results are robust, the SYS-GMM model is applied. According to Blundell and Bond [64] the model is set as follows:

$$GIE_{it} = a_0 + a_1 GIE_{it-1} + a_2 GF_{it} + a_3 X_{it} + \mu_i + n_t + e_{it} \quad (9)$$

Here, GIE_{it-1} is the lag term of GIE_{it} . Other parameters are set according to equation (8).

3.5.2. Mechanism Verification

ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

This study analyzes the potential mechanism (channel) by which GF affects GIE. According to Bauer, et al. [65] the specific validation processes are listed below: When the coefficient α1 in equation (8) is significant, create the regression equation (10) for the effect of GF on the mechanism variable (M). Then, add both GF and M to equation (8) to generate equation (11). Judge whether the above mechanism effect is significant or not based on the coefficients a1 , b1 , g1 , and g2 together. Equations (10) and (11) are expressed as follows:

$$M_{it} = \beta_0 + \beta_1 GF_{it} + \beta_2 X_{it} + \mu_i + v_t + \varepsilon_{it} \tag{10}$$

$$GIE_{it} = \Upsilon_0 + \Upsilon_1 M_{it} + \Upsilon_2 GF_{it} + \Upsilon_3 X_{it} + \mu_i + v_t + \varepsilon_{it} \tag{11}$$

Here, M includes FIN and SOC.

Table 3.
List of variables, definitions, and data sources.

Variable	Definitions	Data sources	Mean	Standard deviation	Minimum	Maximum
GTE	Green technical efficiency: SBM-DAE model measurement	China Urban Statistical Yearbook	0.030	0.086	0.000	1.000
GRE	Green results efficiency: SBM-DAE model measurement	China Urban Statistical Yearbook	0.034	0.091	0.000	1.000
GF	Green finance: the entropy TOPSIS method of measurement	China Urban Statistical Yearbook, Wind database, Cathay Pacific database	0.314	0.105	0.058	0.650
FIN	Financing constraints: measured using year-end financial institution loan	China Urban Statistical Yearbook	0.727	1.087	0.020	16.276
SOC	balances per capita Social consumption: measured using year-end retail social consumption per capita Formal environmental	China Urban Statistical Yearbook Official	0.188	0.183	0.000	1.660
FER	regulation: measured using the frequency of environmental words in government work reports Informal environmental	government website, government work report	0.813	1.036	0.010	13.34
LER	regulation: measured using the share of water, environmental management practitioners	China Urban Statistical Yearbook	0.003	0.001	0.000	0.012
PGDP	Level of economic development: measured using GDP per capita Degree of government	China Urban Statistical Yearbook	0.474	0.338	0.026	4.677
GOV	intervention: measured using government fiscal expenditure as a share of GDP	China Urban Statistical Yearbook	0.238	0.243	0.043	3.875
TRI	Transportation infrastructure: measured using year-end actual paved road area	China Urban Statistical Yearbook	0.194	0.271	0.001	5.050

ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

INS	Upgrading of the industrial structure: measured using the ratio of tertiary sector output to secondary sector output	China Urban Statistical Yearbook	0.988	0.564	0.095	5.348
EDU	Level of educational development: measured using the share of education expenditures in government fiscal expenditures	China Urban Statistical Yearbook	0.181	0.042	0.018	0.377

Regarding the moderating effect of ER on GF, we add the interaction $(GF_{it} \cdot ER_{it})$ containing ER substituting into equation (8) to obtain equation (12).

$$GIE_{it} = a_0 + a_1 GF_{it} + a_2 (GF_{it} . ER_{it}) + a_3 X_{it} + \mu_i + n_t + e_{it} \quad (12)$$

Here, ER includes FER and LER.

3.5.3. Dynamic Threshold Model

In this study, GF is used as a threshold variable to investigate the threshold effect of GF on GIE by tracking the features of changes in the regression coefficients of GF. Equation (13) describes the dynamic threshold model design.

$$GIE_{it} = a_0 + a_1 GIE_{it-1} + a_2\, GF . I(GF \leq C) + a_3 GF . I(GF > C) + a_4 X_{it} + \mu_i + v_t + e_{it} \quad (13)$$

In equation (13), GIE_{it-1} denotes the lag term of GIE_{it} ; I() is the threshold variable term; C is the threshold value of the GF estimation parameter when it changes.

3.5.4. Spatial Durbin Model

To evaluate the spatial effect of China's GF on GIE, this study utilizes the SDM panel model [66].

$$GIE_{it} = \alpha_0 + \rho_1 \sum_{i=1}^{N} W_{ij} \cdot GIE_{it} + \alpha_1 GF_{it} + \rho_2 \sum_{i=1}^{N} W_{ij} \cdot GF_{it} + \alpha_2 X_{it} + \rho_3 \sum_{i=1}^{N} W_{ij} \cdot X_{it} + \mu_i + \nu_t + \varepsilon \quad (14)$$

Here, W_{ij} represents the spatial weight matrix; a and b are the estimated parameters. The spatial lag term of the dependent variable is represented as $W_{ij} . GIE_{it}$, representing the spatial influence of the neighboring region GIE. The spatial lag term of the independent variable is represented as $W_{ij} . GF_{it}$, representing the spatial influence of the neighboring region GF. $W_{ij} . X_{it}$ represents the spatial influence of the control variable in the neighboring region.

In this study, we use three spatial weight matrices, which are 0-1 (W0-1), the geographic distance (Wdis), and the economic distance (Weco) [54]. Appendix. A is the specific calculation method.

In addition, the prerequisite for performing spatial econometric regression is the spatial correlation test. We use the Moran index (Moran's I) to perform the test. The calculation method is shown in Appendix. B.

4. Result Analysis

4.1. Regression Results of the Baseline Model

Table 4 presents the results of the baseline regression based on the estimation of equation (8). Columns (2) and (4) in Table 4 show the estimation results when control variables are added. The estimated coefficient of GF is positive and significant, implying that GF is beneficial to enhancing the degree of GIE, which is similar to and expands on the findings of Lin and Ma [11]. In terms of economic significance, if GF is raised by 1%, GTE and GRE will be raised by 0.203% and 0.258%, respectively. He, et al. [52] and Zhang, et al. [51] stated that the GF plays a fund-oriented role to encourage scientific and technical innovation in key areas including conserving energy and protecting the environment, coal clean utilization technology, and carbon emission reduction technology, so as to enhance the GIE. Consequently, to ensure carbon neutrality and the goal of building a world powerhouse of science, technology, and innovation, China's central government has to broaden its investment in scientific and technological research, development, and innovation. It is also necessary to focus on overcoming the financial constraints that enterprises encounter while carrying out environmentally friendly actions and supporting cutting-edge scientific research projects that are both high-risk and high-return. Only in this way can businesses be encouraged to engage in more innovative R&D activities.

Concerning the impact of control variables, most variables met the significance requirement. In columns (2) and (4), the coefficients of PGDP exhibit a significantly positive relationship, indicating that higher levels of economic development have the potential to simultaneously increase both GTE and GRE. Conversely, the coefficient of GOV is significantly negative, suggesting that as government intervention increases, GTE and GRE decrease. This phenomenon may be attributed to excessive government intervention leading to cumbersome and inefficient decision-making processes [67]. Such interventions can impose unnecessary restrictions and burdens on corporate innovation, thereby reducing the GIE. Therefore, a balanced role for the government in the green innovation process is crucial to ensuring interventions are favorable and promoting the effective enhancement of GIE.The coefficient of TRI is significantly positive, indicating that well-developed transportation infrastructure plays a vital role in enhancing GIE. These findings support the research by Zhao, et al. [68]. TRI facilitates inter-regional economic exchanges and cooperation, accelerating the diffusion and application of green technologies. Through these exchanges and collaborations, enterprises gain access to more innovative resources and knowledge, thereby promoting the innovation and development of green technology.However, the coefficient ofINS only exhibits a significantly positive effect on GTE, suggesting that INS does not significantly enhance GRE. One possible explanation for this is the inadequate interface mechanism between green technology R&D and the transformation of green outcomes. Enterprises may invest substantial resources in green technology R&D, but the lack of corresponding channels for marketing, technology transfer, or industrialization results in a low GRE [69]. Lastly, the coefficient of EDU displays a significantly positive relationship, implying that a higher level of educational development is positively associated with the efficiency of green technology development. This can be attributed to the fact that educational development enhances people's knowledge and skills and fosters innovative thinking and problem-solving abilities. Consequently, cities are better equipped to address environmental challenges and promote green technology innovation [70].

Table 4.
Regression results of the baseline model.

Variables	GTE	GTE	GRE	GRE
	(1)	(2)	(3)	(4)
GF	0.241**	0.203***	0.291***	0.258***
	(0.122)	(0.050)	(0.089)	(0.080)
PGDP		0.044***		0.050**
		(0.009)		(0.023)
GOV		-0.027***		-0.024***
		(0.008)		(0.008)
TRI		0.053***		0.055***
		(0.007)		(0.016)
INS		0.018***		0.017
		(0.005)		(0.019)
EDU		0.035		0.277**
		(0.056)		(0.113)
Constant	-0.036	-0.060***	-0.004	-0.081**
	(0.030)	(0.018)	(0.023)	(0.039)
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Observations	4260	4260	4260	4260
R-squared	0.047	0.233	0.087	0.123

Note: ***, **, and * represent significance at 1%, 5%, and 10%, respectively. Numbers in () are robust standard errors. Same for the table below.

4.2. Regression Results of Endogeneity Test

In the baseline regression model, the main endogeneity risk may arise from the interaction between GF and GIE. Since there may be bidirectional causality between the two, there is a potential endogeneity problem, which may lead to inaccurate model estimates. To address this issue, based on the practice of some scholars [71, 72] GF with one period lag (*L.GF*) was used as an instrumental variable (IV). The *L.GF* is highly correlated with the GF of the current period and uncorrelated with the error term, satisfying the prerequisite of correlation with endogenous variables. Furthermore, the *L.GF* will not directly affect the explanatory variable, satisfying the requirement of the exogeneity of instrumental variables [73]. Therefore, in this paper, *L.GF* is added as an instrumental variable in the analysis and regressed using two-stage least squares (IV-2SLS) and SYS-GMM, respectively, and Table 5 shows the results.

Columns (1)-(3) are the estimation results of the explanatory variable GTE. The IV-2SLS model's results indicated that the Kleibergen-Paaprk LM value was 1091.218 (p = 0.000), which rejected the original hypothesis of unrecognizability, and the order condition and rank condition of instrumental variables were valid, which indicated to some extent that the risk of the existence of weak instrumental variables was small. Meanwhile, the Kleibergen-Paap rk Wald F value is 39500.000, which is greater than the critical value of 10% bias, indicating that the risk of the existence of weak instrumental variables is small. The results in columns (1) and (2) demonstrate that the coefficient of L.GF is positive and significant in the first-stage regression, and the coefficient of GF is positive and significant in the second-stage regression. The SYS-GMM model results show that the p-value ofAR (1) is less than 0.1 and AR (2) is more than 0.1, meaning that the perturbation term has an autocorrelation in the first-order differencing but not in the second-order differencing. Meanwhile, the p-value of Sargan's test is more than 0.1, which validates the original hypothesis and confirms the validity of the instrumental variables [74]. The result in column (3) shows that the estimated coefficient of GF is positive and significant. The above test results indicate that GF development can enhance the level of GTE when talking about the possible endogeneity problem between GF and GTE, which is fully consistent with the previous results.

Columns (4)-(6) present the estimation results of the explanatory variable GRE. The results in columns (4) and (5) demonstrate that the coefficient of L.GF is positive and significant in the first-stage regression and the coefficient of GF is positive and significant in the second-stage regression. The instrumental variables of the SYS-GMM model likewise pass the corresponding hypothesis tests, demonstrating that the instrumental variables are valid. The result in column (6) indicates that the estimated coefficient of GF is positive and significant. The above test results indicate that GF development can enhance the efficiency level of green result transformation after considering the possible endogeneity problem between GF and GRE, which is completely compatible with the above results. Taken together, our results demonstrate that China's GF development has the effectiveness of green technology development and green results transformation.

Table 5.
Regression results of endogeneity test.

Variables	GF	GTE	GTE	GF	GRE	GRE
	IV-2SLS-1	**IV-2SLS-2**	**SYS-GMM**	**IV-2SLS-1**	**IV-2SLS-2**	**SYS-GMM**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
GF		0.042**	0.074**		0.048***	0.067*
		(0.017)	(0.029)		(0.017)	(0.037)
L.GF	0.982***			0.982***		
	(0.005)			(0.005)		
L.GIE			0.658***			0.678***
			(0.097)			(0.233)
Constant	0.006**	-0.058***	0.075***	0.006**	0.009	0.053*
	(0.004)	(0.012)	(0.026)	(0.004)	(0.011)	(0.031)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
K-Paap LM		1091.218			1091.317	
K-Paap Wald F		39500.000			38000.000	
AR(1)			-2.92[0.004]			-1.68[0.003]
AR(2)			0.86[0.392]			1.53[0.126]
Sargan test			13.69[0.396]			51.67[0.998]
Observations	3976	3976	3976	3976	3976	3976
R-squared	0.929	0.264		0.929	0.320	

Note: Columns (1)-(2) and (4)-(5) show the regression results estimated using 2SLS. Columns (3) and (6) show the regression results estimated using SYS-GMM. Numbers in [ ] are the P values of the corresponding test statistics.

4.3. Regression Results of Robustness Tests

This research also employs a robustness test to verify the validity of the findings, as shown in Table 6. Columns (1)-(3) are the results of GTE, and columns (4)-(6) are the results of GRE. We mainly used three separate ways to conduct robustness tests: first, replacing the explanatory variables. The GF index is recalculated to re-estimate the regression by principal component analysis [75] and the results are shown in columns (1) and (4). Second, transform the sample size. Given that the four first-tier cities of Beijing, Shanghai, Guangzhou, and Shenzhen are the economic, financial, and cultural centers of China, attracting large amounts of investment, talent, and resources, and differing significantly from the other cities on many indicators [76] their inclusion in the analysis may yield different results. Columns (2) and (5) are therefore conducted with four cities excluded. Third, add control variables. Although this paper controls for variables that may affect the GIE, there are other control variables that are important for the GIE. Therefore, columns (3) and (6) are the results with the addition of the level of urban built-up (URB), which is determined by the proportion of urban built-up land area in the administrative area of the municipal district. It can be found that the estimated coefficients of

ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

GF are still significantly positive after the above robustness test approach, which indicates the reliability of the findings ofthis paper.

Table 6.
Regression results of robustness tests.

Variables	**GTE**	**GTE**	**GTE**	**GRE**	**GRE**	**GRE**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
GF	0.038* (0.022)	0.139*** (0.048)	0.198* (0.110)	0.031** (0.014)	0.202*** (0.074)	0.245*** (0.077)
URB			0.204 (0.342)			0.470 (0.440)
Constant	-0.018	-0.033*	-0.059	-0.043*	-0.048	-0.079**
	(0.028)	(0.017)	(0.044)	(0.026)	(0.036)	(0.038)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4260	4200	4260	4260	4200	4260
R-squared	0.285	0.153	0.268	0.048	0.114	0.128

Note: Columns (1) and (4) present the test results using the method of replacing the explained variable, columns (2) and (5) present the test results using the transformed sample size method, and columns (3) and (6) present the test results using Test results of the method of adding control variables.

4.4. Regression Results of Mediating Effects

The previous paper portrayed for the overall impact between GF and GIE, and the specific channel mechanism of GF affecting GIE needs to be further investigated. According to the theoretical analysis, this paper selects FIN and SOC as mediating variables to test the specific path of GF to enhance GIE, and Table 7 shows the regression results.

Columns (1)-(3) in Table 7 provide the results with FIN as the mediating variable. The estimated coefficient of GF on FIN is 1.459, which is significant. The estimated coefficients of GF on GTE and GRE remain positive and significant after the addition of FIN, and the estimated coefficients of FIN on GTE and GRE are 0.033 and 0.029 and significant, respectively. The value of the mediating effect of GF on boosting GTE by mitigating the fusion ofFIN is 0.048 (=1.450 × 0.033). This result indicates that every 1% increase in the GF index will indirectly lead to a 0.048% increase in GTE. Similarly, the mediating effect of GF in raising GRE by mitigating FIN is valued at 0.042 (=1.450 × 0.029). This result indicates that every 1% increase in the GF index will indirectly lead to a 0.042% increase in GRE. The above result indicates that financing constraints have partial mediating effects [77], which verifies Hypothesis 2 of this paper, that is, GF is able to promote GTE and GRE enhancement by alleviating FIN.

Columns (4)-(6) in Table 7 show the results with SOC as the mediating variable. The estimated coefficient of GF on SOC is 0.148 and significant. The estimated coefficients of GF on GTE and GRE remain positive and significant after the inclusion of SOC, and the estimated coefficients of SOC on GTE and GRE are 0.199 and 0.233 and significant, respectively. The value of the mediating effect of GF on raising GTE by stimulating SOC growth is 0.029 (=0.148 × 0.199). This result indicates that every 1% increase in the GF index will indirectly lead to a 0.029% increase in GTE. Similarly, the value of the mediating effect of GF in raising GRE by stimulating the growth of SOC is 0.034 (=0.148 × 0.233). This result indicates that every 1% increase in the GF index will indirectly lead to a 0.034% increase in GRE. The above results indicate that social consumption has a partial mediating effect [78] which verifies Hypothesis 3 of this paper, i.e., GF can promote GTE and GRE by stimulating SOC.

DOI: 10.55214/2576-8484.v9i8.9542

Table 7.
Regression results of mediation effect test.

Variables	FIN	GTE	GRE	SOC	GTE	GRE
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
GF	1.450***	0.186*	0.243***	0.148**	0.174*	0.223***
	(0.514)	(0.103)	(0.072)	(0.060)	(0.105)	(0.071)
FIN		0.033***	0.029***			
		(0.007)	(0.006)			
SOC					0.199*** (0.061)	0.233*** (0.078)
Constant	-0.667***	-0.036	-0.060*	-0.097***	-0.041	-0.059*
	(0.163)	(0.039)	(0.036)	(0.027)	(0.041)	(0.033)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4260	4260	4260	4260	4260	4260
R-squared	0.641	0.361	0.142	0.775	0.294	0.147

Note: Columns (1)-(3) show the regression results using FIN as the mediating variable, and columns (4)-(6) show the regression results using SOC as the mediating variable.

4.5. Regression Results of Moderating Effects

To prove that ER has a moderating effect, this paper further enters the interaction term between GF and ER for the regression of the model on the basis of testing the impact of GF on GIE. Table 8 demonstrates that the predicted coefficients of GF and GF*FER in columns (1) and (2) are both positive and significant, implying that formal environmental regulation by the government can influence the upgrading effect of GF on GIE. Similarly, in columns (3) and (4), the estimated coefficients of GF and GF*LER are both positive and significant, showing that informal environmental regulation can also affect the upgrading effect of GF on GIE. These results validate Hypothesis 4 of this paper, which states that ER enhances the contribution of GF to the two-stage GIE. The findings validate the applicability of Porter's hypothesis at the city level in China [79]. Compared to the actual situation of China's environmental regulatory policies, ER has mainly demonstrated a policy-supportive effect in GF. On the one hand, ER stimulates the demand for green technologies and environmental protection programs among enterprises and individuals by setting stringent environmental standards and emission limits and pushing them to take more environmentally friendly actions. On the other hand, ER also encourages firms and individuals to actively participate in green innovation activities by providing policy tools such as tax incentives, loan subsidies, incentives, and compensation. Moreover, previous studies have confirmed that ER has a positive impact on green productivity and GIE [80]. This suggests that the government can utilize ER regulations to stimulate green innovation and promote sustainable development.

Table 8.
Regression results of the moderated effects test.

Variables	GTE	GRE	GTE	GRE
	(1)	(2)	(3)	(4)
GF	0.230***	0.295***	0.121**	0.133*
	(0.051)	(0.082)	(0.050)	(0.077)
GF*FER	0.089***	0.123***		
GF*LER	(0.030)	(0.045)	0.065***	0.098***
			(0.006)	(0.027)
Constant	-0.059***	-0.080**	-0.037**	-0.046
	(0.018)	(0.038)	(0.018)	(0.034)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Observations	4260	4260	4260	4260
R-squared	0.227	0.127	0.360	0.175

Note: Columns (1)-(2) show the regression results using FER as the moderator variable, and columns (3)-(4) show the regression results using LER as the moderator variable.

4.6. Regression Results of Dynamic Threshold Model

In this section, GF was used as the threshold variable in a dynamic threshold model to evaluate the threshold effect. We refer to Hansen [81] for the threshold regression test. According to the threshold test in Fig. 4, it is evident that the research sample is proven to be applicable to the single threshold effect. It was determined that the study sample was appropriate for a single threshold effect, and Appendix C provides the test protocol. The threshold test shows that the threshold values of the effect of GF on GTE and GRE are 0.317 and 0.337, respectively.

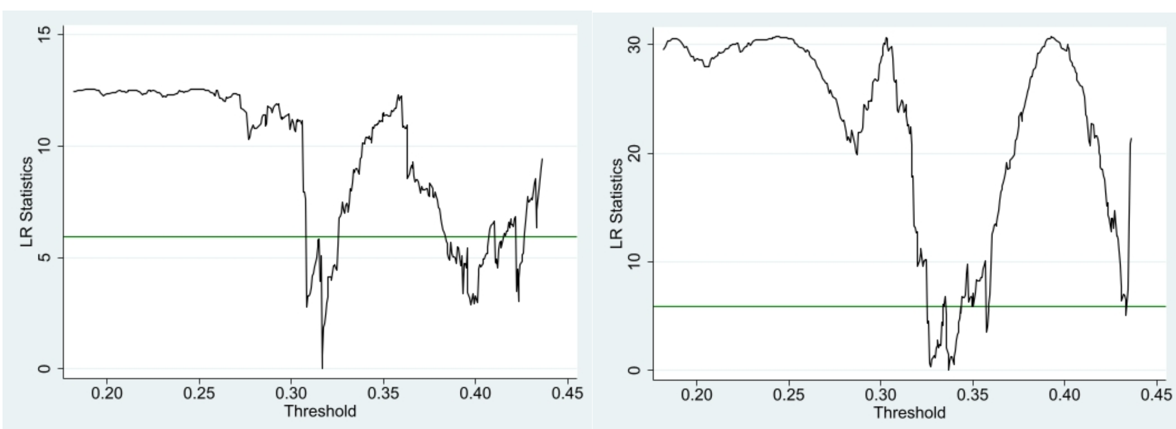

Figure 5.
Dynamic threshold model check.

Table 9 reports the threshold regression results. The results in column (1) indicate that there is a significant threshold effect between GF and GTE. In other words, the effect of GF on GTE shifts from insignificant to a significant positive effect when GF exceeds the threshold value. The results in column (2) indicate that there is a significant threshold effect between GF and GRE, and when GF exceeds the threshold value, the promotion effect of GF on GRE gradually increases. This empirical result verifies Hypothesis 5 and objectively reconfirms the importance of GF in enhancing GIE. In recent years, China has implemented policies such as the Green Finance Reform and Innovation Pilot Zone in order to achieve innovation-driven and dual-carbon goals [16]. Green finance support policies have been implemented, capital investment has been sustained over time, and R&D support has been increasing in strength and scale [10, 76] and China has had a favorable long-term impact on GF development in GIE.

Table 9.
Regression results of the dynamic threshold model.

Variables	GTE	GRE
	(1)	(2)
L.GIE	0.588***	1.054***
GF (GR≤C)	(0.139) -0.153 (0.100)	(0.134) 0.753*** (0.133)
GF (GF＞C)	0.273** (0.129)	0.906*** (0.162)
Control variables	Yes	Yes
Constant	0.124***	-0.181***
 AR(1)	(0.033) -2.49[0.013]	(0.040) -1.66[0.097]
AR(2)	0.83[0.407]	1.51[0.132]
Sargan test	58.48[0.835]	47.05[0.984]
Observations	3976	3976

4.7. Regression results of spatial econometric models

To investigate the spatial influence effect characteristics of GTE and GRE, the spatial correlation results were calculated using three weights (Appendix D). On the whole, using all three spatial weight matrices, China's cities GTE and GRE exhibit positive spatial correlation. Therefore, we can use spatial econometric models to conduct empirical research.

Spatial models include spatial lag models (SLM), spatial error models (SEM), and spatial Durbin models (SDM). One important stage in spatial regression is determining the model's applicability. First, we conduct both the robust and Lagrange multiplier (LM) tests. Next, to make sure that SDM does not degrade into SEM and SLM, we conduct Wald and likelihood- ratio (LR) tests. Finally, we verify that the SDM model with double fixed effects is better suited for the study sample using the Hausman test. The results of the spatial model selection test are shown in Appendix E. To sum up, the SDM model featuring individual dual fixed effects and time was used to examine spatial regression.

Table 10.
Regression results of the spatial Durbin Model.

Variables	GTE	GRE	GTE	GRE	GTE	GRE
	W0- 1		Wdis		Weco	
	(1)	(2)	(3)	(4)	(5)	(6)
GF	0.054*	0.163***	0.094**	0.173***	0.189***	0.408***
	(0.031)	(0.051)	(0.041)	(0.051)	(0.048)	(0.067)
W*GF	0.143***	0.435***	1.480***	3.032***	0.250**	0.295*
	(0.052)	(0.087)	(0.478)	(0.595)	(0.122)	(0.173)
rho	0.007***	0.094***	0.003***	0.322***	0.210***	0.091***
	(0.003)	(0.022)	(0.001)	(0.117)	(0.025)	(0.026)
sigma2_e	0.002***	0.005***	0.003***	0.005***	0.005***	0.010***
Control variables	(0.000) Yes	(0.000) Yes	(0.000) Yes	(0.000) Yes	(0.000) Yes	(0.000) Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4260	4260	4260	4260	4260	4260
R-squared	0.158	0.222	0.242	0.057	0.164	0.059

ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

As shown in Table 10, the estimated coefficients of GF and the lagged term *W*GF* are both positive and significant, indicating that GF has spatial impacts on GTE and GRE in neighboring cities. This is most likely because green innovation often involves the integration of supply chains and industrial linkages, promoting the adoption and spread of green technologies across the region, which in turn increases GIE in the short term. With the eventual development of GF, the related funds may spread to the neighboring regions through exchange, cooperation, and talent flow, thus promoting the green innovation efficiency of neighboring cities in the whole region [48]. We recognize that GF will eventually have a spatial spillover effect on the GIE of nearby cities based on the findings of the aforementioned investigation, verifying hypothesis 6.

4.8. Regression Results of Spatiotemporal Heterogeneity
4.8.1. Temporal Heterogeneity

In August 2016, seven ministries and commissions, including the People's Bank of China and the Ministry of Finance, issued the Guiding Opinions on Building a Green Financial System, which set an overall strategic framework for the development of green finance. In order to analyze the difference in the impact of GF on GIE over time, we divided the study period into two stages, 2007–2015 and 2016–2021, and Table 11 displays results. The estimated coefficients of GF on GTE and GRE are 0.144 and 0.201 (not passing the test of significance) for the period of 2007–2015; for the period of 2016–2021, the estimated coefficients of GF on GTE and GRE are 0.078 and 0.066, and both are significant. This indicates that as the country implements the policy of building a green financial system, it provides financing support, reduces financing costs, improves the innovation environment, and guides the allocation of resources to the field of green innovation [17]. This will promote the development of green innovation, accelerate the emergence and market application of green technologies and solutions, and provide more effective solutions to the challenges of sustainable development and climate change [18].

Table 11.
Regression results for temporal heterogeneity.

Variables	GTE	GRE	GTE	GRE
	2007-2015			2016-2021
	(1)	(2)	(3)	(4)
GF	0.144**	0.201	0.078**	0.066**
	(0.069)	(0.125)	(0.039)	(0.031)
Constant	-0.019	-0.074*	-0.042	-0.087***
	(0.031)	(0.038)	(0.026)	(0.032)
Control variables	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Observations	2556	2556	1704	1704
R-squared	0.115	0.068	0.404	0.375

4.8.2. Spatial heterogeneity

There exist disparities in the degree of economic and financial development among Chinese cities located in the eastern, central, and western regions [11]. Therefore, we also divided the sample into eastern, central, and western regions by region and presented the estimation results in Table 12. The estimated coefficients of GF on both GTE and GRE for cities in the eastern region are positive and significant, but they fail to contribute to both GTE and GRE for cities in the central and western regions. First, cities in the eastern area have more research institutes, colleges and universities, and innovative firms, and they also have higher human resources and technological advancement capability. Second, the eastern region has a more comprehensive and developed financial support system than the central and western regions, which can provide more financing channels and support mechanisms for green technology research and transformation in the cities in the eastern region. Therefore, GF may have a more obvious role in promoting GTE and GRE in eastern cities.

Table 12.
Regression results for spatial heterogeneity.

Variables	GTE	GRE	GTE	GRE	GTE	GRE
	Eastern region		Central region		Western region	
	(1)	(2)	(3)	(4)	(5)	(6)
GF	0.347*	0.253*	0.024	0.232**	0.067	0.027
	(0.192)	(0.138)	(0.034)	(0.106)	(0.224)	(0.112)
Constant	-0.213**	-0.179**	-0.020	-0.033	0.105	0.049
	(0.083)	(0.082)	(0.014)	(0.036)	(0.080)	(0.049)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1515	1515	1470	1470	1275	1275
R-squared	0.482	0.208	0.226	0.440	0.344	0.276

5. Conclusion and Policy Implications

5.1. Conclusions

Green technological innovation is undoubtedly becoming an efficient way to combat climate change and accomplish long-term prosperity, and the development of GF and the increase of capital investment in GIE have become important issues in today's economy and environment [10]. Despite some research that has investigated strategies to promote GIE by alleviating financing constraints and stimulating social consumption, our current understanding of the impact of GF on GIE is not comprehensive enough. Therefore, this work seeks to fill the gap in the literature by measuring the GF development index, assessing the GTE and GRE of Chinese cities based on a two-stage value chain perspective, and examining the impact of GF on GTE and GRE. This research uses FE, SDM, and dynamic threshold models to investigate the mechanisms and impacts of GF on GTE and GRE using balanced panel data from 284 Chinese cities from 2007 to 2021.

Our empirical results show that, first, GF is beneficial for increasing GTE and GRE. For every 1% increase in GF, GTE and GRE will increase by 0.203% and 0.258%, respectively. When we perform some endogeneity and robustness tests, the results remain robust. Second, the results of the impact mechanism analysis show that GF increases GIE mainly by alleviating.

FIN and stimulating SOC, and that FER and LER can positively modulate the impact of GF on GIE. Third, using GF as the threshold, we find that the impact of GF on GTE shows a threshold effect from negative to significantly positive, and the impact of GF on GRE shows an increasing threshold effect. Fourth, GF has a spatial spillover impact on GIE, which can encourage GIE growth in the local region while also driving GIE improvement in nearby regions. Finally, the effect of GF on GIE is characterized by significant spatio-temporal heterogeneity.

5.2. Policy Implications

According to the findings of this research, we make corresponding policy recommendations. Given that GF has a significant impact on GIE, its development should be continued. First, green financial institutions should actively participate in green innovation projects by providing services such as financing and risk management in order to promote the research, development, diffusion, and application of green technologies. Second, it is crucial to acknowledge the spatial and temporal heterogeneity of the impacts of GF on GIE. Different regions exhibit significant variations in the demand for green innovation and the allocation of resources. As a result, government departments must develop targeted financial policies and measures that accommodate these variations and changes. Moreover, the spatial and temporal heterogeneity highlights the need for flexibility and adaptability in the development of GF. It is essential to adjust GF in a timely manner to align with the specific requirements of different regions and evolving circumstances. This necessitates governments possessing a deep understanding of the unique conditions in each region and formulating policies and measures that are highly responsive to local needs. By doing so, governments can effectively promote the sustainable development of green innovation.

Given that GF can increase GIE by easing financing constraints and stimulating social consumption, governments should formulate and implement a series of policies to support GF development. These policies could include measures such as tax incentives, subsidies, and rewards aimed at attracting more capital into green innovation and stimulating green consumption behaviors. In addition, the government could set up specialized green financial institutions or departments to provide special financing and risk management services for green innovation projects. These measures will help promote the sustainable development of GF and further contribute to the improvement of GIE. Finally, considering that environmental regulations can effectively and positively regulate the impact of GF on GIE, governments at all levels must develop and improve environmental regulations. The government should clarify the standards and norms for green innovation so that there is effective guidance and the utilization of green fiscal funds, as well as improve green innovation's efficiency and sustainability.

Given the threshold effect of GF on GIE, the government should formulate comprehensive policies that harmonize environmental regulations, fiscal incentives, and financial policies to create synergies. For example, by combining tax incentives and green innovation funds, it can inspire businesses to pursue green innovation and enhance their financial capabilities, thus realizing leapfrog growth in green innovation efficiency.

Considering the significant spatial spillover effect of GF on GIE, it is crucial for governments at all levels to prioritize inter-city R&D and innovation cooperation. To address the uneven distribution of green financial resources in China, local governments can establish cross-regional innovation platforms based on local green innovation needs and potentials to promote the sharing and optimal allocation of green financial resources and improve green innovation efficiency. In addition, green financial innovation centers and national green financial demonstration zones should be built in regions with high levels of financial development, such as Beijing, Shanghai, Guangzhou, and Shenzhen, to strengthen financial technology innovation and promote the synergistic development of financial technology and green innovation.

Although this study covers the gap in previous research on the effects of GF on GTE and GRE in both stages, some questions remain to be answered, pointing the way for future research. First, our study is preliminary because we only explore the connection between GF and GIE from the city level. However, existing studies on the factors driving green technology innovation have been expanded to include firms. Therefore, it would be interesting to investigate the mechanisms and impacts of nonlinear, mediating, and moderating effects on GF on GIE in a larger sample of firms in the future. Second, this study did not explore relationship between green financial products and green innovation efficiency. Future research could investigate the impact of different forms of green financial products on green innovation efficiency, such as assessing the mechanisms and effects of green financial instruments like green bonds, green credit, and carbon trading. This can further optimize and innovate the design and promotion of green financial products.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Copyright:

References

[1] G. T. Pecl *et al.*, "Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being," *Science*, vol. 355, no. 6332, p. eaai9214, 2017. https://doi.org/10.1126/science.aai9214
[2] IPCC, *Intergovernmental panel on climate change.* Geneva, Switzerland: IPCC, 2022.
[3] S. A. R. Khan, Y. Zhang, A. Kumar, E. Zavadskas, and D. Streimikiene, "Measuring the impact of renewable energy, public health expenditure, logistics, and environmental performance on sustainable economic growth," *Sustainable Development*, vol. 28, no. 4, pp. 833-843, 2020. https://doi.org/10.1002/sd.2034
[4] K. R. Abbasi, K. Hussain, A. M. Haddad, A. Salman, and I. Ozturk, "The role of financial development and technological innovation towards sustainable development in Pakistan: Fresh insights from consumption and territory-based emissions," *Technological Forecasting and Social Change*, vol. 176, p. 121444, 2022. https://doi.org/10.1016/j.techfore.2021.121444
[5] X. Liang, F. Min, Y. Xiao, and J. Yao, "Temporal-spatial characteristics of energy-based carbon dioxide emissions and driving factors during 2004–2019, China," *Energy*, vol. 261, p. 124965, 2022. https://doi.org/10.1016/j.energy.2022.124965
[6] R. Fan, X. Zhang, A. Bizimana, T. Zhou, J.-S. Liu, and X.-Z. Meng, "Achieving China's carbon neutrality: Predicting driving factors of CO2 emission by artificial neural network," *Journal of Cleaner Production*, vol. 362, p. 132331, 2022. https://doi.org/10.1016/j.jclepro.2022.132331
[7] S. Zhang and W. Chen, "Assessing the energy transition in China towards carbon neutrality with a probabilistic framework," *Nature Communications*, vol. 13, no. 1, p. 87, 2022a. https://doi.org/10.1038/s41467-021-27671-0
[8] C.-L. Miao, M.-M. Duan, Y. Zuo, and X.-Y. Wu, "Spatial heterogeneity and evolution trend of regional green innovation efficiency--an empirical study based on panel data of industrial enterprises in China's provinces*," *Energy Policy*, vol. 156, p. 112370, 2021. https://doi.org/10.1016/j.enpol.2021.112370
[9] H. Kuang, Z. Akmal, and F. Li, "Measuring the effects of green technology innovations and renewable energy investment for reducing carbon emissions in China," *Renewable Energy*, vol. 197, pp. 1-10, 2022. https://doi.org/10.1016/j.renene.2022.06.091
[10] C. Lv, C. Shao, and C.-C. Lee, "Green technology innovation and financial development: Do environmental regulation and innovation output matter?," *Energy Economics*, vol. 98, p. 105237, 2021. https://doi.org/10.1016/j.eneco.2021.105237
[11] B. Lin and R. Ma, "How does digital finance influence green technology innovation in China? Evidence from the financing constraints perspective," *Journal of Environmental Management*, vol. 320, p. 115833, 2022. https://doi.org/10.1016/j.jenvman.2022.115833
[12] H. Peng and Y. Liu, "How government subsidies promote the growth of entrepreneurial companies in clean energy industry: An empirical study in China," *Journal of Cleaner Production*, vol. 188, pp. 508-520, 2018. https://doi.org/10.1016/j.jclepro.2018.03.126
[13] M. Irfan, A. Razzaq, A. Sharif, and X. Yang, "Influence mechanism between green finance and green innovation: Exploring regional policy intervention effects in China," *Technological Forecasting and Social Change*, vol. 182, p. 121882, 2022. https://doi.org/10.1016/j.techfore.2022.121882
[14] S. Feng, R. Zhang, and G. Li, "Environmental decentralization, digital finance and green technology innovation," *Structural Change and Economic Dynamics*, vol. 61, pp. 70-83, 2022. https://doi.org/10.1016/j.strueco.2022.02.008
[15] P. Ge, T. Liu, and X. Huang, "The effects and drivers of green financial reform in promoting environmentally-biased technological progress," *Journal of Environmental Management*, vol. 339, p. 117915, 2023.
[16] Z. Zhang, J. Wang, C. Feng, and X. Chen, "Do pilot zones for green finance reform and innovation promote energy savings? Evidence from China," *Energy Economics*, vol. 124, p. 106763, 2023. https://doi.org/10.1016/j.eneco.2023.106763
[17] C. Liu and M. Xiong, "Green finance reform and corporate innovation: Evidence from China☆," *Finance Research Letters*, vol. 48, p. 102993, 2022. https://doi.org/10.1016/j.frl.2022.102993
[18] G. Zhou, J. Zhu, and S. Luo, "The impact of fintech innovation on green growth in China: Mediating effect of green finance," *Ecological Economics*, vol. 193, p. 107308, 2022. https://doi.org/10.1016/j.ecolecon.2021.107308

[19] M. M. Hasan and F. Du, "Nexus between green financial development, green technological innovation and environmental regulation in China," *Renewable Energy*, vol. 204, pp. 218-228, 2023. https://doi.org/10.1016/j.renene.2022.12.095

[20] C.-Y. Cheng, M.-S. Chien, and C.-C. Lee, "ICT diffusion, financial development, and economic growth: An international cross-country analysis," *Economic Modelling*, vol. 94, pp. 662-671, 2021. https://doi.org/10.1016/j.econmod.2020.02.008

[21] J. Yang, D. Shi, and W. Yang, "Stringent environmental regulation and capital structure: The effect of NEPL on deleveraging the high polluting firms," *International Review of Economics & Finance*, vol. 79, pp. 643-656, 2022. https://doi.org/10.1016/j.iref.2022.02.020

[22] J. Banga, "The green bond market: A potential source of climate finance for developing countries," *Journal of Sustainable Finance & Investment*, vol. 9, no. 1, pp. 17-32, 2019. https://doi.org/10.1080/20430795.2018.1498617

[23] J. Shi, C. Yu, Y. Li, and T. Wang, "Does green financial policy affect debt-financing cost of heavy-polluting enterprises? An empirical evidence based on Chinese pilot zones for green finance reform and innovations," *Technological Forecasting and Social Change*, vol. 179, p. 121678, 2022. https://doi.org/10.1016/j.techfore.2022.121678

[24] J. W. Lee, "Green finance and sustainable development goals: The case of China," *Journal of Asian Finance Economics and Business*, vol. 7, no. 7, pp. 577-586, 2020. https://doi.org/10.13106/jafeb.2020.vol7.no7.577

[25] Y. Tan and Z. Zhu, "The effect of ESG rating events on corporate green innovation in China: The mediating role of financial constraints and managers' environmental awareness," *Technology in Society*, vol. 68, p. 101906, 2022. https://doi.org/10.1016/j.techsoc.2022.101906

[26] L. Qiu, X. Jie, Y. Wang, and M. Zhao, "Green product innovation, green dynamic capability, and competitive advantage: Evidence from Chinese manufacturing enterprises," *Corporate Social Responsibility and Environmental Management*, vol. 27, no. 1, pp. 146-165, 2020. https://doi.org/10.1002/csr.1780

[27] U. Awan, R. Sroufe, and A. Kraslawski, "Creativity enables sustainable development: Supplier engagement as a boundary condition for the positive effect on green innovation," *Journal of Cleaner Production*, vol. 226, pp. 172-185, 2019. https://doi.org/10.1016/j.jclepro.2019.03.308

[28] A. N. Sarkar, "Promoting eco-innovations to leverage sustainable development of eco-industry and green growth," *European Journal of Sustainable Development*, vol. 2, no. 1, p. 171, 2013. https://doi.org/10.14207/ejsd.2013.v2n1p171

[29] C.-C. Lee and C.-C. Lee, "How does green finance affect green total factor productivity? Evidence from China," *Energy Economics*, vol. 107, p. 105863, 2022. https://doi.org/10.1016/j.eneco.2022.105863

[30] R. M. Dangelico, "Green product innovation: Where we are and where we are going," *Business Strategy and the Environment*, vol. 25, no. 8, pp. 560-576, 2016. https://doi.org/10.1002/bse.1886

[31] S. Lorek and J. H. Spangenberg, "Sustainable consumption within a sustainable economy – beyond green growth and green economies," *Journal of Cleaner Production*, vol. 63, pp. 33-44, 2014. https://doi.org/10.1016/j.jclepro.2013.08.045

[32] H. Sun and F. Chen, "The impact of green finance on China's regional energy consumption structure based on system GMM," *Resources Policy*, vol. 76, p. 102588, 2022. https://doi.org/10.1016/j.resourpol.2022.102588

[33] Y. Tu and W. Wu, "How does green innovation improve enterprises' competitive advantage? The role of organizational learning," *Sustainable Production and Consumption*, vol. 26, pp. 504-516, 2021. https://doi.org/10.1016/j.spc.2020.12.031

[34] J. Zhang, L. Kang, H. Li, P. Ballesteros-Pérez, M. Skitmore, and J. Zuo, "The impact of environmental regulations on urban Green innovation efficiency: The case of Xi'an," *Sustainable Cities and Society*, vol. 57, p. 102123, 2020. https://doi.org/10.1016/j.scs.2020.102123

[35] Y.-S. Chen, "The driver of green innovation and green image – green core competence," *Journal of Business Ethics*, vol. 81, no. 3, pp. 531-543, 2008. https://doi.org/10.1007/s10551-007-9522-1

[36] K.-H. Wang, Y.-X. Zhao, C.-F. Jiang, and Z.-Z. Li, "Does green finance inspire sustainable development? Evidence from a global perspective," *Economic Analysis and Policy*, vol. 75, pp. 412-426, 2022a. https://doi.org/10.1016/j.eap.2022.06.002

[37] X. Cai, B. Zhu, H. Zhang, L. Li, and M. Xie, "Can direct environmental regulation promote green technology innovation in heavily polluting industries? Evidence from Chinese listed companies," *Science of The Total Environment*, vol. 746, p. 140810, 2020. https://doi.org/10.1016/j.scitotenv.2020.140810

[38] Z. Fang, X. Kong, A. Sensoy, X. Cui, and F. Cheng, "Government's awareness of Environmental protection and corporate green innovation: A natural experiment from the new environmental protection law in China," *Economic Analysis and Policy*, vol. 70, pp. 294-312, 2021. https://doi.org/10.1016/j.eap.2021.03.003

[39] R. M. Dangelico, D. Pujari, and P. Pontrandolfo, "Green product innovation in manufacturing firms: A sustainability-oriented dynamic capability perspective," *Business Strategy and the Environment*, vol. 26, no. 4, pp. 490-506, 2017. https://doi.org/10.1002/bse.1932

[40] P. Soundarrajan and N. Vivek, "Green finance for sustainable green economic growth in India," *Agricultural Economics/Zemědělská Ekonomika*, vol. 62, no. 1, pp. 35-44, 2016. https://doi.org/10.17221/174/2014-AGRICECON

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

[41] C.-H. Yu, X. Wu, D. Zhang, S. Chen, and J. Zhao, "Demand for green finance: Resolving financing constraints on green innovation in China," *Energy Policy*, vol. 153, p. 112255, 2021a. https://doi.org/10.1016/j.enpol.2021.112255
[42] K. Zhang, Y. Li, Y. Qi, and S. Shao, "Can green credit policy improve environmental quality? Evidence from China," *Journal of Environmental Management*, vol. 298, p. 113445, 2021b. https://doi.org/10.1016/j.jenvman.2021.113445
[43] B. Kumar, L. Kumar, A. Kumar, R. Kumari, U. Tagar, and C. Sassanelli, "Green finance in circular economy: A literature review," *Environment, Development and Sustainability*, vol. 26, no. 7, pp. 16419-16459, 2024. https://doi.org/10.1007/s10668-023-03361-3
[44] G. Wu, Q. Xu, X. Niu, and L. Tao, "How does government policy improve green technology innovation: An Empirical study in China," *Frontiers in Environmental Science*, vol. 9, 2022. https://doi.org/10.3389/fenvs.2021.799794
[45] H. Chen and X. Zhao, "Use intention of green financial security intelligence service based on UTAUT," *Environment, Development and Sustainability*, vol. 25, no. 10, pp. 10709-10742, 2023. https://doi.org/10.1007/s10668-022-02501-5
[46] H. Hou, Y. Zhu, J. Wang, and M. Zhang, "Will green financial policy help improve China's environmental quality? The role of digital finance and green technology innovation," *Environmental Science and Pollution Research*, vol. 30, no. 4, pp. 10527-10539, 2023. https://doi.org/10.1007/s11356-022-22887-z
[47] P. M. Falcone, "Environmental regulation and green investments: The role of green finance," *International Journal of Green Economics*, vol. 14, no. 2, pp. 159-173, 2020. https://doi.org/10.1504/IJGE.2020.109735
[48] S. Shao, Y. Wang, W. Yan, L. Yang, and J. Yin, "Administrative decentralization and credit resource reallocation: Evidence from China's "Enlarging Authority and Strengthening Counties" reform," *Cities*, vol. 97, p. 102530, 2020. https://doi.org/10.1016/j.cities.2019.102530
[49] Y. Wen, M. Zhao, L. Zheng, Y. Yang, and X. Yang, "Impacts of financial agglomeration on technological innovation: A spatial and nonlinear perspective," *Technology Analysis & Strategic Management*, vol. 35, no. 1, pp. 17-29, 2023/01/02 2023. https://doi.org/10.1080/09537325.2021.1963702
[50] K. Gao and Y. Yuan, "Government intervention, spillover effect and urban innovation performance: Empirical evidence from national innovative city pilot policy in China," *Technology in Society*, vol. 70, p. 102035, 2022. https://doi.org/10.1016/j.techsoc.2022.102035
[51] S. Zhang, Z. Wu, Y. Wang, and Y. Hao, "Fostering green development with green finance: An empirical study on the environmental effect of green credit policy in China," *Journal of Environmental Management*, vol. 296, p. 113159, 2021c. https://doi.org/10.1016/j.jenvman.2021.113159
[52] L. He, R. Liu, Z. Zhong, D. Wang, and Y. Xia, "Can green financial development promote renewable energy investment efficiency? A consideration of bank credit," *Renewable Energy*, vol. 143, pp. 974-984, 2019. https://doi.org/10.1016/j.renene.2019.05.059
[53] R. Liu, D. Wang, L. Zhang, and L. Zhang, "Can green financial development promote regional ecological efficiency? A case study of China," *Natural Hazards*, vol. 95, no. 1, pp. 325-341, 2019. https://doi.org/10.1007/s11069-018-3502-x
[54] J. Li and Y. Du, "Spatial effect of environmental regulation on green innovation efficiency: Evidence from prefectural-level cities in China," *Journal of Cleaner Production*, vol. 286, p. 125032, 2021. https://doi.org/10.1016/j.jclepro.2020.125032
[55] K. Tone and M. Tsutsui, "Network DEA: A slacks-based measure approach," *European Journal of Operational Research*, vol. 197, no. 1, pp. 243-252, 2009. https://doi.org/10.1016/j.ejor.2008.05.027
[56] H. Ke, S. Dai, and H. Yu, "Effect of green innovation efficiency on ecological footprint in 283 Chinese Cities from 2008 to 2018," *Environment, Development and Sustainability*, vol. 24, no. 2, pp. 2841-2860, 2022. https://doi.org/10.1007/s10668-021-01556-0
[57] L. Zhu, J. Luo, Q. Dong, Y. Zhao, Y. Wang, and Y. Wang, "Green technology innovation efficiency of energy-intensive industries in China from the perspective of shared resources: Dynamic change and improvement path," *Technological Forecasting and Social Change*, vol. 170, p. 120890, 2021. https://doi.org/10.1016/j.techfore.2021.120890
[58] R. Kiani Mavi, R. F. Saen, and M. Goh, "Joint analysis of eco-efficiency and eco-innovation with common weights in two-stage network DEA: A big data approach," *Technological Forecasting and Social Change*, vol. 144, pp. 553-562, 2019. https://doi.org/10.1016/j.techfore.2018.01.035
[59] N. Zhao, X. Liu, C. Pan, and C. Wang, "The performance of green innovation: From an efficiency perspective," *Socio-Economic Planning Sciences*, vol. 78, p. 101062, 2021. https://doi.org/10.1016/j.seps.2021.101062
[60] H. Yu, L. Liao, S. Qu, D. Fang, L. Luo, and G. Xiong, "Environmental regulation and corporate tax avoidance : A quasi-natural experiments study based on China's new environmental protection law," *Journal of Environmental Management*, vol. 296, p. 113160, 2021b. https://doi.org/10.1016/j.jenvman.2021.113160
[61] T. Ge, W. Qiu, J. Li, and X. Hao, "The impact of environmental regulation efficiency loss on inclusive growth: Evidence from China," *Journal of Environmental Management*, vol. 268, p. 110700, 2020. https://doi.org/10.1016/j.jenvman.2020.110700

[62] C.-C. Hsu, N. Quang-Thanh, F. Chien, L. Li, and M. Mohsin, "Evaluating green innovation and performance of financial development: Mediating concerns of environmental regulation," *Environmental Science and Pollution Research*, vol. 28, no. 40, pp. 57386-57397, 2021. https://doi.org/10.1007/s11356-021-14499-w

[63] W. Ben Arfi, L. Hikkerova, and J.-M. Sahut, "External knowledge sources, green innovation and performance," *Technological Forecasting and Social Change*, vol. 129, pp. 210-220, 2018. https://doi.org/10.1016/j.techfore.2017.09.017

[64] R. Blundell and S. Bond, "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, vol. 87, no. 1, pp. 115-143, 1998. https://doi.org/10.1016/S0304-4076(98)00009-8

[65] D. J. Bauer, K. J. Preacher, and K. M. Gil, "Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: New procedures and recommendations," *Psychological methods*, vol. 11, no. 2, p. 142, 2006. https://doi.org/10.1037/1082-989X.11.2.142

[66] F. Belotti, G. Hughes, and A. P. Mortari, "Spatial panel-data models using stata," *The Stata Journal*, vol. 17, no. 1, pp. 139-180, 2017. https://doi.org/10.1177/1536867x1701700109

[67] J. Rentschler, R. Bleischwitz, and F. Flachenecker, "On imperfect competition and market distortions: The causes of corporate under-investment in energy and material efficiency," *International Economics and Economic Policy*, vol. 15, no. 1, pp. 159-183, 2018. https://doi.org/10.1007/s10368-016-0370-2

[68] P.-J. Zhao, L.-E. Zeng, H.-Y. Lu, Y. Zhou, H.-Y. Hu, and X.-Y. Wei, "Green economic efficiency and its influencing factors in China from 2008 to 2017: Based on the super-SBM model with undesirable outputs and spatial Dubin model," *Science of The Total Environment*, vol. 741, p. 140026, 2020. https://doi.org/10.1016/j.scitotenv.2020.140026

[69] M. Jänicke, ""Green growth": From a growing eco-industry to economic sustainability," *Energy Policy*, vol. 48, pp. 13-21, 2012. https://doi.org/10.1016/j.enpol.2012.04.045

[70] X. Luo and W. Zhang, "Green innovation efficiency: A threshold effect of research and development," *Clean Technologies and Environmental Policy*, vol. 23, no. 1, pp. 285-298, 2021. https://doi.org/10.1007/s10098-020-01977-x

[71] X. Wang and Q. Wang, "Research on the impact of green finance on the upgrading of China's regional industrial structure from the perspective of sustainable development," *Resources Policy*, vol. 74, p. 102436, 2021. https://doi.org/10.1016/j.resourpol.2021.102436

[72] Z. Yan, B. Zou, K. Du, and K. Li, "Do renewable energy technology innovations promote China's green productivity growth? Fresh evidence from partially linear functional-coefficient models," *Energy Economics*, vol. 90, p. 104842, 2020. https://doi.org/10.1016/j.eneco.2020.104842

[73] C. Machado, A. M. Shaikh, and E. J. Vytlacil, "Instrumental variables and the sign of the average treatment effect," *Journal of Econometrics*, vol. 212, no. 2, pp. 522-555, 2019. https://doi.org/10.1016/j.jeconom.2018.04.007

[74] J. Wang, B. Wang, K. Dong, and X. Dong, "How does the digital economy improve high-quality energy development? The case of China," *Technological Forecasting and Social Change*, vol. 184, p. 121960, 2022b. https://doi.org/10.1016/j.techfore.2022.121960

[75] C.-C. Lee, F. Wang, R. Lou, and K. Wang, "How does green finance drive the decarbonization of the economy? Empirical evidence from China," *Renewable Energy*, vol. 204, pp. 671-684, 2023. https://doi.org/10.1016/j.renene.2023.01.058

[76] W. L. Lin, A. B. Mohamed, M. Sambasivan, and N. Yip, "Effect of green innovation strategy on firm-idiosyncratic risk: A competitive action perspective," *Business Strategy and the Environment*, vol. 29, no. 3, pp. 886-901, 2020. https://doi.org/10.1002/bse.2405

[77] P. Gomber, R. J. Kauffman, C. Parker, and B. W. Weber, "On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services," *Journal of Management Information Systems*, vol. 35, no. 1, pp. 220-265, 2018. https://doi.org/10.1080/07421222.2018.1440766

[78] H. Zhao, W. Zheng, and I. Loutfoullina, "Digital finance and collaborative innovation: Case study of the Yangtze River Delta, China," *Sustainability*, vol. 14, no. 17, p. 10784, 2022. https://doi.org/10.3390/su141710784

[79] H. Wang, Z. Chen, X. Wu, and X. Nie, "Can a carbon trading system promote the transformation of a low-carbon economy under the framework of the porter hypothesis? —Empirical analysis based on the PSM-DID method," *Energy Policy*, vol. 129, pp. 930-938, 2019. https://doi.org/10.1016/j.enpol.2019.03.007

[80] M. Zhang, Y. Hong, P. Wang, and B. Zhu, "Impacts of environmental constraint target on green innovation efficiency: Evidence from China," *Sustainable Cities and Society*, vol. 83, p. 103973, 2022b. https://doi.org/10.1016/j.scs.2022.103973

[81] B. E. Hansen, "Threshold effects in non-dynamic panels: Estimation, testing, and inference," *Journal of Econometrics*, vol. 93, no. 2, pp. 345-368, 1999. https://doi.org/10.1016/S0304-4076(99)00025-1

Appendix

Appendix A. Spatial weight matrix.

According to previous studies, we developed three spatial weight matrices to evaluate the spat ial regression results: 0-1, geographic distance, and economic distance.

First, the 0-1 matrix was constructed as Equation (1).

$$W_{ij(0-1)} = \begin{cases} 1, i = j \\ 0, i \neq j \end{cases} (1)$$

Second, the geographic distance matrix was defined as Equation (2). In this matrix, $D^{\sigma}_{ij(dis)}$ denotes the straight-line distance between the geographic centers of gravity of city i and j. σ denotes the attenuation index, which is often set to 2 [54].

$$W_{ij(dis)} = \begin{cases} 1/D^{\sigma}_{ij(dis)}, i \neq j \\ 0, i \neq j \end{cases} \quad (2)$$

Finally, by employing the amount of economic differences between the two cities, an eco nomic distance matrix was created, as shown in Equation (3), where GDP_i represents the avera ge GDP value of city i from 2007 to 2021.

$$W_{ij(eco)} = \begin{cases} \left(1/\left|GDP_i - GDP_j\right|\right) / \left(1/\sum_j \left|GDP_i - GDP_j\right|\right), i \neq j \\ 0, i=j \end{cases} \quad (3)$$

Appendix B. Spatial correlation test.

Equation (4) represents Moran's I formula, where $S^2 = \sum_{i=1}^{n}(x_i - \bar{x}), x_i = \frac{1}{n}\sum_{i=1}^{n} x_i$, n denotes the nu mber of cities, in this paper is 284.

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (4)$$

Appendix C.

Test of the threshold model.

Dependent variable	Threshold variable	Model	F-test value	P-value	BS	Threshold value	95% confidence interval
GTE	GF	Single threshold	73.39**	0.002	500	0.317	[0.308, 0.426]
		Double threshold	12.98	0.188	500	0.438	-
GRE	GF	Single threshold	177.69***	0.000	500	0.337	[0.325, 0.433]
		Double threshold	37.15	0.296	500	0.443	-

Note: ***, **, and * represent significance at 1%, 5%, and 10%, respectively. - that obtaining the indicates confidence interval for the threshold value is difficult under typical conditions.

ISSN: 2576-8484
Vol. 9, No. 8: 1039-1068, 2025
DOI: 10.55214/2576-8484.v9i8.9542

Appendix D.
Global spatial autocorrelation test: Moran's I.

Year	**Moran's I ofGTE**					
	W0- 1		**Wdis**		**Weco**	
2007	0.024*	[0.085]	0.001***	[0.010]	0.020*	[0.089]
2008	0.028**	[0.037]	0.004*	[0.059]	0.016**	[0.040]
2009	0.169***	[0.000]	0.010***	[0.000]	0.223***	[0.000]
2010	0.023*	[0.085]	0.005***	[0.013]	0.041**	[0.033]
2011	0.063***	[0.004]	0.008***	[0.000]	0.078***	[0.000]
2012	0.013**	[0.015]	0.003**	[0.011]	0.010**	[0.015]
2013	0.047**	[0.041]	0.011***	[0.000]	0.091***	[0.000]
2014	0.058***	[0.010]	0.013***	[0.000]	0.077***	[0.000]
2015	0.109***	[0.000]	0.023***	[0.000]	0.075***	[0.001]
2016	0.099***	[0.002]	0.017***	[0.000]	0.063**	[0.011]
2017	0.109***	[0.001]	0.021***	[0.000]	0.140***	[0.000]
2018	0.140***	[0.000]	0.035***	[0.000]	0.161***	[0.000]
2019	0.113***	[0.001]	0.030***	[0.000]	0.253***	[0.000]
2020	0.044*	[0.092]	0.016***	[0.000]	0.134***	[0.000]
2021	0.018**	[0.017]	0.001*	[0.076]	0.012*	[0.069]

Note: ***, **, and * represent significance at 1%, 5%, and 10%, respectively. P-values are shown in [ ].

Year	**Moran's I ofGRE**					
	W0- 1		**Wdis**		**Weco**	
2007	0.144***	[0.000]	0.032***	[0.000]	0.171***	[0.000]
2008	0.068**	[0.031]	0.029***	[0.000]	0.157***	[0.000]
2009	0.119***	[0.001]	0.037***	[0.000]	0.159***	[0.000]
2010	0.048*	[0.077]	0.020***	[0.000]	0.165***	[0.000]
2011	0.058**	[0.029]	0.018***	[0.000]	0.090***	[0.000]
2012	0.089***	[0.006]	0.031***	[0.000]	0.074***	[0.005]
2013	0.083***	[0.008]	0.020***	[0.000]	0.041*	[0.063]
2014	0.027*	[0.067]	0.003**	[0.050]	0.013*	[0.059]
2015	0.055*	[0.058]	0.016***	[0.000]	0.006*	[0.082]
2016	0.008**	[0.034]	0.001**	[0.017]	0.021**	[0.014]
2017	0.011**	[0.021]	0.000**	[0.032]	0.002**	[0.025]
2018	0.012***	[0.002]	0.000**	[0.025]	0.023*	[0.085]
2019	0.021*	[0.071]	0.004**	[0.042]	0.015***	[0.009]
2020	0.027**	[0.050]	0.002**	[0.030]	0.005*	[0.083]
2021	0.017*	[0.098]	0.001*	[0.075]	0.087***	[0.002]

Note: ***, **, and * represent significance at 1%, 5%, and 10%, respectively. P-values are shown in [ ].

Appendix E.
Test of spatial model selection.

Dependent variable: GTE				
LM test	**LM (lag)** **103.45*** [0.000]**	**LM (error)** **944.68*** [0.000]**	**Robust LM (lag)** **113.77*** [0.000]**	**Robust LM (error)** **953.12*** [0.000]**
LR test	H0: SLM model 18.17*** [0.006]		H0: SEM model 20.23*** [0.003]	
Wald test	Wald (lag) 18.15*** [0.006]		Wald (error) 20.66*** [0.002]	
Hausman test	H0: City fixed model 106.76*** [0.000]		H0: Time fixed model 82.44*** [0.005]	

Note: ***, **, and * represent significance at 1%, 5%, and 10%, respectively. P-values are shown in [].

Dependent variable: GRE				
LM test	**LM (lag)** **272.64*** [0.000]**	**LM (error)** **1474.03*** [0.000]**	**Robust LM (lag)** **274.68*** [0.000]**	**Robust LM (error)** **1472.74*** [0.000]**
LR test	H0: SLM model 49.41*** [0.000]		H0: SEM model 48.72*** [0.000]	
Wald test	Wald (lag) 49.67*** [0.000]		Wald (error) 50.55*** [0.000]	
Hausman test	H0: City fixed model 49.77*** [0.000]		H0: Time fixed model 66.64*** [0.000]	

Note: ***, **, and * represent significance at 1%, 5%, and 10%, respectively. P-values are shown in [].