The Economics and Finance Letters
2026 Vol. 13, No. 3, pp. 213-230
ISSN(e): 2312-430X
ISSN(p): 2312-6310
DOI: 10.18488/29.v13i3.5140

Green innovation efficiency, green finance, and industrial upgrading in China: A VECM and NARDL analysis

Lingyan Du[1,2]
Abdul Rais Abdul Latiff[1+]

[1]*School of Social Sciences, Universiti Sains Malaysia, 11800, Gelugor, Penang, Malaysia.*
[2]*School of Business, Guangzhou College of Technology and Business, 510850, Guangzhou, Guangdong Province, China.*
[1,2]*Email: dulingyan@student.usm.my*
[1]*Email: abdulrais@usm.my*

(+ Corresponding author)

Article History
Received: 12 March 2026
Revised: 1 June 2026
Accepted: 30 July 2026
Published: 2 September 2026

Keywords
ARDL
Green finance
Green innovation efficiency
NARDL
VECM model.

JEL Classification:
Q56; O31; L16; G28; C32.

ABSTRACT

The coordination among green finance (GF), industrial upgrading (IS), and green innovation efficiency (GIE) is crucial for sustainability. Few studies focus on the asymmetric impacts of GF. Controlling for the 2009 policy shock, this study examines the dynamic and asymmetric effects of green finance from a city-level perspective. By employing the Vector Error Correction Model (VECM) and the nonlinear autoregressive distributed lag (NARDL) model, we find that GF significantly drives GIE in the long run. The ARDL results reveal that a one-standard-deviation increase in GF significantly improves GIE by 0.35 units. The NARDL model reveals the asymmetric impacts of GF in the short run, showing that credit contraction can lead to a more severe decline in GIE; yet these frictions gradually dissipate in the long term. These findings suggest the necessity for targeted GF policies to smooth short-term frictions during the transformation of manufacturing cities.

Contribution/Originality: This study advances the literature by investigating the dynamics among green finance, green innovation efficiency, and industrial upgrading from a novel municipal perspective. By integrating VECM and NARDL models, it systematically unpacks the linear and non-linear asymmetric effects of green finance, filling a critical research gap.

1. INTRODUCTION

The transition toward high-quality manufacturing necessitates the coordination of green finance (GF), industrial upgrading (IS), and green innovation efficiency (GIE) (Bao & Nguyet, 2025; Takalo, Tooranloo, & Shahabaldini Parizi, 2021). While the manufacturing sector fosters green progress, it also emits large amounts of pollutants (Zhang et al., 2023). Consequently, leveraging GF and IS to promote GIE is critical for the manufacturing sector.

While an extensive body of literature examines the drivers of GIE, the dynamic and non-linear interactions among these three variables remain underexplored. Previous studies predominantly explore green finance through static models, ranging from micro-level policy impacts on firms and cities (Hou & Shi, 2024; Ma, Sha, Wang, & Zhang, 2023; Wang, 2023; Zhang & Li, 2022) to macro-level spatial spillovers (Huang, Chen, Lei, & Zhang, 2022). Although rationalization of IS is known to reduce pollution in the long run (Wang et al., 2023) and thereby enhance GIE, the short-term crowding-out effects and asymmetric impacts are frequently omitted.

The manufacturing cities, where the structural contradiction between economic growth and environmental sustainability is most acute, remain under-explored in prior research on national or provincial panel data (Wang, Zhao, Lei, & Long, 2021; Zhao, Lei, Zhao, & Wang, 2025).

To overcome the above limitations, this study explores the dynamic relationships and asymmetric effects, focusing on a typical manufacturing city. Specifically, the analysis aims to: (1) evaluate the asymmetric impacts of GF on GIE; (2) model the long-run cointegrating relationships and short-run error correction dynamics; (3) identify the dynamic transmission channels to quantify their relative contributions.

1.1. Contributions of the Study

This study employs the NARDL model to overcome the constraints of linear and static analyses, capturing the asymmetric effect of GF on GIE; the VECM elucidates the long-term equilibrium relationships among variables and their dynamic transmission pathways.

By focusing on a typical manufacturing city, the analysis broadens the spatial scope of GIE research and provides new evidence to help mitigate the risk of industrial hollowing out.

This research examines a representative manufacturing city in China, but its analytical methods and findings will also benefit other developing countries facing conflicts between economic development and environmental sustainability. These insights can assist these nations in achieving more favorable industrial transformations and optimizing the utilization of green financial instruments.

2. LITERATURE REVIEW

2.1. Green Finance and Green Innovation Efficiency

2.1.1. Theoretical Foundations for the Impact of Green Finance on Green Innovation Efficiency

Rooted in Schumpeterian theory, Schumpeter (1934) emphasized the relationship between finance and innovation, which emphasized the importance of financial support for innovation. By easing information frictions and slashing transaction barriers, advanced financial systems act as a conduit for R&D funding (Levine, 1997).

As an environmental regulation tool, GF tends to allocate credit to enterprises with strong green innovation capabilities (Hong, Li, & Drakeford, 2021). Besides lowering financing costs, green financial instruments signal environmental commitment to capital markets and broaden investor participation (Hermala, Sunitiyoso, & Sudrajad, 2025). However, its misallocation can act as a barrier to GIE (Xue, Feng, & Xue, 2026). Strict GF policies encourage listed firms to increase compliance-oriented innovation rather than capability-enhancing innovation (Wang, 2023). Complementing this micro-level evidence, Huang et al. (2022) found that GF enhances local green innovation capabilities and generates cross-provincial spillover effects. Li, Ma, Ma, and Gao (2024) substantiated the findings by employing Spatial Durbin Models (SDMs) to demonstrate that GF fosters innovation networks.

2.1.2. Transmission Mechanisms of Green Finance on Green Innovation Efficiency

Existing studies have verified multiple channels through which GF affects GIE. It improves enterprises' financial and environmental performance and promotes the internalization of pollution costs for high-polluting enterprises (Zhang, Wang, & Liu, 2022). The effective operation of the financial system reduces information asymmetry in financing processes, helping investors better assess project risks and providing financial support for green technology R&D and commercialization (Xiao & Zhao, 2012). Given the persistent capital commitment demanded by sustainable innovation, green finance acts as a pivotal mediating mechanism. For example, Archer, Sharma, and Su (2020) found heterogeneous impacts of credit constraints on corporate innovation between developed and developing countries, while Liu (2024) demonstrated that new financial instruments like supply chain finance significantly boost innovation capabilities through the mediating effect of alleviating financing constraints. The effect of GF on GIE is also subject to the non-linear effect of R&D investment. The inhibitory effect caused by excessive R&D input may offset the promotional effect of GF on GIE (Liao, 2025).

Although the aforementioned studies have explored numerous mechanisms, most are limited to linear assumptions, and few have examined the potential nonlinear effects of green finance.

2.2. Industrial Upgrading and Green Innovation Efficiency

Empirical research is scarce on the direct causal impact of industrial structure on green innovation efficiency. At the industry level, Li, Liu, Huang, Li, and He (2023) demonstrated that IS has a significant positive impact on the GIE of construction enterprises, a finding that has also been confirmed in the logistics industry (Xu, Yang, Lu, Guo, & Wu, 2025). A substantial body of literature has also explored the indirect effects of industrial upgrading, such as moderating effects, mediating mechanisms, and spatial spillover effects.

2.2.1. Moderating and Mediating Effects of Industrial Upgrading

In much of the literature, industrial upgrading is regarded as a key moderating variable for enhancing GIE. For instance, recent studies indicate that the digital economy and infrastructure development indirectly promote GIE at the firm or provincial level by optimizing industrial structure (Hu, Chen, Fan, & He, 2024; Liu, Jiang, & Long, 2025; Zhiyong, Yongbin, & Jiaying, 2024). Moreover, a nonlinear relationship exists between IS and GIE; for instance, in the tourism industry, the structural impact of industrial agglomeration on GIE exhibits an inverted U-shaped curve (Liu, An, & Jang, 2023).

2.2.2. Spatial Dimensions and Spillover Effects

In addition to examining the moderating and mediating mechanisms of industrial upgrading, scholars are increasingly focusing on its geographical impact on GIE. Using spatial Durbin models, Guo, Li, Zhou, Sun, and Ren (2025) and C. Xu et al. (2025) found that a rationalized industrial structure significantly improves regional GIE by optimizing resource allocation. Taking into account the heterogeneity of environmental regulations, Hao, Xu, Chen, Yuan, and Wu (2024) and Ying, Fang, and Ji (2023) emphasized that industrial restructuring, by aligning firms' production activities with environmental constraints, serves as a key driver of GIE improvement. Wang, Bian, and Cheng (2022) noted that industrial upgrading facilitates the formation of spatial networks of GIE, leading to cross-regional technology spillovers.

Beyond spatial effects, industrial relocation within the regions is associated with GIE. By reallocating production factors and transforming regional energy consumption profiles, such relocation directly optimizes both desirable and undesirable environmental outputs Mao and Liu (2025). Industrial synergy, particularly the integration of manufacturing and modern services, introduces non-linear threshold effects that significantly boost regional GIE Zhang, Nie, and Wan (2025).

While the positive impacts of industrial upgrading on GIE were supported by many scholars, others have raised doubts. Yi, Wang, Yan, Fu, and Zhang (2020) argued that short-term resource misallocation during structural transformation can also lead to inefficiencies.

Insufficient research on the dynamic nexus can obscure the transmission channels of industrial structural changes on GIE, overlooking the factor crowding-out risks faced by manufacturing industries.

2.3. The Nexus of Green Finance, Industrial Upgrading and Green Innovation Efficiency

The existing literature has laid a solid foundation for understanding the relationship among these three factors. On the one hand, GF can optimize resource allocation and alleviate firms' financing constraints, providing critical financial support for green technology R&D and reducing the costs of green innovation, thereby stimulating green innovation (Hong et al., 2021; Huang et al., 2022; Li et al., 2024; Liao, 2025; Wang, 2023). On the other hand, GF drives industrial structural transformation through two channels: first, it incentivizes firms to pursue technological innovation, accelerating the transition toward high-value-added and low-carbon industrial sectors (Li & Luo, 2024; Ren, Zeng, & Gozgor, 2023; Zhao et al., 2025); second, by restricting financing channels for high-pollution industries and increasing their financing costs, it facilitates the reallocation of financial resources across industries, thereby promoting green industrial transformation and optimizing the industrial structure (Xu, Zhu, & Chen, 2024).

Although there is a wealth of research on the pairwise relationships among these variables, systematic studies examining the interrelationships among GF, IS, and GIE remain insufficient. These studies tend to fragment the relationships, focusing on either the indirect role of IS or the policy effects of GF pilots. By relying on static frameworks, these studies overlook the dynamic adjustment paths.

2.4. Research Gap

Although previous literature has examined the relationship between GF and GIE, it primarily relies on static, linear methods. These approaches overlook the asymmetric effects of GF and neglect the dynamics of manufacturing-intensive cities. Consequently, current research lacks a framework capable of capturing both dynamic adjustments and nonlinear effects within the manufacturing sector.

2.5. Theoretical Framework

This study constructs a theoretical framework based on Porter's Hypothesis, financial development theory, and industrial restructuring theory.

While traditional views emphasize the burden of compliance costs, whereby environmental mandates such as GF policies inflate operating expenses and suppress productivity (Gray & Shadbegian, 2003; Ma et al., 2023), Porter's Hypothesis offers the opposite perspective. It argues that well-designed regulations can produce compensatory effects, with technological progress offsetting the compliance burdens (Porter & van der Linde, 1995). The differing results observed indicate the need to clearly distinguish between long-term and short-term dynamics, and the VECM and ARDL frameworks are well-suited for this task. Resource misallocation in GF leads to inefficient innovation (Xue et al., 2026), implying that the policy effects may be non-linear, thus justifying the employment of NARDL to capture the asymmetry.

By acting as a capital allocation tool, GF directs liquidity toward eco-innovation (Chen, Fu, Yu, Yu, & Li, 2025). This aligns with Schumpeter (1934) assertion that financial capital is a catalyst for technological breakthroughs. Similarly, Hicks (1969) points out that finance-driven innovation exhibits path dependence. To track dynamically adjusted paths, a VECM approach is utilized in this research to analyze the long-run association.

According to industrial restructuring theory, high-quality financial development promotes efficient industrial transformation (Appiah, Gyamfi, Adebayo, & Bekun, 2023). Alignment between financial supply and industrial demand is crucial for optimizing credit structure and directing capital towards green industries (Li & Luo, 2024), thereby promoting industrial upgrading.

3. METHODOLOGY

3.1. Vector Error Correction Model (VECM)

The VECM is specified in Equation 1:

$$\Delta GIE_t=\mu_0+\alpha_1 ECT_{t-1}+\sum_{j=1}^{p-1}\beta_j \Delta GIE_{t-j}+\sum_{j=1}^{p-1}\gamma_j \Delta GF_{t-j}+\sum_{j=1}^{p-1}\delta_j \Delta IS_{t-j}+\varepsilon_t \quad (1)$$

where the parameter $p-1$ represents the optimal lag length determined by the information criteria. The coefficient of ECT_{t-1}, α_1, dictates the speed of adjustment toward the steady-state equilibrium following a short-term shock. Additionally, to quantify the dynamic contributions and interdependencies, IRF and variance decomposition analyses were conducted within the VECM framework.

3.2. Autoregressive Distributed Lag (ARDL) Model

To further verify the symmetric and asymmetric impact of GF on GIE, this paper uses an ARDL model after the VECM model. The ARDL model assumes weak exogeneity of the explanatory variables, effectively avoiding biases that may arise from model complexity or endogeneity assumptions in VECM (Adnan & Billah, 2025). Furthermore, the sample period in this paper is 2003–2022, representing a typical small-sample study. The parameter estimation and boundary tests of the ARDL model are more robust to small samples and can more efficiently capture long-term and short-term relationships between variables (Pattichis, 1999; Zhao et al., 2025).

Consistent with established literature, we specify the long-run model for green innovation efficiency by incorporating green finance and industrial upgrading.

$$GIE_t = \alpha_0 + \alpha_1 GF_t + \alpha_2 IS_t + \varepsilon_t \quad (2)$$

GIE_t denotes green innovation efficiency in period t, while the parameters α_1 and α_2 capture the enduring impacts of green finance and industrial upgrading, respectively.

Equation 2 reports the long-run estimation results. To quantify the short-run effects of green finance, this equation is re-specified as an error correction model (ECM). Following the framework of Pesaran, Shin, and Smith (2001) lagged terms of green finance are incorporated into the baseline specification, permitting the concurrent estimation of both short-term dynamics and long-term multipliers via ordinary least squares (OLS), as detailed in Equation 5.

$$\Delta GIE_t = \alpha_0 + \sum_{k=1}^{p} \zeta_k \Delta GIE_{t-k} + \sum_{k=0}^{q_1} \eta_k \Delta GF_{t-k} + \sum_{k=0}^{q_2} \theta_k \Delta IS_{t-k} + \beta_1 GIE_{t-1} + \beta_2 GF_{t-1} + \beta_3 IS_{t-1} + \varepsilon_t \quad (3)$$

As indicated by Equation 3, the parameters associated with the first-differenced terms encapsulate the short-term effects. Conversely, the long-run multipliers are obtained by normalizing (β_2,β_3) against β_1.

To evaluate the potential asymmetric effects of green finance, we employ the NARDL method extended by Shin, Woo, Huh, Lee, and Jeong (2014). This technique segregates the core variables into cumulative upward and downward variations, thereby facilitating a more precise estimation of their heterogeneous impacts. The partial sums for green finance are formulated as follows:

$$GF_t^+ = \sum_{j=1}^{t} \Delta GF_t^+ = \sum_{j=1}^{t} max(\Delta GF_j, 0) \quad (4a)$$

$$GF_t^- = \sum_{j=1}^{t} \Delta GF_t^- = \sum_{j=1}^{t} min(\Delta GF_j, 0) \quad (4b)$$

Where GF^+ and GF^- signify the respective cumulative expansions and contractions in green finance. By substituting Equations 4a and 4b back into Equation 5, the NARDL specification can be shown as:

$$\Delta GIE_t = \alpha_0 + \sum_{k=1}^{p} \zeta_k \Delta GIE_{t-k} + \sum_{k=0}^{q_1} \eta_k^+ \Delta GF_{t-k}^+ + \sum_{k=0}^{q_2} \eta_k^- \Delta GF_{t-k}^- + \sum_{k=0}^{q_3} \theta_k \Delta IS_{t-k} + \beta_1 GIE_{t-1} + \beta_2 GF_{t-1}^+ + \beta_3 GF_{t-1}^- + \beta_4 IS_{t-1} + \varepsilon_t \quad (5)$$

Given that ARDL models remain valid even with sample sizes as small as T=20 (Pattichis, 1999), the NARDL model, which is based on the ARDL method, is equally applicable to the dataset in this study. In addition, recent empirical studies that are similarly constrained by environmental data and have finite T ($20<T<30$) (Jahanger et al., 2024; Ramos-Herrera, 2025; Saqib & Dincă, 2024) have adopted the NARDL method and noted its ability to correct for small-sample bias.

Given the strict temporal constraints of the available green data, the NARDL model is clearly a suitable method for testing the short-run and long-run asymmetries in this study.

3.3. Variable Selection and Data Collection

3.3.1. Green Finance

Following the methodologies outlined in the prior literature by Bai and Lin (2024) and Xiong, Wang, Liu, He, and Yu (2023), this study employs an entropy-weighted approach to construct a green finance (GF) index using four sub-indicators: green credit, green investment, green insurance, and green securities. Table 1 presents the specific evaluation indicators and their data sources.

Table 1. Green finance evaluation indicator.

Dimension	Indicator Description	Source
Green Credit	Interest expenditure of six high-energy-consuming industries / Aggregate industrial interest outlays	Statistical Yearbook
Green Investment	Environmental protection expenditure / total fiscal expenditure	Statistical Yearbook
	Pollution control investment / GDP	China City Statistical Yearbook
Green Insurance	Agricultural insurance expenditure/insurance expenditure	EPS database
Green Securities	Market value of environmentally friendly companies / total market value	Wind database

3.3.2. Industrial Upgrading

Based on the theory of industrial structure transformation, this study uses the ratio of value added in the tertiary sector to that in the secondary sector as a proxy indicator of industrial upgrading (IS). In the post-industrial era, agriculture accounts for a very small share of the overall economy; industrial upgrading primarily refers to the shift from highly polluting, energy-intensive industrial sectors to the service sector, that is, "tertiarization." Data for this variable are drawn from the Foshan Statistical Yearbook.

3.3.3. Green Innovation Efficiency

3.3.3.1. Measurement Index System

Following practices in the literature, this study evaluates the GIE of Foshan City using a super-efficiency SBM model incorporating undesirable outputs.

Table 2. Green innovation efficiency evaluation indicator system.

Category		Specific indicators	Unit	Source
Input Indicators		R&D activity personnel	Personnel	Statistical Yearbook
		R&D internal expenditures	million yuan	Statistical Yearbook
Output Indicators	Expected Output	Number of patents authorized	Pieces	Statistical Yearbook
		Total profit	Billions of Yuan	
	Non-expected output	Industrial wastewater discharge	Million tons	China City Statistical Yearbook
		Industrial sulfur dioxide emissions	Million cubic meters	
		Industrial particulate matter (Dust) emissions	Tons	

Regarding input indicators, human capital and physical capital are proxied by the number of R&D personnel and internal R&D expenditure, respectively. Patents granted enable manufacturing enterprises to enhance the technological value-added of their products, strengthening corporate competitiveness as well as boosting profits. Therefore, drawing on the research by Yuan, Ye, and Sun (2021) and considering the outcomes and economic value of green innovation, this study selects the number of granted patents and total profits of industrial enterprises above a designated size as desirable outputs. Environmental pollution generated during the innovation process constitutes undesirable outputs, including industrial wastewater, sulfur dioxide, and particulate matter (dust), traditionally referred to as the "three wastes". The index system is detailed in Table 2.

3.3.3.2. Indicator Weights and Comprehensive Score Calculation

In this study, manufacturing enterprises above the designated size are selected as the decision-making units (DMUs) for the super-efficiency SBM model. They provide more comprehensive statistical data for SBM estimations. The dominance in both R&D spending and energy use makes them the core of eco-innovation. Conducting empirical research focused on these entities targeted by green finance ensures that our findings can be directly translated into actionable policy interventions. The Super-efficiency SBM model extended by Tone (2001) outperforms traditional CCR methods. This model avoids estimation biases arising from radial assumptions and the neglect of slack variables.

To elaborate on its evaluation mechanism, the following formulations were introduced: Consider a set of n decision-making units (DMUs), where each DMU consumes m types of inputs to produce t_1 types of desirable outputs and t_2 types of undesirable outputs. The inputs, desirable outputs, and undesirable outputs are represented by X, Y_p, and Y_q, respectively. This study selects manufacturing enterprises above designated size as DMUs primarily based on the following three considerations: First, such enterprises possess standardized and detailed statistical data, which ensures the robustness of the SBM estimations; Second, these enterprises are the main contributors to industrial R&D investment and energy consumption, playing a central role in advancing green innovation; Finally, as key targets of current low-carbon and green finance policies, focusing on these enterprises can significantly enhance the practical significance and policy reference value of this study's empirical findings.

The evaluation model is as follows:

$$\rho^* = \min \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ih}}}{1-\frac{1}{t_1+t_2}\left(\sum_{r=1}^{t_1}\frac{s_r^p}{y_{rh}^p}+\sum_{k=1}^{t_2}\frac{s_k^q}{y_{kh}^q}\right)} \tag{6}$$

$$s.t.\begin{cases} x_{ih} \geq \sum_{j\neq 1, j\neq h}^{n}\lambda_j x_{ij} - s_i^-, i=1,\dots, \ m \\ y_{ik} \geq \sum_{j\neq 1, j\neq h}^{n}\lambda_j y_{rj} + s_r^p, r=1,\dots, \ t_1 \\ y_{kh} \geq \sum_{j\neq 1, j\neq h}^{n}\lambda_j y_{kj} - s_k^q, k=1,\dots, \ t_2 \\ 1-\frac{1}{t_1+t_2}\left(\sum_{r=1}^{t_1}\frac{s_r^p}{y_{rh}^p}+\sum_{k=1}^{t_2}\frac{s_k^q}{y_{kh}^q}\right) > 0 \\ s_i^- \geq 0, \ s_r^p \geq 0, \ s_k^q \geq 0 \end{cases} \tag{7}$$

Where ρ^* denotes the green innovation efficiency score, while λ represents the weight vector. Furthermore, s^-, s^p, and s^q correspond to the slack variables for inputs, desirable outputs, and undesirable outputs, respectively. Based on the evaluation indicator system in Table 2, we calculated the GIE of Foshan City from 2003 to 2022. The temporal evolution of the GIE is depicted in Figure 1.

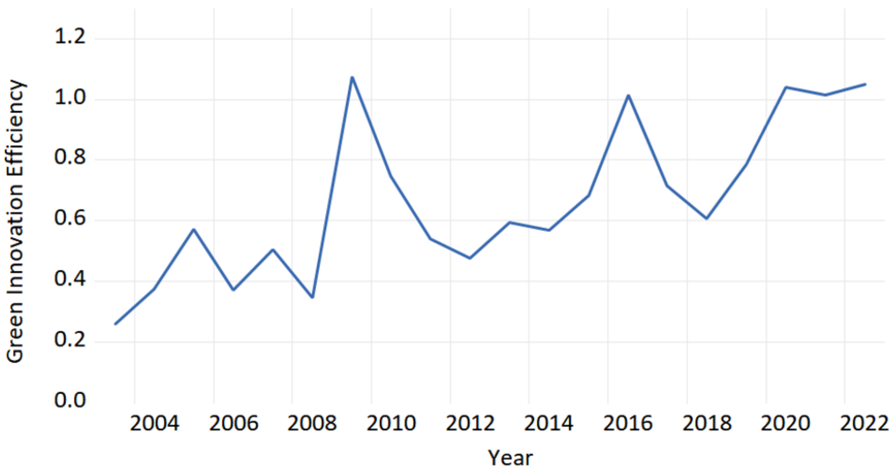

Figure 1. Green innovation efficiency of Foshan City (2003–2022).

As shown in Figure 1, the GIE exhibits an overall upward trend with a clear structural break that occurred in 2009. This surge reflects the "4 trillion yuan" capital stimulus plans implemented following the 2008 global financial crisis, which unlocked R&D financing. We therefore introduce a 2009 dummy variable (DUM09) into the ARDL analysis. Although GIE peaks appeared in 2016 and 2020, these were largely "statistical artifacts". The short-term production halts caused by the environmental inspections in 2016 and the COVID-19 lockdowns in 2020 led to passive drops in pollutant emissions, which in turn artificially inflated the GIE values. DUM09 takes the value 1 in 2009 and 0 in all other years in both the ARDL and NARDL frameworks.

3.3.4. Data Sources

We construct our sample using the China EPS database for environmental pollution and agricultural insurance data, and Wind for the market capitalization of listed firms. All other series derive from the *Foshan Statistical Yearbook* and the *China City Statistical Yearbook*.

4. EMPIRICAL RESULTS

4.1. Descriptive Summaries

As summarized in Table 3, the mean GIE is 0.667 with a standard deviation of 0.258. Although the peak GIE value exceeds 1, this moderate average indicates that Foshan's capacity for green innovation is still consolidating. The low mean value of GF (0.357) reveals that the region's green finance remains underdeveloped, lacking targeted green capital issuance. The average IS of 0.645 reflects a relatively high degree of tertiarization in Foshan.

Table 3. Descriptive statistics of variables.

Variables	Observed value	Mean value	Standard Deviation	Minimum value	Maximum value
GIE	20	0.667	0.258	0.260	1.074
GF	20	0.357	0.061	0.243	0.446
IS	20	0.645	0.099	0.522	0.841

4.2. Unit Root Test of Variables

Table 4 presents the DF, PP, and ADF unit root test results. The evidence shows that GF, GIE, and IS are non-stationary at levels but become stationary after first differencing, confirming they are all I (1) processes. This satisfies the prerequisite for the Johansen test.

Table 4. Unit root test.

Variables	DF test	PP test	ADF test	Unit root
GIE	-2.302	-2.456	-2.457	Yes
GF	-0.787	-0.547	-0.986	Yes
IS	-2.692	-1.312	-0.939	Yes
DGIE	-5.893***	-13.491***	-5.751***	No
DGF	-6.041***	-7.670***	-6.501 ***	No
DIS	-1.963**	-2.786*	-2.786*	No

Note: *, ** and *** denote significant at 10%, 5% and 1% level respectively.

4.3. Determination of the Optimal Lag Order of the VECM

Before applying the Johansen cointegration procedure, it is essential to determine the optimal lag length of the underlying VAR system. As detailed in Table 5, the AIC, BIC, and HQ information criteria suggest an optimal lag order of one. Therefore, the lag parameter p in the VECM model is set to 1.

Table 5. Optimal lag order of the VECM model.

Lag order	LR	FPE	AIC	SC	HQ
0	NA	3.02e-07	-6.443	-6.296	-6.429
1	44.796*	3.02e-08*	-8.830*	-8.242*	-8.772*
2	8.683	4.15e-08	-8.640	-7.611	-8.537
3	4.623	8.90e-08	-8.241	-6.771	-8.095

Note: * indicates lag order selected by the criterion.

Table 6. Johansen cointegration test.

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5% CV (Trace)	Max-Eigen Statistic	5% CV (Max-Eigen)
None (r=0)	0.684	34.859**	29.797	20.708*	21.132
At most 1 (r≤1)	0.538	14.151	15.495	13.911	14.265
At most 2 (r≤2)	0.013	0.240	3.842	0.240	3.842

Note: CV stands for Critical Value; **, * represent rejection of the null hypothesis at 5% and 10% significance level, respectively.

4.4. Johansen Cointegration Test

As shown in Table 6, the Johansen test confirms the existence of a long-run equilibrium among GF, IS, and GIE. Although the results of the Maximum Eigenvalue test were close to the critical value ($p = 0.0572$), the trace test strongly indicates the presence of at least one cointegration vector at the 5% significance level. Given that the trace test exhibits greater robustness for small sample sizes (Alemu, Jayamohan, & Mulugeta, 2026; Cheung & Lai, 1993), this study adopts the conclusions derived from this statistic. This finding suggests that, despite short-term fluctuations caused by exogenous shocks, a long-run equilibrium relationship exists among these variables, providing an empirical basis for the estimation of the VECM.

4.5. Vector Error Correction Model Analysis

After establishing the long-run equilibrium, the VECM was estimated. The standardized long-run equations are shown below (standard errors are in parentheses):

$$GIE_{t-1} = \underset{(0.8674)}{5.1756}\, GF_{t-1} - \underset{(0.4289)}{0.8415}\, IS_{t-1} - 0.6577 \quad (8)$$

Subsequently, Table 7 reports the short-run dynamics and the error correction mechanism of the VECM.

In the long run, GF exerts a significant positive impact on GIE. Specifically, for every 0.01-unit increase in the GF index (marginal), GIE increases by approximately 0.052 units. Using a one-standard-deviation increase as a benchmark, a one-standard-deviation increase in the GF index (0.061) implies a 0.316-unit increase in GIE. It follows that an increase in green capital translates into a higher GIE. Green financial instruments accelerate the green transition in energy-intensive industries (such as building ceramics) by channeling capital into sustainable projects. The positive impact of GF on GIE provides empirical support for Porter's Hypothesis.

Table 7. Short-run dynamics of the VECM.

Variables	ΔGIE_t	ΔGF_t	ΔIS_t
ECT_{t-1}	-0.9960*** (0.3321)	-0.0258 (0.0415)	-0.1119** (0.0563)
ΔGIE_{t-1}	0.0643 (0.2315)	-0.0211 (0.0289)	0.0325 (0.0392)
ΔGF_{t-1}	-2.4366 (2.4582)	-0.5831* (0.3073)	-0.4123 (0.4168)
ΔIS_{t-1}	-2.2835* (1.3254)	-0.2287 (0.1657)	0.2425 (0.2247)
C	0.0591 (0.0506)	0.0175*** (0.0063)	0.0057 (0.0086)

Note: Standard errors are in parentheses.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

In the short term, GFt, 1 is statistically insignificant in the VECM, and an increase in GF does not definitely lead to an improvement in GIE. This finding is consistent with the long-term nature and high-risk characteristics of green innovation R&D, reflecting the time lag in the outcomes of green R&D.

IS exerts a significant negative impact on GIE in both the short and long term. That is, tertiarization does not promote green innovation; rather, the relative contraction of the secondary sector constrains the advancement of green technologies. From a practical standpoint, the tertiary sector (e.g., services, finance, real estate, etc.) is not the primary driver of green innovation (Arranz, Arroyabe, Li, Arranz, & Fernandez de Arroyabe, 2023). Green technologies are concentrated in the secondary sector, particularly manufacturing. An increase in the IS index means that the tertiary sector is growing faster than the secondary sector, reflecting a shift from manufacturing to services. This transition may weaken the foundation on which green technology R&D is rooted and exert a "crowding-out effect" on green innovation, leading to a decline in GIE.

4.6. Impulse Response Analysis

To describe the dynamic transmission among GF, GIE, and IS, this study uses the Bootstrap method to generate a 10-period impulse response function (IRFs). The specific results are shown in Figure 2.

4.6.1. Dynamic Response of GIE to GF Shocks

As depicted in Figure 2b, when received with a standard deviation shock of GF, the positive response of GIE exhibits significant lag. As we all know, financing constraints are the key bottleneck restricting the breakthrough of green technologies in the manufacturing industry. The green financial system can enhance the GIE of environmental protection enterprises by prioritizing credit allocation and providing interest subsidies. However, this positive effect can only be manifested after going through the cycles of project application, equipment procurement, and research and development investment. In the long term, the transformation of green technologies requires the support of green finance as "patient capital" (Sun, Zhang, & Yao, 2026).

4.6.2. Dynamic Response of GIE to IS Shocks

As shown in Figure 2c, GIE exhibits a significant negative response to IS. A higher IS index represents a rapid rise in the relative share of the tertiary sector.

The expansion of the tertiary sector draws production factors, such as capital and high-skilled labor, away from manufacturing, inhibiting green innovation. This resource mismatch weakens the foundation for green technology R&D (Si, Wang, Cao, & Yao, 2026). Tertiarization also drives up factor prices (such as rents and wages), squeezing the profits of manufacturing firms. The resulting margin compression forces manufacturers to reduce green innovation investment. Given that service industries face less stringent environmental requirements and generate fewer green patents than the manufacturing sector (Arranz et al., 2023), this shift inevitably depresses overall GIE (Zeng, Li, & Huang, 2021).

4.6.3. Dynamic Response of IS to GIE Shocks

Figure 2g indicates that IS responds negatively to GIE shocks. This suggests that improvements in GIE tend to redirect factors back toward industrial sectors, restoring the comparative advantage of advanced manufacturing (Acemoglu, Aghion, Bursztyn, & Hemous, 2012). Unlike business model innovation in the tertiary sector, green innovation is concentrated in the secondary sector. When green innovation achieves breakthroughs, the resulting "technological dividend" initially boosts productivity in the manufacturing sector. These technological breakthroughs not only significantly reduce the costs of environmental compliance and emissions reduction in traditional industries but also propel them upstream of the value chain, thereby substantially enhancing the value added and profitability of high-end green manufacturing (Wang, Su, & Liu, 2025). This dynamic mechanism causes the value added and scale of the secondary sector to surpass those of the tertiary sector, ultimately leading to a decline in the IS index. These findings confirm that a higher GIE serves as a key defense against premature servitization and industrial hollowing-out.

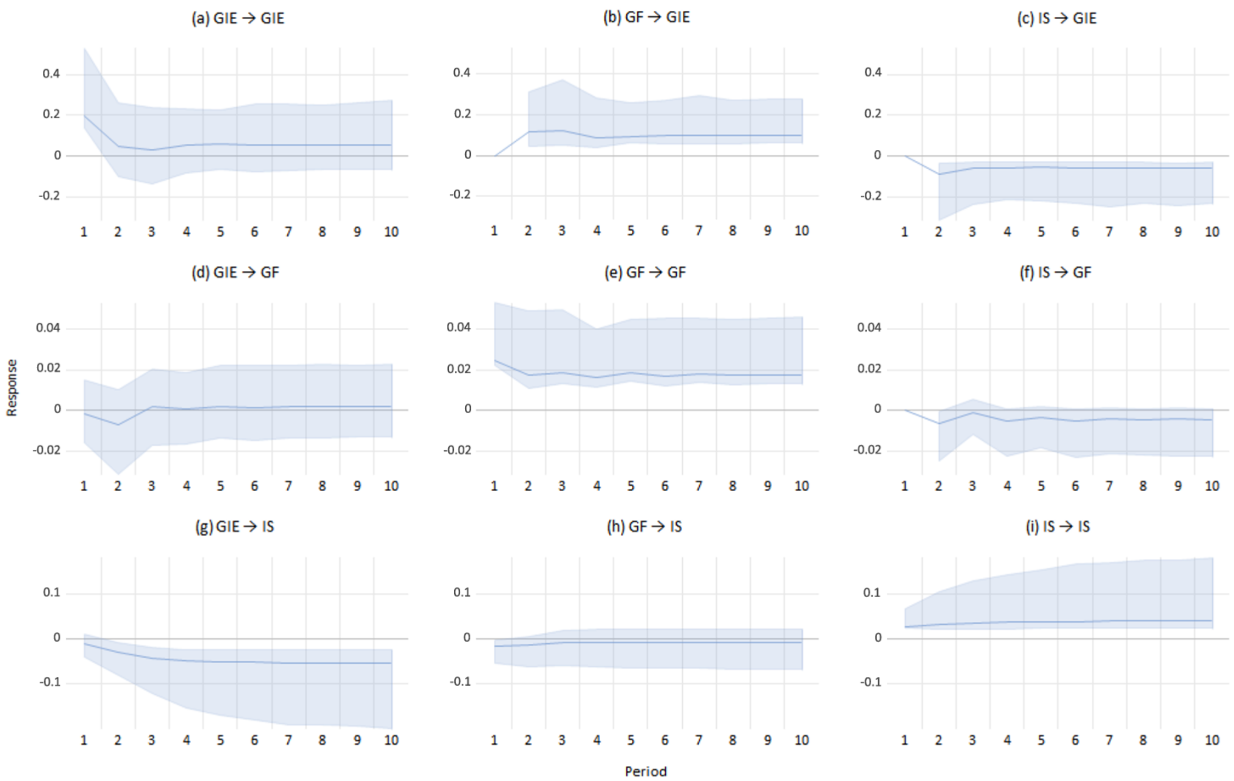

Figure 2. Impulse responses among GIE, GF, and IS.

4.6.4. Dynamic Response of IS to GF Shocks

The response trajectory of IS to the shock of GF fluctuates around the zero axis (see Figure 2h). This indicates that the impact of positive GF shocks on IS is not statistically significant. Considering the response of GIE to GF and that of IS to GIE, this reveals that preventing the "hollowing out" of manufacturing cannot be avoided merely through the direct injection of green funding. Instead, it must be realized indirectly through the mechanism of green technology breakthroughs and efficiency improvements (Xiong et al., 2023).

4.6.5. Exogeneity of Green Finance Policy and System Stability

The response trajectories of GF to GIE and IS shocks consistently remain close to the zero axis and are not statistically significant, confirming the strong exogeneity of green finance policy (see Figures 2d and 2f). Additionally, when faced with a shock of one standard deviation in their own values, all variables exhibit a clear convergence trend, indicating that the VECM system possesses good stability.

Based on the VECM, this study subsequently applies variance decomposition to quantify the relative explanatory power of each variable in this transmission mechanism.

4.7. Variance Decomposition

As shown in Table 8, periods 1, 2, 3, 5, and 10 are selected as representative observation periods to capture the system's trajectory from initial shocks to a long-run steady state.

The result reveals that GF effectively drives improvements in GIE. Analysis of GIE variance decomposition shows that initially, GIE is mainly driven by its own inertia. However, from the second period onward, the explanatory power of GF increases significantly, eventually surpassing that of GIE itself. This suggests that green capital injections effectively alleviate financing constraints on green technology R&D. Nevertheless, GIE's own shocks can still account for about one-third of its fluctuations in the long run. This indicates a strong path dependence; historical inertia and past technological accumulation remain foundational to GIE's development.

The steady increase in the contribution of IS to the variance of GIE reveals that the resource reallocation associated with tertiarization is not a transitory phenomenon but will persist. Policymakers should carefully account for the frictional costs in service-oriented transformation.

Table 8. Variance decomposition results.

Response variance	Period	Shock variable		
		GIE	GF	IS
GIE	1	100.00	0.00	0.00
	2	66.91	21.58	11.50
	3	52.12	34.85	13.03
	5	44.37	40.75	14.89
	10	33.79	48.93	17.28
GF	1	0.34	99.66	0.00
	2	5.03	90.44	4.53
	3	4.03	92.47	3.51
	5	2.94	92.64	4.42
	10	2.02	92.65	5.33
IS	1	13.54	21.47	64.99
	2	33.27	13.50	53.23
	3	46.61	7.79	45.60
	5	55.58	4.61	39.82
	10	60.66	2.90	36.44

GF exhibits strong policy-driven exogeneity. Following an initial shock, the variance of GF is mainly explained by its own shocks, reaching as high as 92%. This confirms that the green capital allocation within Foshan City is dictated by local monetary and financial policies.

The contribution of GIE to the variance of IS continues to grow, eventually reaching 60%. This identifies GIE as a dominant force in shaping industrial upgrading. Breakthroughs in green technology can reshape the industrial value chain; the spillover effects generated by green innovation optimize both upstream and downstream industrial structures. These advancements can compel enterprises across the supply chain to transform towards green and environmentally friendly practices.

5. FURTHER ANALYSIS

5.1. Baseline ARDL analysis

To explore the asymmetric effects of GF, this study estimated an ARDL model as a baseline for the NARDL. A dummy variable, DUM09, was introduced to control for exogenous shocks in 2009 in the model.

As shown in column 1 of Table 9, the coefficient of GF is 5.74, indicating that GF exerts a positive impact on GIE in the ARDL model. This is consistent with Porter's Hypothesis and the results of the VECM. However, in the short run, the effect of GF on GIE is not statistically significant. This does not mean that GF is ineffective; rather, it indicates that an asymmetric relationship between GF and GIE may exist in the short term. Therefore, this study introduces the NARDL model to decompose the GF shock into a positive component and a negative component, thereby capturing the asymmetric effects of green finance in the short and long term.

5.2. Short-Term Asymmetric Effects of Green Finance

The Wald test in Table 9 (column 4) reveals the asymmetric impact of GF on GIE in the short-term. As we can see, the positive shock of GF hurts GIE, with a coefficient of -3.81. Given the high investment and long cycle of green innovation, the influx of green funds is temporarily used to meet green regulatory requirements or eliminate polluted capacity, thereby crowding out R&D funds and leading to the decline of GIE.

Table 9. ARDL and NARDL estimates.

	ARDL Coefficient	Std. error	t-Statistics	NARDL Coefficient	Std. error	t-Statistics
Panel A: short-run estimates						
ΔGF_t	-1.338	1.108	-1.207	—		
ΔGF_t^+	—			-3.812**	1.368	4.853
ΔGF_t^-	—			13.323**	4.853	2.745
ΔGF_{t-1}	-1.722	1.156	-1.489	—	—	—
ΔIS_t	-3.073***	0.968	-3.175	-1.668	1.039	-1.605
ΔIS_{t-1}	—			1.272**	0.508	2.503
DUM09	0.652***	0.106	6.176	0.549***	0.095	5.799
Panel B: long-run estimates						
GF	5.744***	1.316	4.364	—		
GF_{t-1}^+	—			4.438***	0.959	4.627
GF_{t-1}^-	—			8.504**	3.309	2.570
IS	-0.543	0.614	-0.886	0.901	0.791	1.139
C	-1.013***	0.288	-3.515	-0.157	0.363	-0.431
Panel C: diagnostic tests						
F test	13.518***			16.838***		
ECT_{t-1}	-0.873***	0.161	-5.434	-0.518***	0.136	-3.815
LM test	1.010			1.482		
RESET	1.400			4.572		
Adj-R2	0.859			0.920		
CUSUM	Stable			Stable		
CUSUM-squares	Stable			Stable		
WALD-GF SR (Short-run Asymmetry)				9.423**		
WALD-GF LR (Long-run Asymmetry)				2.338		

Note: GF^+ and GF^- represent cumulative expansions and contractions in green finance.
, and * indicate statistical significance at, 5%, and 1% levels, respectively. ΔGF_t denotes the first difference operator. ECT represents the error correction term.

Conversely, the coefficient of negative shock of GF is 13.32, suggesting that a contraction of GF will lead to a substantial drop in GIE. This reveals the vulnerability of green R&D to financing constraints. Given the long cycle and irreversibility of green innovation activities, any tightening or interruption of green credit supply will trigger severe liquidity constraints. The sunk costs already invested not only fail to generate innovative outcomes but also cause acute financial distress, forcing R&D projects to stop or be abandoned, leading to a sharp decline in GIE. Comparing the absolute values of the coefficients ($|13.32| > |-3.81|$), it can be seen that GIE is far more sensitive to capital withdrawal than to capital injection.

5.3. Long-Term Effects of Green Finance

Compared to short-term asymmetry, long-term estimates show a convergent trend. Both GF_{t-1}^+ and GF_{t-1}^- exhibit positive coefficients. This study, based on the NARDL model, estimates long-term elasticity by dividing the coefficients of positive and negative lag terms by the absolute value of the ECT coefficient (as shown in Table 10). The results show that a 1% cumulative expansion of GF will lead to an 8.56% intertemporal increase in GIE; conversely, a 1% contraction of GF (negative shock) will result in a 16.40% decrease in GIE. This demonstrates that GF is the core engine driving GIE in manufacturing.

But the Wald test failed to reject the symmetry in the long-term. This further confirms the finding of this paper: although short-term fluctuations in GF policies may cause asymmetric shocks, their long-term trajectory is stable. Positive and negative shocks eventually converge to have a long-term promoting or inhibiting effect on GIE of equal magnitude. Once enterprises adapt to the green finance policies and overcome the technological R&D threshold, green capital can be effectively transformed into technological accumulation and outputs. The dissipation of asymmetry in the long run suggests that developing green finance can overcome short-term policy disturbances and bring lasting benefits to green innovation.

Besides, the dummy variable (DUM09) remains significant in both models, indicating it absorbs the omitted-variable bias caused by exogenous shocks and ensuring the rigor of the model specification.

Table 10. Long-run asymmetric elasticities of green finance on GIE.

Variables	Lagged Coefficient	ECT (ρ)	Long-run Elasticity	P-value
Positive Shock (GF+)	4.438	-0.518	8.560	0.002***
Negative Shock (GF−)	8.504	-0.518	16.400	0.033**

Note: GF^+ and GF^- represent cumulative expansions and contractions in green finance.
, and * indicate statistical significance at the 5%, and 1% levels, respectively.

6. CONCLUSIONS AND POLICY RECOMMENDATIONS

6.1. Main Conclusion

The main aim of this research is to examine the dynamic relationship between GF, IS, and GIE in Foshan City by employing VECM and to quantify the asymmetric effect of GF by using NARDL analysis. The main findings are as follows:

First, GF is more effective than IS in promoting the development of GIE. The ARDL results show that for a 1% increase in green finance, GIE will significantly increase by 5.744% in the long term, while the impact of IS is not statistically significant. Variance decomposition analysis further confirms this conclusion, showing that in the long term (period 10), the GF shock can explain nearly 49% of the changes in GIE, while IS can only explain 17%.

Secondly, the short-term impact of GF is highly asymmetric, characterized by transitional fractions. NARDL analysis shows that the injection of GF will slightly inhibit GIE in the short term as environmental compliance costs crowd out R&D investment. Conversely, the liquidity constraints caused by negative shocks will lead to a sharp decline in GIE.

Finally, long-term Wald tests confirm that the initial transitional frictions will eventually dissipate. In the long run, both positive and negative shocks from GF will have a significant impact on GIE.

6.2. Policy Implications for Manufacturing-Intensive Cities

First, given that the long-term impact of GF on GIE is far stronger than IS, Foshan policymakers should not rely solely on the industrial structure to shift towards the tertiary sector. Utilizing green bonds and green credit to upgrade manufacturing bases is more favorable and can help high-energy-consuming sectors achieve a green transition.

Second, considering the GF's short-term frictions, governments should formulate R&D tax incentives or subsidies for equipment updates to help manufacturing enterprises offset the compliance costs without diverting the R&D funds.

Third, empirical results show that contraction of GF in the short run is destructive. For that, financial regulators should ensure the continuity of green credit. Policy reversals or sudden credit cuts need to be avoided to protect the R&D capital chains.

6.3. Limitations and Future Research Directions

While this study provides reliable insights about the asymmetric effects of GF and the dynamic relationship among GF, IS, and GIE, some limitations remain to be investigated further. First, this study is limited by its time span due to a lack of city-level data on GF in the early days. Although this study covers the critical period of green transformation from 2010 to 2020, and the ARDL method is robust to small samples, the sample size remains limited. Future studies could validate these estimations with an extended time dimension. Second, this study focuses on Foshan City, a manufacturing-intensive city. Although this city is representative, the conclusions may not be generalizable to regions dominated by service industries or resource extraction. Conducting cross-provincial or cross-country analyses would help uncover how spatial heterogeneity affects the asymmetric effects of green finance.

Funding: This research is supported by the 2024 Foshan City Social Science Planning Project, China (Grant number: 2024-GJ132).
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

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