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Foreign direct investment and green innovation: Regional disparities and panel quantile regression analysis from China's coastal and inland areas

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Abstract

This study discusses the role of Foreign Direct Investment (FDI) in China's Green Innovation (GI) in coastal and inland areas, especially regional disparities. Quantile regression is used to study the panel data of 31 provinces (2010-2020) to explore the impact of FDI on GI at different stages of development. Key variables are FDI, financial development, industrialization, service sector growth, trade, and cultural environment. The results indicate that FDI significantly increases GI, especially in regions of inland areas with low innovation. In coastal areas, however, the effect of FDI on GI lessens as the local industries excel in green technologies. Financial development improves GI in the coastal regions; industrialization and service sector growth have mixed results. Policymakers should focus their FDI strategies on areas of lower innovation in order to enact sustainable development. Future research needs to consider the global relevance of the results by looking at countries with different economic backgrounds and examining the long-term effects of FDI, taking into account government policies and environmental regulations. This study contributes to the understanding of the dynamics of FDI and GI in China, which can provide information applicable to the development of sustainable growth policies.

Keywords: China, Coastal area, Foreign direct investment, Green innovation, Inland area, Quantile regression.
JEL Classification: F21; O31; R11; C21; O14; F14.

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Contents

Contribution of this paper to the literature
This paper analyzes the differential effect of Foreign Direct Investment (FDI) on Green Innovation (GI) in China's coastal and inland areas using the quantile regression method. It offers valuable insights on how to optimize FDI to promote sustainable innovation at different stages of development.

1. Introduction

The global environment has deteriorated and faced pollution over the past three decades, posing substantial threats to human development and existence. Sustainable development requires effective solutions to environmental challenges amid rapid global economic growth. Pollution reduction and initiatives to decrease greenhouse gas emissions directly enhance human health outcomes (Xue, Zhu, Zheng, & Zhang, 2019). The environmental crisis has driven 197 nations to pledge to cut global industrial gas emissions while keeping temperature increases under 2 degrees Celsius this century. China continues rapid economic growth, with its GDP rising from $0.43 trillion in 1992 to $17.82 trillion in 2022. This growth has caused significant environmental damage, leading to polluted air, climate change, and health risks (Lin et al., 2023).

China's projected carbon emissions for 2020 are nearly 11 billion tons, with a growth rate of 5.5% since the 2.4 billion tons recorded in 1992. Balancing economic development and environmental protection requires understanding. New technologies and innovative processes reduce pollution. Implementing these policies will create economic value and promote sustainable development that balances environmental protection and economic progress (Wang, Yu, Yan, Yao, & Liu, 2017). GI needs promotion to enable China to achieve coordinated economic growth with environmental protection and advance its development standards. Scholars have developed the GIE index to measure GI progress (Miao, Duan, Zuo, & Wu, 2021; Zhao, Lu, Kou, & Du, 2023). The input-output ratio of innovation resources and environmental impacts is used to measure the extent to which they are in the advanced stages of GI.

Since implementing economic reforms and opening-up policies, the Chinese economy has steadily grown in foreign direct investment (FDI). Ministry of Commerce of the People's Republic of China (2022) shows FDI utilization rose from $111.716 billion in 2012 to $173.48 billion in 2021, a more than 55 percent increase. For over three decades, China has been the world's second-largest FDI destination and the first developing country to attract FDI. China's economic development largely depends on FDI, its primary driving force. This research focuses on FDI technology spillovers, which are key to China's innovation progress (Yi, Hou, & Zhang, 2023).

Studies show that FDI yields stronger positive results for Green Innovation (GI) in coastal areas than in inland areas. Coastal areas implement green FDI technology more successfully due to better infrastructure, stronger marketization, and well-developed policy frameworks (Chen, Guo, & Huang, 2023; Wu, Lu, Liao, Liu, & Zhu, 2021. Poor infrastructure and weak innovation in inland areas hinder FDI's positive impact on GI (Chen et al., 2023).

This study investigates FDI's impact on GI in China's coastal and inland areas, using quantile regression to capture varying effects at different innovation stages. Research shows FDI significantly influences innovation, but further analysis is needed to understand its varying effects on green innovation across different areas. It addresses the knowledge gap by examining FDI and GI relationships in developing areas at various economic levels. The study employs quantile regression techniques to analyze nonlinear data patterns, showing FDI's role in promoting GI at various stages. The research also explores the impact of financial development, industrialization, and service development on GI. This research enriches academic knowledge by exploring FDI optimization strategies for sustainable development, particularly in areas with weak innovation capabilities, and recommends policy frameworks to support FDI-based GI.

The research is organized as follows: This study further includes Section 2: a review of previous literature, Section 3: the sources of data collection and research methodology used, Section 4: a discussion of the results, and Section 5: the conclusion of the research.

2. Review of Literature

FDI allows local firms to observe and imitate foreign technologies and practices, leading to increased GI through this adoption process (Demena & van Bergeijk, 2019; Luo, Salman, & Lu, 2021; Qin et al., 2022). Local companies must innovate to stay competitive as foreign firms enter the market, driving them to increase GI activities (Demena & van Bergeijk, 2019). It is a collaboration between foreign and local companies via Foreign Direct Investment (FDI), which facilitates the exchange of knowledge and technology between foreign and local companies. This effect enables local businesses to enhance their GI capabilities (Melane-Lavado & Alvarez-Herranz, 2020). A fundamental way by which technology is diffused is through the transfer of personnel between multinational and local companies. The transfer of personnel between international companies and local businesses is a means by which local businesses can obtain specialized knowledge, thereby improving their capabilities for innovation and green technology (Demena & van Bergeijk, 2019; Melane-Lavado & Alvarez-Herranz, 2020). The effectiveness of FDI's influence on GI depends on three crucial regional elements: absorptive capacity, environmental regulations, and the economic environment. Areas with strong absorptive capacity and active policy systems benefit the most through the use of FDI to promote GI (Luo et al., 2021; Qin et al., 2022; Qin, Gao, Ge, & Zhu, 2023).

FDI produces different effects on GI throughout China's various areas. The relationship between FDI and GI remains positive in eastern and western China but shows weaker or negative results in central China (Chen et al., 2023). The stronger impact of FDI on GI is observed in both coastal and inland areas, as these areas have more developed markets and infrastructure (Lei, Xie, & Chen, 2023). Environmental regulations at various levels play a crucial role in controlling the relationship between FDI and GI. FDI's positive impact on GI becomes stronger when environmental regulations become stricter because such regulations promote cleaner technological approaches and operational practices (Dai, Mu, Lee, & Liu, 2021; Luo et al., 2021). Marketization, together with supportive policy environments, creates additional positive effects of FDI on GI. Marketization at high levels and supportive environments help companies achieve maximum foreign capital utilization for their GI activities (Chen et al., 2023; Zhong, Zhou, & Jing, 2024). The regional development strategy determines the extent to which FDI influences GI.

The economic benefits from FDI investments in GI reach their highest potential in areas with moderate catch-up strategies; however, areas with well-developed market systems receive minimal benefits (Shao, Huang, & Wen, 2024).

Environmental rules of different strengths modify the relationship between FDI and GI. The impact of FDI on GI can be positively or negatively affected by stricter regulations, depending on specific circumstances (Chen, Hu, He, & Zhang, 2024; Qiu, Wang, & Geng, 2021; Xu et al., 2021). The development of innovative cities depends on economic growth because FDI generates greater benefits for these cities (Qin et al., 2022).

FDI's ability to enhance GI depends on an area's absorptive capacity, including human capital and the technology gap. Regions with better infrastructure and absorptive capacity maximize FDI for improved GI outcomes (Qin et al., 2022; Qin et al., 2023).

High-tech sectors situated in coastal areas receive significant value from FDI because they can adopt contemporary foreign technologies and innovations, which lead to improved GI efficiency (Wu et al., 2021; Zhong et al., 2024). The traditional resource extraction and processing methods employed by inland resource-based industries limit their ability to leverage FDI for GI, as these methods lack advanced technological capabilities (Li & Bi, 2020).

Areas that already possess established innovation systems require less outside FDI to advance their technology, as they have the internal capabilities to develop innovation. These areas have their own innovative assets, which enable them to develop new technologies without substantial FDI participation (Sun, 2024). FDI spillover benefits are lower in advanced industrial specialization. Specialized industries gain little from FDI due to their focus on specific domains. FDI spillover effectiveness relies on urbanization levels and stages of economic development. In developed economies with high urbanization, additional FDI returns diminish as these areas have efficient innovation systems (Liu, Meng, & Yu, 2022).

FDI's regional distribution in China significantly impacts GI and sustainable development. Policymakers can use this knowledge to target FDI attraction in underdeveloped areas, enhancing these initiatives. A positive relationship between FDI and GI emerges as policy environments and marketization improve, suggesting that upgrades in inland areas could boost FDI attraction (Chen et al., 2023). FDI stimulates both local green total-factor productivity (GTFP) and enhances neighboring areas, demonstrating opportunities for regional policy coordination (Wang, He, & Zhang, 2021). Implementing policies that facilitate the movement of innovation factors, including technology and skilled workers, can enhance green economic performance in underdeveloped areas (Zhuo & Deng, 2020). The FDI's progressive effect on GI depends on the regional absorptive capacity, which can be increased through investments in human capital and industry expansion (Qin et al., 2022).

Government policy should enhance development conditions through coordinated financial systems and attract innovative businesses to inland China. Measures like attracting FDI and elevating GI promote sustainable growth across all areas.

The study highlights regional differences in the FDI-GI relationship. It shows that FDI significantly boosts economic growth in eastern and western China, while its effects are limited in the central regions. Specific policies for each area are necessary to maximize FDI's benefits on GI growth. Additionally, the policy environment and marketization are key factors enhancing FDI's impact on GI; thus, regional policymakers should consider these elements (Chen et al., 2023).

The study shows that FDI has a greater positive impact on sustainability in coastal areas compared to inland areas. Coastal areas benefit from advanced technology and a stronger industrial structure, which enhances FDI effectiveness. In contrast, lower FDI activity in inland areas results in reduced sustainable development outcomes (Ouyang & Fu, 2012; Zhong et al., 2024). The research suggests that FDI in coastal cities can stimulate growth in inland cities. However, the extent to which an inland city can benefit from this investment depends on its level of industrial development (Ouyang & Fu, 2012).

China's GI level is below average, but it aims to improve market clarity and infrastructure. The programs guide firms in various locations to achieve GI status and attract FDI to areas with basic GI levels (Yahaya & Augustine, 2023). Green technology spillover effects from FDI decrease in countries with high GI levels. Local companies show exceptional innovation capabilities, reflected in high GI rates. However, these industries fail to illustrate the benefits of FDI operations. This research leads to the hypothesis that FDI significantly impacts countries, particularly those with lower GI levels.

A study analyzed the effects of FDI on different GI levels across provinces (Chen et al., 2023). The research discussed a comprehensive understanding of this specific relationship, enabling researchers to examine GI's spatial sector effects. They adopted a regionally dependent analytical framework in their methodology. The study includes an analysis of the division between inland and coastal areas that affect the 31 provinces of China.

The coastal and inland results provide insightful analyses linking FDI and GI, supporting the proposed hypotheses. In the coastal area, results confirm hypothesis 1, indicating FDI positively influences GI nationwide, even in areas with lower GI levels. A consistent positive correlation across quantiles suggests FDI promotes GI by closing the innovation gap with access to green technologies, enhancing local skills, and improving infrastructure. This effect is especially pertinent in less established GI sectors, confirming that foreign investment can stimulate innovation.

The core business operations of coastal companies are centered in high-tech sectors, characterized by exceptional capabilities for innovative development and creative solutions. Environmental regulations encourage clean businesses to adopt green technologies developed by other clean businesses, thereby fostering their own innovative capabilities (Mushafiq, 2023; Tchouto, 2023). Initiatives seeking GI benefit from superior market systems and infrastructure in coastal areas, building solid foundations for their efforts. Coastal areas with FDI distribute advanced green technology, supporting neighboring businesses. Attention is needed on GI performance diversity among different provinces (Raihan, 2023). Several coastal cities have green technology systems that meet international standards. They already possess green manufacturing technology comparable to what FDI would offer, making new investments unnecessary. Areas with minimal GI discover better services, more financial resources, and improved environmental regulations. These regions find it easier to absorb technological spillovers from FDI due to these factors, enhancing their GI capabilities.

Inland areas, unlike coastal ones, focus on supply-based businesses primarily in conventional heavy industries. These typically involve basic manufacturing and raw material processing, showing limited innovation and creativity (Motla, Kumar, Saxena, & Sana, 2023). Concerns about financial growth may lead inland communities to relax environmental regulations to support these sectors. The adoption of green technology spillovers from FDI is hindered by poor infrastructure, flawed market processes, and weak intellectual property protection, making imitation and innovation difficult.

Hypothesis 2 suggests that FDI's impact on GI varies by geography. Coastal areas with lower innovation levels show a notable positive influence, while inland areas with higher GI levels exhibit a similar effect.

FDI is crucial in coastal areas, particularly those with lower GDP, as the infrastructure, market systems, and capital flow absorb green technologies and enhance GI capacity. However, in established coastal cities with high GI levels, FDI's influence diminishes as local enterprises excel in green technology, aligning with the theory that FDI's effect reduces in highly developed GI areas. The inland area shows a consistently strong connection between FDI and GI, emphasizing the need for foreign investments to drive innovation in sectors lacking resources. Though FDI is vital in both areas, its effectiveness hinges on the local GI level, confirming that FDI and GI relationships are regional.

These findings underscore FDI's role in enhancing GI, especially in low-innovation areas like the coastal regions. The varying impacts across areas highlight the complex FDI-GI relationship, demonstrating the value of quantile regression in capturing these dynamics across different development levels.

Inland areas with high GI can access FDI's technical spillover benefits, while local businesses in low-GI areas often lack the material standards and innovative skills to replicate and absorb this expertise, hindering their GI development. Our research yields the following hypothesis based on these findings.

FDI's influence on GI varies across areas. It has a strong positive effect in low-innovation coastal areas and advanced GI inland areas. This study addresses the gap in understanding FDI's regional impact, factoring in innovation levels, environmental guidelines, and market differences. Using quantile regression, it assesses FDI's effect on GI through different innovation stages, offering insights into FDI strategies for green regional growth. The findings will deepen the understanding of FDI in GI methods and suggest policy guidelines for low-innovation areas, especially inland, optimizing FDI for sustainability. This research will enhance the economic viability of coastal regions and guide balanced policy and investment in GI development.

3. Data and Methodology

3.1. Baseline Panel Model

The equation represents a baseline model for analyzing the impact of various factors on Green Innovation (GI) in different provinces over time.

$$\log(GI_{it}) = \beta_0 + \beta_1 \log(FDI_{it}) + \beta_2 \log(FD_{it}) + \beta_3 \log(ID_{it}) + \beta_4 \log(SV_{it}) + \beta_5 \log(TD_{it}) + \beta_6 \log(CT_{it}) + u_i + \varepsilon_{it} \quad (1)$$

Where:

$\log(GI_{it})$: Green Innovation in the province i at time t.

$\log(FDI_{it})$: Foreign Direct Investment in the province i at time t.

$\log(FD_{it})$: Financial development in the province i at time t.

$\log(ID_{it})$: Industrialization in the province i at time t.

$\log(SV_{it})$: Service sector development in the province i at time t.

$\log(TD_{it})$: Trade openness in the province i at time t.

$\log(CT_{it})$: Cultural environment in the province i at time t.

u_i : Province-specific fixed effects.

ε_{it} : Idiosyncratic error term.

3.2. Extended Model with Regional Interaction Terms

To assess how FDI's impact on GI varies by region (coastal vs. inland), an interaction term is added.

$$\log(GI_{it}) = \beta_0 + \beta_1 \log(FDI_{it}) + \beta_2 (\log(FDI_{it}) \times Area_i) + \beta_3 \log(FD_{it}) + \beta_4 \log(ID_{it}) + \beta_5 \log(SV_{it}) + \beta_6 \log(TD_{it}) + \beta_7 \log(CT_{it}) + u_i + \varepsilon_{it} \quad (2)$$

Where:

Area $_i$ is a binary variable indicating whether the province is coastal $(=1)$ or inland $(=0)$.

The interaction term $\log(FDI_{it}) \times$ Area $_i$ captures how FDI's impact on GI differs by region.

3.3. Panel Quantile Regression Model

To account for non-normal distribution and heterogeneous effects of predictors, a panel quantile regression approach is used, estimating the model at various quantiles (e.g., 25th, 50th, 75th percentiles).

$$Q_\tau(\log(GI_{it}) \mid X_{it}) = \beta_0(\tau) + \textstyle\sum_{k=1}^{6} \beta_k(\tau) \log(X_{kit}) + \gamma(\tau)(\log(FDI_{it}) \times \text{ Area }_i) + u_i + \varepsilon_{it}(\tau) \quad (3)$$

Where:

- $Q_\tau(\cdot)$: Conditional quantile of $\log(GI_{it})$ at quantile τ.
- $\beta_k(\tau)$: Quantile-specific coefficients for predictors.
- $\gamma(\tau)$: Quantile-specific coefficient for the regional interaction term.
- $\varepsilon_{it}(\tau)$: Idiosyncratic error term at quantile τ.

3.4. Variable Selection

3.4.1. Explained Variable Green Innovation (GI)

China, despite the abstract nature of green innovation and the lack of a consistent assessment index system, patent numbers may be a valid indication of quantifying innovation. Therefore, one may assess the green innovation capacity of a certain area using the quantification of green patents (Tolliver, Fujii, Keeley, & Managi, 2021).

In this study, the degree of green innovation is evaluated using the count of inventive patent applications as an appropriate surrogate. Applications for invention patents undergo a thorough review process that requires significant improvements and advances over current technology (El Hafdaoui, Jelti, Khallaayoun, Jamil, & Ouazzani, 2024; Shahid, Shahid, Shijie, & Jian, 2024).

The time it takes to approve an innovation patent, which is normally three years, is determined by elements including the social environment, review procedures, and testing. Consequently, evaluating inventive patent applications offers a more appropriate measure of the yearly innovation performance of an area than the count of approved patents. This research uses the natural logarithm of the number of green invention applications and patents in each province to represent regional green innovation. This variable is also used as the dependent variable in the analysis.

3.4.2. Core Explanatory Variables: Foreign Direct Investment (FDI)

The primary explanatory variable is foreign direct investment (FDI). This article measures the average yearly FDI in each province in proportion to GDP, according to the practice of traditional literature (Song & Han, 2022).

3.4.3. Control Variables

Financial development (Finance). Green finance substantially and favorably impacts GI in all regions of China, as explained by Yang, Su, and Yao (2022). As a result, it is essential to consider the financial development variable when examining the effects of FDI on GI. For this inquiry, economic development is defined as the percentage of financial commerce in the GDP.

Industry. Current research proposes that secondary industrial intelligence aids in the creation of a "technology promotion effect" and a "cost reduction effect." As a result, this helps to accelerate the development of green technology (Yang et al., 2022). Values are weighted to characterize industries and account for their influence.

Service industry (Service). The tertiary sector has a considerable effect on the success of environmentally friendly innovation in the region. As a result, one of the control variables is the service sector, which is quantified using the tertiary industry-to-GDP ratio (Zhao, Zhou, Jiang, & Yan, 2022).

Trade. Coordinated trade with economic, environmental, and energy policies to increase investment in GI. This study defines trade as a control variable using the trade-to-GDP ratio (Meng, Wu, Wang, & Duan, 2022).

Cultural environment (culture). Existing research has demonstrated that green culture influences organizational green performance and provides a modest advantage via the intermediate function of GI (Wang, 2019). As a result, while evaluating GI, the cultural context must be included as a control variable. This article uses the quantification of public libraries as a metric for measurement. Table 1 displays the definitions for all variables.

3.5. Data Source and Processing

This study employs panel data from 31 provincial-level administrative regions in China, covering the period from 2010 to 2020, excluding Hong Kong, Macao, and Taiwan due to incomplete data. Following the global financial crisis in 2008, China's foreign direct investment experienced notable fluctuations and has since shown a consistent growth pattern. As the foremost recipient of foreign direct investment among developing countries, China offers a significant context for analysis. The period of 2010-2020 allows for a complete examination of the influence of China's FDI on GI. Since 2010, China has gradually tightened controls on foreign investment, imposing limits on extremely polluting industries aiming to join the market and preferring foreign corporations with environmentally compassionate technologies. This strategic approach helps China develop green technology and encourages the spread of such technologies through these firms. The data for green invention patents is acquired from the CNRDS Platform, whilst data for other variables is derived from the official website of the NBS.

Table 1. Abbreviation of main variables.

Variable	Label	Definition	Sources
Green innovation	GI	Logarithm of applications for patents on inventions	CNRDS
Foreign direct investment	FDI	The ratio of FDI compared to GDP	NBS
Financial development	FD	The financial industry's proportion of GDP	NBS
Industrialization	ID	The secondary sector's proportion of GDP	NBS
Service development	SV	The third industry's share	NBS
Trade	TD	The trade-to-GDP ratio	NBS
Culture environment	CT	The number of public libraries	NBS

Note: (1) CNRDS denotes Chinese Research Data Services. NBS denotes the National Bureau of Statistics of China. (2) Table 1 comprises all the variables used in the model, the variable labels, the variable definitions, and the data sources.

4. Results and Discussion

Table 2 summarizes regression statistics for a comprehensive understanding of variable associations, particularly with skewness or non-normal distributions, seen in logFDI and logCT's variability in Coastal and Inland areas. LogFDI has a wide range (16.33 Coastal; 0.05 Inland) and a significant positive skew (2.81 Coastal; 0.41 Inland), suggesting traditional regression may not fully capture its relationship. LogCT has a high standard deviation (48.01 Coastal; 45.39 Inland) and a large range (156 Coastal; 203 Inland), with negative skewness and kurtosis indicating heavy tails. Unlike OLS regression, which estimates the mean, quantile regression examines predictor influence across different distribution parts, offering insights at various quantiles (25th, 50th, 75th). This approach is particularly useful for heterogeneous data, where predictor effects may vary and capture nuances missed by OLS, especially with significant outliers.

Table 2. Summary statistics for variables.

Variable	n	Mean	SD	Min.	Max.	Range	Skew	Kurtosis	SE
Coastal area									
logGI	121	3.5300	0.5300	2.0500	4.4100	2.3600	-0.6100	0.3200	0.0500
logFDI	121	1.4900	4.6400	0.0000	16.3300	16.3300	2.8100	5.9500	0.4200
logFD	121	3.3100	0.4200	2.1500	4.0600	1.9100	-0.3700	-0.2400	0.0400
logID	121	4.0000	0.4400	2.8700	4.7400	1.8700	-0.7100	0.5000	0.0400
logSV	121	4.1400	0.3800	3.1300	4.8500	1.7200	-0.2800	-0.2500	0.0300
logTD	121	7.8800	0.6100	6.3300	8.9000	2.5800	-0.1600	-0.5000	0.0600
logCT	121	97.5200	48.0100	20.0000	176.0000	156.0000	-0.4800	-1.0000	4.3600
Inland area									
logGI	220	3.0600	0.6800	0.0000	4.3800	4.3800	-1.0000	2.2900	0.0500
logFDI	220	0.0200	0.0100	0.0000	0.0500	0.0500	0.4100	-0.7800	0.0000
LogFD	220	3.0000	0.4400	1.4900	3.9100	2.4100	-0.6700	0.6400	0.0300
logID	220	3.7700	0.4600	2.3500	4.5400	2.1800	-0.8000	0.3200	0.0300
logSV	220	3.8700	0.4400	2.6100	4.6700	2.0600	-0.6700	-0.0400	0.0300
logTD	220	7.1500	0.7100	5.2500	8.4600	3.2100	-0.5300	-0.2800	0.0500
logCT	220	101.6900	45.3900	4.0000	207.0000	203.0000	-0.0700	-0.4400	3.0600

Note: This table presents the summary statistics for each variable in the dataset, including the mean, standard deviation (SD), minimum, maximum, range, skewness, kurtosis, and standard error (SE) for 220 observations.

Table 3 and Figure 1 show correlation matrices for Coastal and Inland areas, highlighting varying linear relationships between variables. In the Coastal area, logFD and logSV (0.97) and logFD and logTD (0.93) have strong positive correlations; logGI and logFDI (0.22) and logFDI and logCT (0.11) show weak correlations. In the Inland area, logFD and logSV (0.98) and logFD and logTD (0.86) have strong correlations, while logGI and logCT (0.22) demonstrate a weak correlation. The heatmaps illustrate these links; deeper blues indicate stronger correlations and lighter blues indicate weaker ones. For variables with skewed or non-normal distributions, like logFDI, patterns suggest that some variables are significantly associated while others show negligible connections, emphasizing the need for quantile regression to explore how predictors affect different distribution parts.

Table 3. Correlation matrix for variables in coastal and inland areas.

Variable	logFDI	logFD	logID	logSV	logTD	logCT
Coastal area						
logGI	0.22	0.88	0.81	0.88	0.86	0.32
logFDI	1	-0.08	0.08	0	-0.14	0.11
logFD	-0.08	1	0.78	0.97	0.93	0.28
logID	0.08	0.78	1	0.85	0.82	0.56
logSV	0	0.97	0.85	1	0.92	0.44
logTD	-0.14	0.93	0.82	0.92	1	0.26
logCT	0.11	0.28	0.56	0.44	0.26	1
Inland area						
Variable	**logFDI**	**logFD**	**logID**	**logSV**	**logTD**	**logCT**
logFDI	1	0.65	0.62	0.67	0.7	0.22
logFD	0.65	1	0.79	0.98	0.86	0.38
logID	0.62	0.79	1	0.85	0.82	0.57
logSV	0.67	0.98	0.85	1	0.88	0.50
logTD	0.70	0.86	0.82	0.88	1	0.38
logCT	0.22	0.38	0.57	0.5	0.38	1

Note: This table shows a correlation matrix for coastal and inland variables, indicating the strength and direction of their linear relationships. Values near 1 or -1 suggest strong positive or negative connections, while those near 0 indicate little association. This method clarifies how key factors interact in each area.

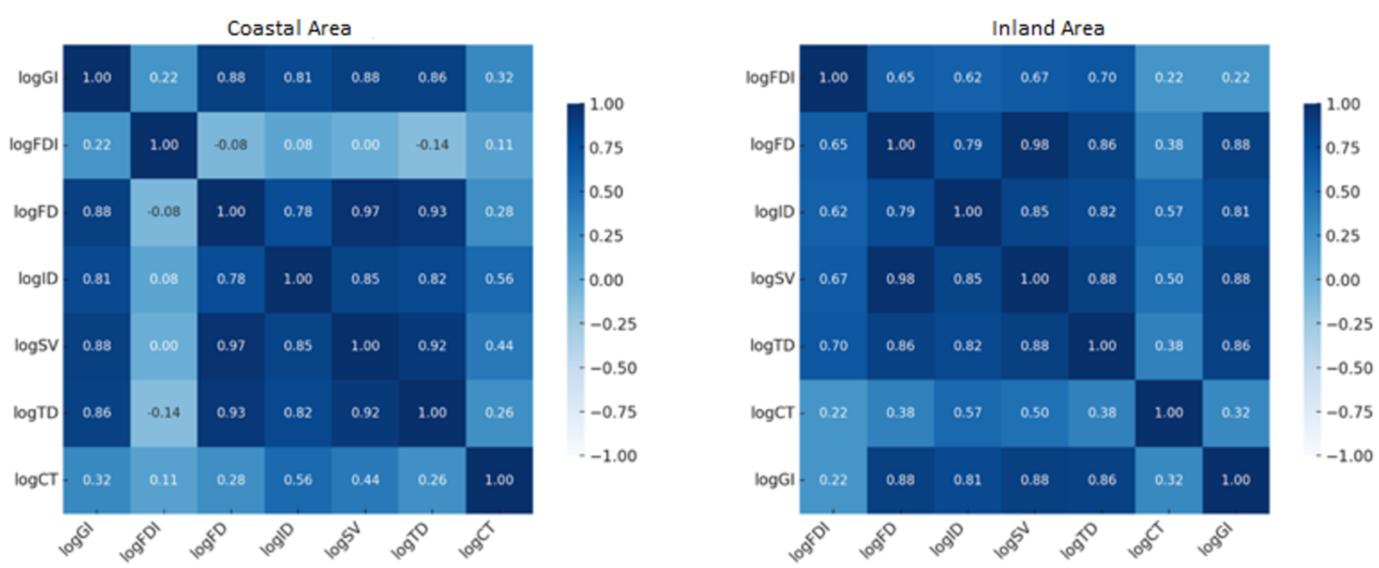

Figure 1. Correlation matrix plot.

Table 4 shows the connection between Green Innovation and predictor factors across quantiles in the Coastal Area. FDI consistently positively associates with GI, indicating foreign investment provides crucial resources, skills, and technology to promote innovation. Because FDI supports technical breakthroughs through capital inflows, its steady effect across quantiles suggests its influence on GI is stable, irrespective of the country's development level. Financial Development (FD) has a significant positive influence at the 25th percentile, but it diminishes and becomes negative at higher quantiles, likely because financial development at lower quantiles enhances capital access, fostering green technology innovation. In contrast, at higher quantiles, a mature financial sector may prioritize traditional sectors over green innovation. Industrialization (ID) shows a moderate positive effect, increasing slightly at higher quantiles due to the challenges and opportunities for innovation presented by advanced industrialization, which provides more infrastructure for GI. Service Development (SV) has a negative relationship at lower quantiles but turns positive at the 75th percentile, as services may not focus on technology and innovation at lower levels. At higher levels, advanced services like R&D and IT support green innovation. Trade (TD) exhibits a progressively stronger positive effect with increasing quantiles, suggesting that greater access to international markets facilitates the diffusion of green technologies, promoting innovation. The Cultural Environment (CT) minimally affects lower quantiles but turns negative at the 75th percentile, indicating that in developed areas, public libraries have little impact on fostering GI, as factors like government policies and industrial capabilities are more significant.

In the Inland Area, FDI shows a large, consistent positive relationship with GI across all quantiles, as foreign investment is vital for providing capital, technology, and expertise in resource-limited areas. FD's positive effect slightly decreases at higher quantiles, as the financial sector matures and becomes less focused on supporting green technologies. Industrialization (ID) shows weak links to GI, implying that industrialization in the Inland area may be less sophisticated than in the Coastal area, limiting notable GI stimulation. Similarly, service development (SV) undergoes positive to negative shifts across quantiles, as the technologically focused service sector begins supporting GI through research and green tech adoption. Trade (TD) shows a negative relationship at the 25th percentile but turns positive at the 75th percentile, reflecting limited access to international markets at lower levels and increased flows of goods and ideas fostering green innovation at higher levels. The weak negative effects of the Cultural Environment (CT) on GI suggest cultural institutions like public libraries marginally influence GI in the Inland area, while industrial and financial factors probably play larger roles.

The research highlights various factors impacting GI across geographical areas. The coastal area has established financial sectors and greater foreign investment access, making predictors like FDI and FD more influential. FDI is the primary stable factor in the inland area, as most GI derives from it. Examining GI through quantile regression reveals how these variables impact GI across distribution points, as Industrialization (ID), Service Development (SV), Trade (TD), and Cultural Environment (CT) show varied effects across both areas. Quantile regression provides deeper insights into the complex, non-linear relationships between development factors and GI along different distribution points.

Table 4. Quantile regression for coastal and inland areas.

Variable	QR 25 Coeff	QR 25 SE	QR 25 lower bound	QR 25 upper bound	QR 50 Coeff	QR 50 SE	QR 50 lower bound	QR 50 upper bound	QR 75 Coeff	QR 75 SE	QR 75 lower bound	QR 75 upper bound
Coastal area (Intercept)	0.1124*	0.3201	-0.513	0.9691	-0.5816	0.4983	-1.9692	0.2828	-2.5927**	0.5867	-2.8996	-1.2665
logFDI	0.0426***	0.0045	0.0331	0.0456	0.0402***	0.0039	0.0327	0.0448	0.0339***	0.0042	0.027	0.0435
logFD	1.6281***	0.1859	1.2563	2.0697	1.2387*	0.4092	0.4236	1.7442	-0.1379	0.402	-0.6719	0.7755
logID	0.1355**	0.0613	0.0415	0.4563	0.1762**	0.0609	0.0642	0.5003	0.2356***	0.0584	0.1583	0.3486
logSV	-1.1096***	0.2174	-1.6189	-0.5458	-0.9355*	0.2175	-1.5085	-0.081	0.3187	0.3382	-0.5318	0.7602
logTD	0.2277**	0.0721	-0.0039	0.2921	0.3792***	0.0496	0.2803	0.4924	0.5699***	0.0549	0.3022	0.7695
logCT	0.0013*	0.0004	0.0001	0.0018	0.0013*	0.0004	0.0002	0.0018	-0.0009	0.0005	-0.0026	0.001
Variable	**QR 25 Coeff**	**QR 25 SE**	**QR 25 lower bound**	**QR 25 upper bound**	**QR 50 Coeff**	**QR 50 SE**	**QR 50 lower bound**	**QR 50 upper bound**	**QR 75 Coeff**	**QR 75 SE**	**QR 75 lower bound**	**QR 75 upper bound**
Inland area (Intercept)	-0.8338**	0.3124	-1.3586	-0.6251	-1.0300***	0.3692	-1.3793	-0.6474	-1.0731***	0.4019	-1.6016	-0.4828
logFDI	6.4503***	1.5504	2.9443	8.1737	6.3322***	1.6297	3.9679	10.5397	7.2006***	1.6889	2.7415	11.9961
logFD	1.6174***	0.1004	1.366	1.8244	1.2412***	0.1889	0.7803	1.6756	0.9911***	0.1549	0.7748	1.4727
logID	0.2159**	0.0733	0.0686	0.4314	0.1399**	0.0701	0.0197	0.4162	0.13	0.0814	0.067	0.2607
logSV	-0.0999	0.2211	-0.5392	0.3141	0.1271	0.2087	-0.2992	0.689	0.3265	0.2101	-0.1651	0.5719
logTD	-0.2110**	0.0359	-0.281	-0.095	-0.0838**	0.0454	-0.1692	-0.0087	-0.0593	0.0615	-0.1521	0.0548
logCT	-0.0008	0.0006	-0.002	0	-0.0014**	0.0005	-0.0022	-0.0008	-0.0016**	0.0004	-0.0021	-0.0006

Note: Statistical significance is indicated by asterisks: p ⩽ 0.10 (*), p ⩽ 0.05 (**), and p ⩽ 0.01 (***), and this table displays the coefficients and associated confidence intervals at the 25th, 50th, and 75th percentiles for each variable, emphasizing the influence of predictors across multiple distribution points.

Figure 2 presents quantile regression coefficients for logGI across predictor variables in coastal and inland areas. Coastal coefficients differ across quantiles, with higher quantiles showing greater coefficients for FDI, indicating its essential role in promoting GI in more developed locations. LogFD also shows a significant influence at higher quantiles, reinforcing its importance for GI. In contrast, logSV, logID, and logCT exhibit smaller impacts, suggesting a lesser role in the coastal area, particularly at higher quantiles. This supports the idea that FDI and FD primarily drive GI in this area.

In the inland area, FDI displays a significant positive influence, particularly in regions with lower GI levels, indicating that FDI significantly impacts GI across quantiles. While logFD, logID, and logSV have weaker but still positive effects at lower quantiles, they contribute less than FDI. Visual data indicate that FDI significantly impacts GI in areas with lower innovation, with the inland area showing the strongest effect.

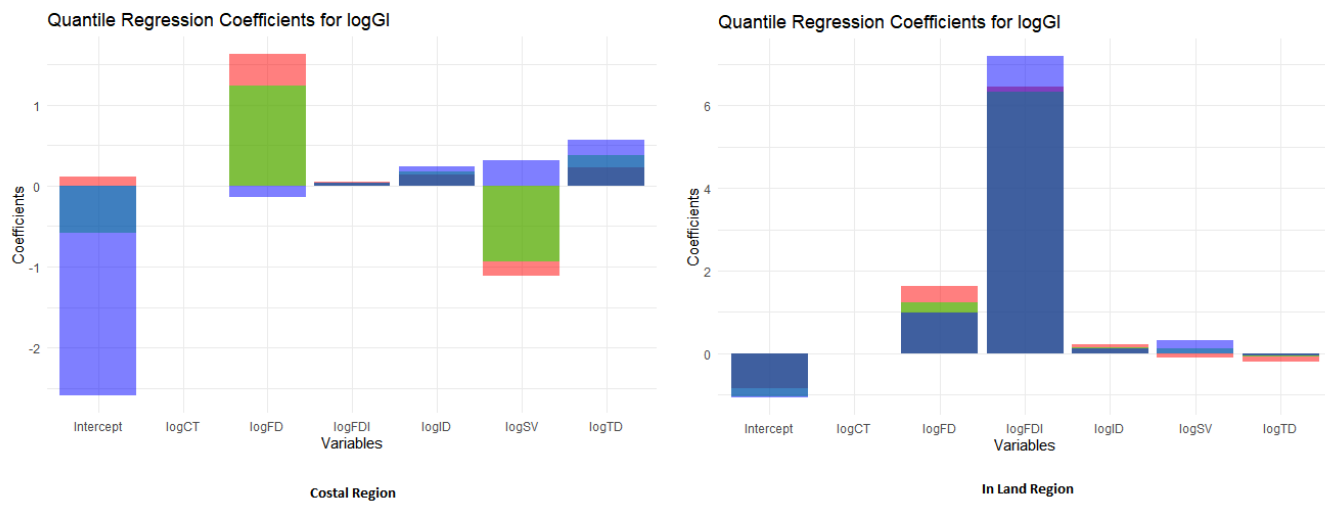

Figure 2. QR coefficient for the coastal and inland area.

4.1. Robustness Tests of Coastal and Inland Areas

Figure 3 shows a Normal Q-Q Plot comparing sample quantiles to theoretical quantiles of a normal distribution in the coastal area. The points closely follow the diagonal line, indicating the model's residuals approximate a normal distribution. This suggests that normality, while not a strict assumption for quantile regression, indicates the residuals are close to normal, and the model is likely well-specified regarding error distribution.

Figure 3: Inland area shows a Q-Q plot of residuals from quantile regression. The points in this plot also closely follow the red reference line, indicating that the residuals of the quantile regression model are approximately normally distributed. Although quantile regression does not require normally distributed residuals, this plot further supports the idea that the residuals are well-behaved in distribution, with no significant deviations or heavy tails.

Both plots indicate that the quantile regression model's residuals for this data are roughly normally distributed, supporting the assumption of well-behaved residuals for further analysis, despite normality not being strictly required.

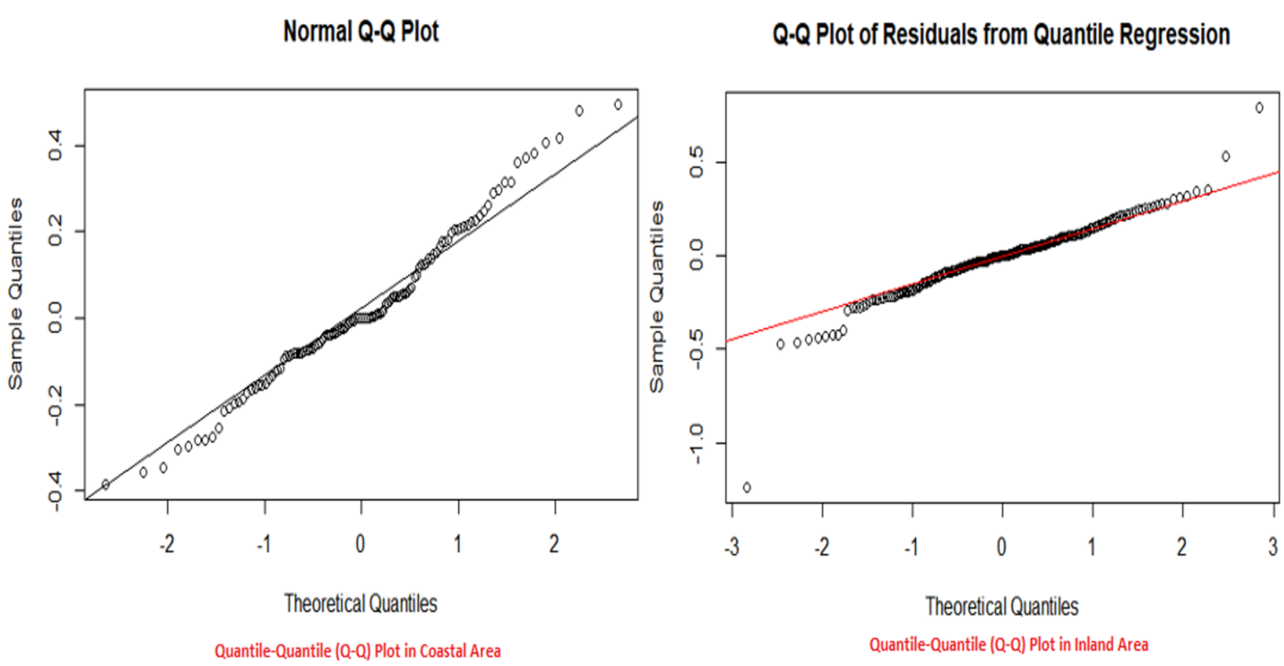

Figure 3. Quantile-Quantile (Q-Q) Plot of the coastal and inland area.

Table 5 shows that FDI and Financial Development (logFD) positively impact Green Innovation (logGI), with FDI's low VIF (1.39) indicating minimal multicollinearity. LogFD also positively affects logGI but has a moderate VIF (3.56), indicating some multicollinearity. Industrialization (logID) positively affects logGI, but its VIF of 4.62 indicates higher multicollinearity that may affect stability. Service Development (logSV) negatively relates to logGI with a VIF of 4.76, suggesting moderate multicollinearity. Trade (logTD) positively affects logGI with a low VIF (1.95), showing no multicollinearity concerns. The Cultural Environment (logCT) shows a slight positive effect, and a VIF of 3.26 indicates moderate multicollinearity. Overall, FDI and FD are key drivers of logGI, while multicollinearity may obscure interpretations of logID and logSV.

Table 5. Quantile regression coefficients and confidence intervals, and multicollinearity for the coastal area.

Variable	Coefficients	Lower bd	Upper bd	VIF
(Intercept)	-0.5816	-1.9692	0.2828	
logFDI	0.0402	0.0327	0.0448	1.3858
logFD	1.2387	0.4236	1.7442	3.5574
logID	0.1762	0.0642	0.5003	4.6248
logSV	-0.9355	-1.5085	-0.0810	4.7596
logTD	0.3792	0.2803	0.4924	1.9467
logCT	0.0013	0.0002	0.0018	3.2614

Note: This table presents the quantile regression coefficients, confidence intervals, and Variance Inflation Factors (VIF) for the coastal area.

Table 6 shows that FDI and FD significantly boost logGI in the Inland Area with low VIFs, indicating no major multicollinearity issues. Industrialization (logID) and Service Development (logSV) have mixed effects, with higher VIFs (4.64 and 3.91), suggesting moderate multicollinearity. Trade (logTD) positively influences logGI but has a VIF of 4.37, indicating some multicollinearity, similar to logSV and logID. Cultural Environment (logCT) has a small positive effect and an acceptable VIF of 2.22, indicating no significant multicollinearity. Overall, FDI and FD are the key drivers of logGI, though multicollinearity may affect some predictors.

Table 6. Quantile regression coefficients and confidence intervals, and multicollinearity in the inland area.

Variable	Coefficients	Lower bd	Upper bd	VIF
(Intercept)	-0.5816	-1.9692	0.2828	
logFDI	0.0402	0.0327	0.0448	2.0796
logFD	1.2387	0.4236	1.7442	1.0341
logID	0.1762	0.0642	0.5003	4.6447
logSV	-0.9355	-1.5085	-0.0810	3.9065
logTD	0.3792	0.2803	0.4924	4.3723
logCT	0.0013	0.0002	0.0018	2.2229

Note: This table presents the quantile regression Coefficients, confidence intervals, and Variance inflation factors (VIF) for the inland area.

In Figure 4, the Coastal Model (left plot) shows the quantile regression coefficients in red, with black error bars for confidence intervals, highlighting the uncertainty of the estimates. Wider intervals reflect greater uncertainty, while narrower ones suggest reliability. The Inland Model (right plot) presents coefficients in green, with blue error bars for narrower confidence intervals for most variables, indicating more reliable estimates than the Coastal Model.

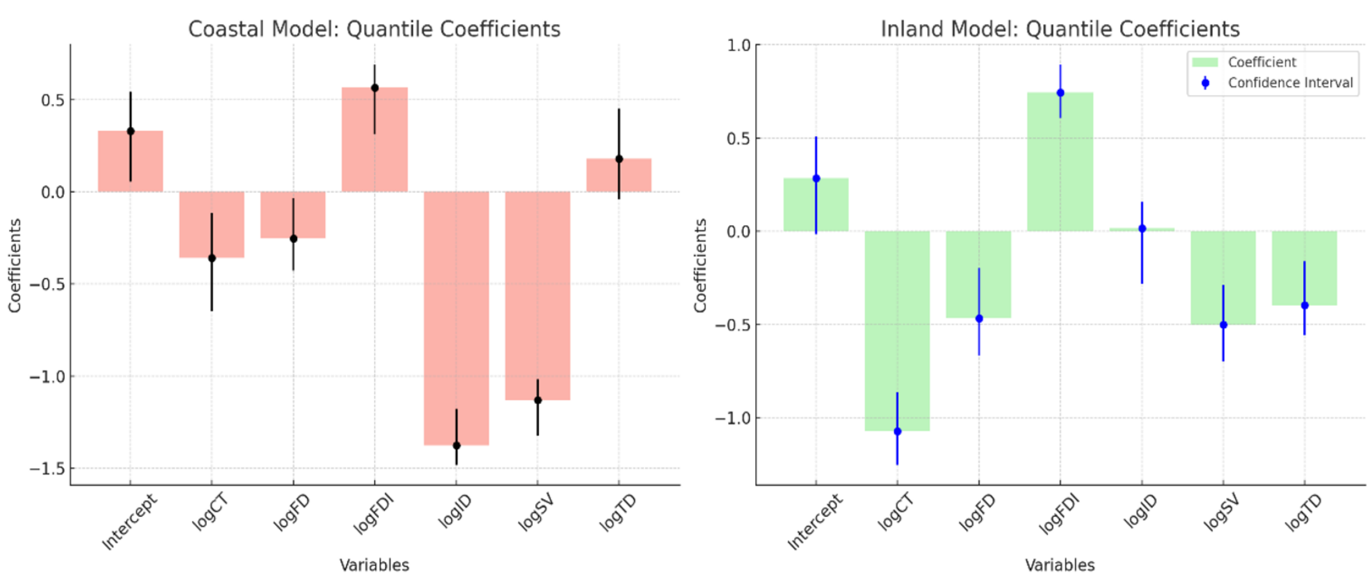

Figure 4. Coastal model: Quantile coefficients" and "Inland model: Quantile coefficients.

5. Conclusion

This study investigates the relationship between Foreign Direct Investment (FDI) and Green Innovation (GI) in various regions of China, focusing on coastal and inland areas. Using quantile regression, it examines FDI's effects on GI across different distribution points, addressing non-normality and skewness in the data. The study clarifies whether FDI's influence differs by geography and enhances GI in areas with varying development levels.

The findings show that FDI significantly and positively affects GI, especially where GI levels are low, supporting Hypothesis 1. In coastal areas, FDI correlates positively with logGI across all quantiles, facilitating cash flow, modern technologies, and knowledge, bridging innovation gaps. This is especially true in less developed coastal areas, where FDI improves technologies and infrastructure. However, in established coastal cities with higher GI, FDI's impact is reduced as local businesses adopt green technology.

In the inland area, FDI consistently positively influences GI, confirming Hypothesis 2, which suggests that FDI's effect varies by area. Limited infrastructure, financial resources, and technical expertise make the inland area particularly receptive to FDI, which promotes green innovation.

Financial development positively impacts GI in coastal areas, while industrialization and service development show mixed results; service development has a negative relationship at lower quantiles but becomes positive at higher ones. Trade and cultural environment also influence GI to a lesser extent.

This research explores FDI's role in promoting green innovation across Chinese provinces, analyzing geographical differences. By employing quantile regression, the study captures the non-linear impacts of FDI and other factors, enhancing understanding of FDI's relationship with green innovation.

Notably, the study's use of quantile regression reveals distinct effects of FDI on GI at various development stages in coastal and inland areas, filling research gaps regarding regional variations in GI levels and FDI's differing operations.

The study addresses the problem of understanding FDI's role in promoting GI in varying development areas. FDI significantly benefits areas with lower growth by providing capital, technology, and expertise. For policymakers, attracting foreign investment to lower GI areas, especially inland, is crucial for stimulating innovation. Enhancing infrastructure, market mechanisms, and intellectual property protection can help absorb technological spillovers from FDI.

One study limitation is its reliance on cross-sectional data, which may not capture the temporal dynamics of FDI and GI. Future research could use panel data for tracking long-term FDI effects. While focused on China, the findings may have implications for other developing nations, though their applicability to countries with different economic and institutional frameworks remains uncertain.

Future studies should consider a wider range of countries with diverse development levels to test the global applicability of identified trends. Examining the effects of under-researched factors such as government policies, environmental restrictions, or Service Development (SV) may yield further insights. Additionally, employing panel data to study the FDI-green innovation relationship over time will deepen understanding of long-term impacts and causal relationships.

The paper clarifies the link between FDI and GI, which is essential for formulating policies to attract foreign investment in low-innovation areas. FDI's influence varies by quantile and area, as shown by quantile regression, highlighting the complexities of fostering green innovation in diverse economic environments.

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