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Green Total Factor Productivity and Its Nonlinear Relationship With Coordinated FDI Development: Evidence From Panel Models

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ABSTRACT

This study investigates the underexplored nonlinear impact of coordinated foreign direct investment on green total factor productivity in the context of China. While existing literature acknowledges the role of FDI in fostering economic growth and environmental development, it has yet to thoroughly address the synchronizing effects of inward and outward FDI on factor productivity, particularly in alignment with Sustainable Development Goals (SDGs) and ESG principles. Using provincial-level data from 1995 to 2022 and employing a panel model, we analyze the U-shaped relationship between FDI coordination on factor productively in the context of China. Our findings reveal that synchronized FDI significantly boosts GP in the economically advanced eastern provinces, whereas the effect is complex and region-dependent in central and western areas, where structural and economic disparities play a more pronounced role. These results contribute to existing knowledge by clarifying the pathway through which coordinated FDI can enhance sustainable development. Our study concludes with policy recommendations emphasizing region-specific strategies that balance economic growth and environmental goals, fostering a comprehensive approach to sustainable development.

1 | Introduction

The TFP calculations, as initially proposed by Solow, have become common practice in portraying the quality of economic growth. GP augments this by incorporating financial and environmental perspectives into one measure of performance, which captures both desirable and undesirable outcomes, as by Ahmad and Wu (2022), Gohar, Bhatty, et al. (2022), Gohar, Salman, et al. (2023). GP is an important indicator of sustainable economic growth and harmonizes with the “win–win” concept in the aspect of environmental protection and economic development (Maydybura et al. 2023; Zhu, Huang, and Ma 2023; Xu, Jiang, and Wang 2022; Gao et al. 2022).

China's Dual Circulation strategy is to pursue high-quality economic growth with consideration for environmental sustainability, balancing domestic development and global integration. Green Total Factor Productivity (GP) has thus become an important index of sustainable development, reflecting both ecological and financial considerations. FDI, which is also bound to innovation and industrial modernization, significantly boosts productivity. The impact of the synchronized inward and outward FDI on GP across regions with different economic conditions, however, remains less explored with the recent large-scale investments of China in both types of FDI.

Hasty economic expansion of China, as mentioned by Ouyang, Li, and Du (2020), conforms to an approach categorized by

Summary

- Study focuses on China's "Dual Circulation" policy's approach to energy and environmental challenges.
- Data from 2005 to 2020 measures green productivity and FDI synchronization.
- Utilized SBMGML method and capacity coupling model for measurements.
- Nonlinear effects of FDI coordination on green productivity explored.
- GTFP saw minor increases, with variations across eastern, central, and western regions.
- Eastern China benefits most from FDI coordination in green productivity growth.

intense pollution, extreme emission, and substantial consumption of energy. In 2022, data from Columbia and Yale Universities ranked China 160th out of 180 countries in the global environmental performance index. In response to international economic instability and "secular stagnation," China suggested a Dual Circulation strategy in which the prime position was given to the domestic market while specifying a pattern of integration between not only domestic but also international markets. This strategy aims at balancing high-quality economic growth with increased energy consumption and environmental protection (Chang 2020; Noman et al. 2023; Ali et al. 2022; Uche, Chang, and Effiom 2022).

In a similar vein, Pata et al. (2024) examine how the implementation of EU SDGs through ESG market dynamics is influenced by climate-risk uncertainties—including transitional and physical risk, carbon allowances (EU ETS), and technological progress (MSCI). The study therefore uses quantile-on-quantile regression over the period between November 2007 and January 2023, which indicates that in higher quantiles, TRI and PRI raise ESG market development, while EU ETS and technological progress decrease demand for the ESG market. This, therefore, recommends stricter environmental standards as a measure to combat climate risks in EU countries.

The drive for this investigation is motivated by the need to better comprehend how coordinated foreign direct investment (FDI) influences Green Total Factor Productivity (GP), a significant operator of sustainable development in the context of China's Dual Circulation strategy. The core literature engrossed on in this investigation contains works on green productivity, the ecological influences of foreign direct investments, and the role of synchronized FDI in financial and ecological procedure (Chang, Rajput, Ahmed, et al. 2020; Chang, Rajput, Bhutto, et al. 2020; Chang, Sharif, et al. 2020; Liu and Feng 2023). Additionally, this investigation adds to the attainment of SDGs (Sustainable Development Goals), particularly SDG 13 (Climate Action) and SDG 7 (Affordable and Clean Energy), by investigating how FDI can encourage sustainable financial development.

These facts introduce the relationship of FDI and economic growth based on the Endogenous Growth Theory, emphasizing how FDI promotes technological innovation and advancement in productivity. The Green Total Factor Productivity deduced from an augmented Solow Growth Model embodies environmental constraints and therefore is a complete indicator of sustainable development. Based on the Dunning OLI framework, CDU, or coordinated development index FDI, focuses on how inward and outward FDI synergistically enhance productivity through capital and technology transfers. In drawing on New Economic Geography, this study reassesses regional disparities in China through threshold variables like GDP per capita and industrial structure to realize the differential capturing effects of FDI on GP across regions. This theoretical grounding can well rationalize the variables at play and interact nonlinearly with region-specific interactions.

Over the last few years, much of this framing has been discussed through two complementary frameworks: Environmental, Social, and Governance (ESG) for one, and the United Nations Sustainable Development Goals. While ESG principles give metrics toward the sustainability of companies with a focus on the environmental impact, social viewpoint, and governance practices; SDG sets broader targets for the world at large in the achievement of development in a sustainable manner by 2030. The intrinsic connection between these frameworks is evident, as both are targeted at conditioning the course of action, so these are funneled into sustainability on a long-term basis. In this respect, the coordinated inward and outward FDI development that we are going to analyze in this study constitutes an appropriate pre-condition for enhancing GP and contributes to all aspects of both ESG and SDG goals. This will also align with SDG 7, Affordable and Clean Energy, and SDG 13, Climate Action, since through the promotion of clean energy use, technological innovation, and resource efficiency, FDI synchronization supports environmental performance—one of the core pillars of ESG. Therefore, this research not only contributes to the understanding of how FDI affects GP but also its wider implications for corporate sustainability and global development goals. Another highly relevant framework is that of ESG since the current study explores how the related environmental dimension, in terms of green productivity, is influenced by foreign investments in this area of corporate governance.

Işık, Ongan, Islam, Balsalobre-Lorente, et al. (2024), Işık, Ongan, Islam, and Menegaki (2024), Işık, Ongan, Islam, Pinzon, et al. (2024), and Işık, Ongan, Islam, Sharif, et al. (2024) present the ECON-ESG quadruple by adding an economic dimension to the conventional ESG framework and evaluating the impact thereof on LCF in G7 countries. According to their CS-ARDL model, while governance improves LCF, it is affected adversely by economic factors, reflecting that high productivity and consumption stress biocapacity. They further mention that policymakers should harmonize economic and governance policies regarding sustainability through adopting a holistic approach to ECON-ESG.

Similarly, Işık, Ongan, Islam, Balsalobre-Lorente, et al. (2024), Işık, Ongan, Islam, and Menegaki (2024), Işık, Ongan, Islam, Pinzon, et al. (2024), and Işık, Ongan, Islam, Sharif, et al. (2024) draw on the analysis of ECON-ESG factors and SDGs across 33 OECD countries. Their findings indicate that among the economic factors, environmental considerations, and SDGs, there is promotion of natural resource rents (NR), while technological aspects and governance are deterring. Policymakers need to harmonize ECON-ESG with global supply chain sustainability to offer sustainability in natural resource rents. In another investigation, Işık, Ongan, Islam, Balsalobre-Lorente, et al. (2024), Işık, Ongan, Islam, and Menegaki (2024), Işık, Ongan, Islam, Pinzon, et al. (2024), and Işık, Ongan, Islam, Sharif, et al. (2024) studied ECON-ESG's influence on SDG-based energy efficiency (EE) in G7 states, creating the "ECON-growth-paradox." Their CS-ARDL outcomes disclose that financial aspects hamper EE whereas ecological aspects augment it. The paradox holds true for Canada, Italy, and the USA, while the UK is in E-growth harmony and draws a need for reconciling economic and environmental policies.

Moreover, Chen et al. (2024) investigate the impact of climate risk on firms' performance with regard to environmental, social, and governance aspects, taking into consideration data from Chinese A-share listed firms for the period 2010-2019. The study reveals that climate risk significantly decreases ESG performance; however, it is more pronounced in state-owned firms, firms in growth or decline, and those with a higher share of institutional investor shareholders. Furthermore, the peculiar factors of financing constraints, corporate diversification, and media attention intensify this negative impact. The results suggest that policies related to climate risks are relevant to achieve SDGs.

Bose, Khan, and Bakshi (2024) also seek to investigate the determinants and outcomes of firm-level SDG disclosure based on a total number of 6941 firm-year observations from 30 countries for the period 2016-2019. The findings prove that ESG performance, stakeholder engagement, and standalone sustainability reports positively influence SDG disclosure, which is associated with higher firm value in turn. These findings provide important implications for global decision-makers focused on SDGs.

China has emerged as a substantial player in bilateral investment abroad. Despite the challenges thrown by the coronavirus pandemic, FDI in China has been on a gradual growth path. In 2020, FDI attained $14.54 billion, increasing by 14.9% in 2021% and 6.3% in 2022. During 2022, the cumulative FDI in all industries was in excess of $14.33 billion, up 5.2% compared with the same period a year ago. Another underlying important trend is an increasing substitution and interrelationship between outward FDI and inward FDI regarding the Dual Circulation strategy of China. OFDI and IFDI are becoming interlinked, where OFDI promotes IFDI and vice-versa (Syed, Malik, and Chang 2019; Hashmi, Chang, and Shahbaz 2021; Hashmi, Chang, and Rong 2021; Hashmi et al. 2022; Ahmed and Ibrahim 2019; Chang, Rajput, Bhutto, et al. 2020; Chang, Sharif, et al. 2020).

Additionally, Tyan, Liu, and Fu (2024) investigates the impact of ESG strategy, ESG implementation, and governance structure on SDGs through a contingency mediation-moderation model among 552 Taiwanese listed companies. Their results indicate that ESG implementation mediates the relationship between ESG strategy and the impact on SDG, while governance structure may lead to moderation in the relationship between ESG implementation and SDGs. Furthermore, the embeddedness of strategy positively influences SDG impact, providing valuable insight into how to promote firms' contributions toward the SDGs.

In light of Wang, Wang, and Teng (2017), OFDI and IFDI have to do with anything beyond basic capital shift but reach out to broad areas of management knowledge transfer, technology, financial elements, and labor. What truly relates to outward and inward foreign direct investment effects on green total factor productivity is inconclusive. While some academics believe that the contribution of both factors is most influential to Green TFP growth, some scholars are skeptical about the relationship between Green Total Factor Productivity and OFDI/IFDI (Chang, Rajput, Ahmed, et al. 2020; Zheng and Ran 2018; Gong, Liu, and Jiang 2019).

This research is therefore motivated by the limited investigation that has occurred relating to how synchronized foreign direct investment—both inward and outward—affects Green Total Factor Productivity nonlinearly. While previous literature such as that by Wang, Xue, and Zhao (2022) exists that calculated the impacts of green productivity due to FDI, most of them only focus on the different influences brought by inward and outward FDI independently, ignoring the interactional and coordinative impacts between the two variables altogether.

Although considerable literature exists on FDI and GP, the literature on the coordinated impact of CDU on GP remains unexploited. While previous studies have focused on either the inward or outward FDI separately, they have overlooked the possibility that coordination between the two is likely to yield greater synergistic gains. This omission acquires special relevance in the context of China's Dual Circulation strategy, which was put forward with the aim of striking a proper balance between the domestic and international markets for maintaining steady economic growth. To fill this gap, this study investigates the following research questions: (1) How does synchronization of the inward and outward FDI affect GP in different regions of China? and (2) what are the nonlinear dynamics between FDI synchronization and GP under varying levels of economic development and industrial structure in the eastern, central, and western regions of China? (3) What are the ways in which policy recommendations could be designed to support both economic growth and environmental sustainability based on the findings? In this respect, an attempt has been made in this study to contribute to the existing literature by analyzing nonlinear and region-specific dynamics of CDU and GP and providing insights into sustainable development policies that are concurrent with economic and environmental objectives.

The model proposed in this paper is embedded within the broader context of the Dual Circulation approach towards national development in China, centering the focus on the relationship between Green Total Factor Productivity and coordinated development of FDI. Using regional data at the provincial level across 1995 to 2022, this paper will analyze the nonlinear relationship between I-FDI and O-FDI across the eastern, central, and western regions of China. The disparities of the regional economy, in general, are confined within such variables as differences in GDP per capita and structural composition in industries, that is, threshold variables to modify the impact of FDI coordination on GP. These constructs are context-dependent, and thus, especially in the eastern region, the synchronization of FDI affects GP most when there is higher economic development coupled with more advanced industrial structures, while in the central and western regions, the results turn out to be more complex and varied. In this manner, the model findings are applicable on a larger scale to economies passing through similar development phases and experiencing analogous environmental and economic challenges.

Wang, Wang, and Teng (2017) have mentioned that IFDI and OFDI have different influences on GP in various regions of China. Gohar, Chang, et al. (2022), Wang et al. (2024), and Feng, Wang, and Hu (2021) have shown that OFDI has an overall positive influence on GP; however, its impact remains insignificant with respect to China's GDP. Recent studies have focused more on the interaction between IFDI and OFDI and their impact on GP. Peng et al. (2022) and Gong, Liu, and Jiang (2019) highlight that both complementarity and substitution processes shape this relationship. To put it another way, when complementarity dominates substitution, the growth of OFDI and IFDI accelerates. Capability-based analyses by Hashmi and Chang (2021) and Uche, Chang, and Gohar (2022) demonstrate that enhanced production processes have greatly reduced environmental pollution. Gohar, Bagadeem, et al. (2022), Gohar, Osman, et al. (2022), Dong, Zhang, and Liu (2021), and Wang, Xue, and Zhao (2022) provide further evidence for integrating environmental concerns with OFDI and IFDI under a unified framework.

Generally, favorable FDI is expected to inspire technological innovation, optimize industrial structures, develop a fairer distribution of assets, and relieve resource scarcity. All these allow local firms to increase their OFDI and enhance international competitiveness. Naturally, such reorganization of inefficient local firms is also made possible with FDI through mergers, international investments, and pollution control (Li et al. 2021; Chang et al. 2024; Gohar, Chang, et al. 2023; Imbruno et al. 2022). This can further maximize the reverse technological spillover effect of OFDI and raise research collaboration with advanced economies (Imane et al. 2023; Gong et al. 2023; Chang et al. 2022). This will enhance domestic finances, raise the entry threshold for IFDI, and promote national technological progress. Accordingly, OFDI and IFDI together can facilitate steady improvement in GP over the long term and promote high-quality economic growth.

Large-scale IFDI that is resource-intensive may drive out local capital and cause resource depletion, leading to so-called "pollution haven" effects (Ouyang, Li, and Du 2020; Lu et al. 2023). It may over-rely on IFDI, suppress local innovation, and independent R&D, undermining the long-term growth of domestic firms and economic development. The reduction in the independence of OFDI may result in OFDI flows being overly dependent on low technology-level regions, which inhibits its reverse technology spillover effect. This would negatively impact national economic ties, leading to economic hollowing out, making key sectors less attractive for foreign investment, and decreasing local economic growth. Consequently, reduced interaction between OFDI and IFDI could hinder GP growth (Salman, Razzaq, et al. 2023; Salman, Chang, et al. 2023).

Several econometric methods are applied to test the relationship between GP and FDI. There are also some popular linear methods, such as the panel fixed effects model by Dong, Zhang, and Liu (2021) and the reasonable generalized least squares technique by Qiu, Wang, and Geng (2021). The various methodologies that have been used in analyses through which temporal and regional differences in GP have been made include the generalized method of moments by Guo and Wang (2023), panel vector autoregression by Huang, Liu, and Xie (2018), and the spatial Durbin model by Feng, Wang, and Hu (2021).

Işık, Ongan, Islam, Balsalobre-Lorente, et al. (2024), Işık, Ongan, Islam, and Menegaki (2024), Işık, Ongan, Islam, Pinzon, et al. (2024), and Işık, Ongan, Islam, Sharif, et al. (2024) researched BRICS-11 countries in light of the effects of ESG factors on SDGs by using various models, showing negative environmental impacts in some countries such as Argentina, Ethiopia, and China, while positive social and governance impacts were iteratively observed in other countries. Correspondingly, no significant performance could be detected for Brazil, Russia, India, and Egypt. Such results point out country-specific variations within the ESG-SDG association and emphasize the need for balanced economic and environmental strategies. Recent studies have employed panel threshold methods to study the nonlinear relationship between GP and FDI to ensure better development of GP. Compared to traditional regressions, these perform better because they resolve heterogeneity in distribution and lower the chances of bias by classifying conditions according to their endogenous features. More importantly, these methods identify exogenous conditions that enable GP, providing strategic guidance for targeted GP development.

Furthermore, Teng et al. (2023) researched the spatial spillover of inward and outward FDI on China's ecological well-being and found significant impacts on ecological performance. The contribution of digital service trade to technological innovation was discussed in Wen, Chen, and Zhou (2023), providing key international insights. Additionally, Zheng, Zhou, and Wen (2022) studied the relationship between trade liberalization and environmental pollution in China, offering perspectives on how trade policy can influence environmental performance.

In the context of the Dual Circulation strategy, the interaction between OFDI and IFDI may produce a greater and more complex effect on GP. However, most literature has looked at either the respective effects of OFDI or IFDI on GP, neglecting the potential synergy between them, which could induce a greater combined effect when integrated. In addition, traditional panel threshold methods often fail to address cross-sectional dependence, resulting in inaccurate analyses of the nonlinear relationship between GP and FDI.

Based on the capacity coupling framework and the slacks-based measure-global Malmquist-Luenberger (SBM-GML) method, this study first conducted an analysis of the Coupling Degree of Inward and Outward Foreign Direct Investment (CDU) and Green Total Factor Productivity (GP) from 2005 to 2020. Then, with PTIFE that incorporates interaction effects, the nonlinear effect of CDU on the GP of China was estimated. Finally, the regional heterogeneity across western, central, and eastern regions in China was analyzed, and corresponding policy suggestions were provided accordingly.

This research contributes to the existing literature in several ways: it mathematically evaluates the CDU using the capacity coupling method to explore the nonlinear effects of CDU on GP under different conditions, integrating GP and CDU into a single framework. It introduces threshold parameters such as industrial structure, GP, CDU, and economic development, offering new insights to promote high-quality economic growth and GP improvement. Moreover, by relying on PTIFEs, the study diminishes cross-sectional dependency, accounting for time-varying disturbances, leading to more accurate estimates of CDU's nonlinear impact on GP under changing external conditions.

In our research, we detail the complex interactions of economic growth with environmental sustainability within a province-level analysis for China, focusing on green total factor productivity and how IFDI and OFDI interact. Our research is aligned with China's Dual Circulation strategy, utilizing the SBMGML method and the capacity coupling model. However, the implications extend beyond China, offering valuable insights for other nations navigating the challenges of globalization. As the world strives to balance economic expansion with environmental conservation, our findings contribute to the global dialogue on sustainable practices. By taking an international perspective, we emphasize the interconnectedness of global efforts to achieve sustainable development goals. Through this research, we hope to bridge China's unique experience with the broader pursuit of sustainability in the context of economic growth worldwide.

This is how the remainder of the paper is organized. The study methods and data are briefly described in Part 2, the empirical findings are presented in Part 3, followed by an analysis in Part 4, and the results and policy recommendations are presented in Part 5. The investigation's statistical framework is shown in Figure 1.

2 | Data and Methodology

2.1 | The Panel Threshold Interactive Fixed Effects Models

2.1.1 | Framework Setting

Conventional panel regressions typically assume that random disturbance factors are homogeneous. However, when confounding variables introduce diversity in these random disturbances, it leads to significant cross-sectional dependence prejudice (Chudik et al. 2017; Dogan and Seker 2016). To tackle this, Bai (2009) introduced IFEs (Interactive Fixed Effects), which incorporate specific and temporal association influence into a symmetric panel approach. IFEs resolve endogeneity issues stemming from unobservable factors that vary across time and individuals, while also capturing hidden heterogeneities. Based on this, Miao, Li, and Su (2020) further developed the panel threshold approach with interaction effects (PTIFEs) to address nonlinear issues.

Given its particular suitability for capturing nonlinear relationships and cross-sectional dependencies, the interaction between synchronized inward and outward foreign direct investment (IFDI and OFDI) and Green Total Factor Productivity (GP) was analyzed using the Panel Threshold Interactive Fixed Effects Models (PTIFEs) in this study. For example, the complexity of the relationships dealt with inhibits the possibility of conventional estimations, such as OLS or simple panel data models, capturing those relationships, especially when regional heterogeneity and interactive effects feature. The flexibility of the PTIFEs framework in allowing for multiple thresholds and interaction terms makes it optimal for uncovering nonlinear dynamics and regional variations in how IFDI and OFDI jointly determine GP across different regions in China.

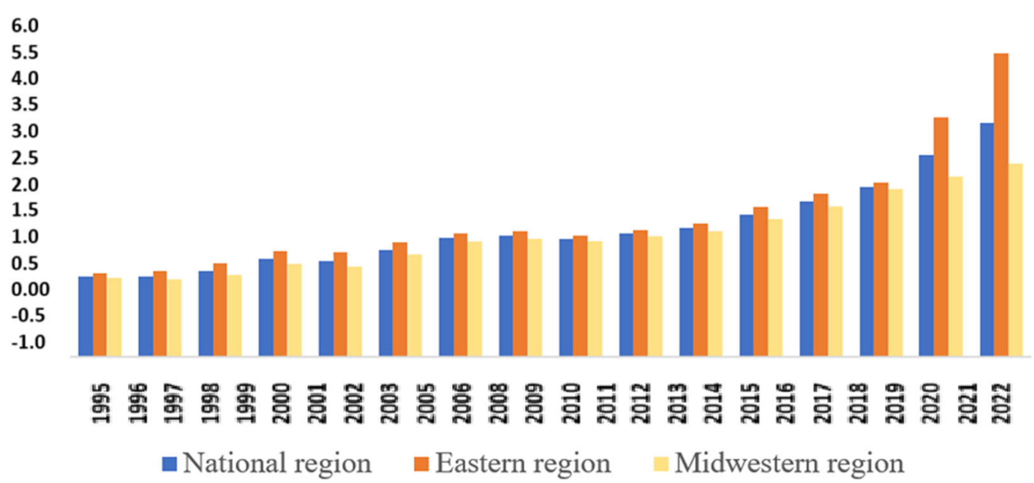

FIGURE 1 | Movements in GP countrywide, in the midwestern and eastern areas, 2005–2020.

Additionally, the available alternative methods, such as fixed or random effects models, rely on the homogeneity of disturbance terms, which can bring in biased results when unobservable factors vary across regions and over time. PTIFEs overcome these issues by accounting for unobservable time-varying heterogeneities, leading to more accurate and reliable estimates. It is, therefore, the best method to investigate the nonlinear and region-specific effects that are central to this research.

The proposed model is important because it fills a vital gap in the existing literature with respect to the analysis of nonlinear relationships between inward and outward synchronized FDI and GP under China's Dual Circulation strategy. In contrast to earlier analyses, which treat IFDI and OFDI separately, the model stresses their coordinated impact for a deeper understanding of how they interactively affect GP. The cross-sectional dependencies and regional heterogeneity are considered in the PTIFEs applied in this study, enabling a more nuanced analysis of how these impacts differ across eastern, central, and western regions in China. Previous approaches often overlooked these aspects, relying on linear models that could not capture such interactive effects and regional disparities. This study fills a critical gap in the literature by introducing this model, providing new insights into how synchronized FDI promotes both economic growth and environmental sustainability, central to China's sustainable development goals. The PTIFEs were constructed, following Miao, Li, and Su (2020), to investigate the nonlinear impacts of CDU on GP:

$$GTFP_{kl} = \rho_0(P_{kl} \le \mu) + \rho_1 CDIFDI_{kl}(P_{kl} \le \mu) + \rho_2 CDIFDI_{kl}(P_{kl} > \mu) + \rho' B_{kl} + \delta'_k E_l + c_{kl} \tag{1}$$

2.1.2 | Framework Estimation

Equation (1) may be changed into Equation (2) by the method of group regression as follows:

$$GTFP_{kl} = \rho' CDIFDI_{kl} + \lambda' CDIFDI_{kl} f_{kl}(\mu) + \delta'_k E_l + c_{kl} \tag{2}$$

here $f_{kl}(\mu) = 1(P_{kl} \le \mu)$. Equation (3) may be expressed as the vector version of Equation (2):

$$\begin{aligned} GTFP_l &= CDIFDI_l \rho + CDIFDI_l(\mu)\lambda + \Gamma E_l + c_l \\ &= CDIFDI_{l,\mu}\Theta + \Gamma E_l + c_l \end{aligned} \tag{3}$$

here $\Theta = (\rho' \lambda')$ and $CDIFDI_{l,\mu} = CDIFDI_l \rho + CDIFDI_l(\mu)$. ΓE_l indicates Common time-varying factors that may influence the GP in year l, such as macroeconomic conditions. The Gaussian quasi-maximum likelihood estimate for the particular common variable number R is carried out using Equation (4):

$$\begin{aligned} (\hat{\Theta}, \hat{\Gamma}, \hat{\mu}) &= arg\min \xi(\Theta, \Gamma, \mu) \\ &\quad + arg\ \min \sum_{l=1}^{L} (GTFP_l - CDIFDI_{l,s}\Theta)' \mathbb{R}_X \\ &\quad (GTFP_l - GTFP_l) \quad s.\ t.\ \Gamma'\Gamma/\mathrm{L} = J_R, \mathrm{E}' \\ &\quad \mathrm{E} = diagonal \end{aligned} \tag{4}$$

In two phases, the aforementioned simplification challenge is resolved. To determine $\hat{\Theta}(\mu)$, $\hat{\Gamma}(\mu)$ with an integer μ, first reduce Equation (4) to get $\xi^*(\hat{\Theta}(\mu), \hat{\Gamma}(\mu), \mu)$. Next, determine the lowest residual sum of squares, denoted by $\Lambda = [\underline{\mu}, \bar{\mu}]$. $\hat{\mu} = arg\ \min \xi^*(\mu)$ throughout the whole threshold variable's quantitative range using a grid-based search quantile. Next, by resolving Equation (5), the asynchronously coherent gauges of Θ and Γ are found:

$$\begin{aligned} \hat{\Theta} &= \left(\sum_{l=1}^{L} CDIFDI'_{l,\hat{\mu}} \mathbb{R}_{\hat{\Gamma}} CDIFDI_{l,\hat{\mu}} \right)^{-1} \sum_{l=1}^{L} CDIFDI'_{l,\hat{\mu}} \mathbb{R}_{\hat{\Gamma}} CDIFDI_{l,\hat{\mu}} \left[\frac{1}{NL} \sum_{l=1}^{L} \left(GTFP_l - CDIFDI_{l,\hat{\mu}}\, \hat{\Theta} \right) \right. \\ &\quad \left. \left(GTFP_l - CDIFDI_{l,\hat{\mu}}\, \hat{\Theta} \right)' \right] \hat{\Gamma} = \hat{\Gamma}\, W_{NL} \end{aligned} \tag{5}$$

In this equation, the Green Total Factor Productivity is denoted by $GTFP_{kl}$ in year l for province k, seizing the province's productivity under ecological restraints. The main independent variable is $CDIFDI_{kl}$, which denotes the coordinated development index of Inward Foreign Direct Investment (IFDI) and Outward Foreign Direct Investment (OFDI). The equation presents a threshold variable P_{kl} that describes the situations under which the association between CDU and GP may vary, created on the threshold value μ. The approach permits for various influences of CDU on GP depending on whether P_{kl} is above or below the threshold. Control variables are comprised in the vector B_{kl}, and IFEs are apprehended through $\delta'_k E_l$, with c_{kl} on behalf of random disturbances that account for heteroscedasticity and time-varying shocks, and E_{kl} is a vector of common factors with δ_k being the suitable variable weighting.

Here, the diagonal matrix is represented by W_{NL}, whose diagonal components are the R's major eigenvalues, that is, $\sum_{l=1}^{L}(GTFP_l - CDIFDI_{l,\hat{\mu}}\, \hat{\Theta})(GTFP_l - CDIFDI_{l,\hat{\mu}}\, \hat{\Theta})'$, and the crosswise components are ordered in downward order.

2.1.3 | The Determination of Variables' Number

In practice, determining the precise common factors' number (R) is challenging. The two-step singular value threshold approach for calculating R (Moon, Shum, and Weidner 2018) was refined by Miao, Li, and Su (2020). The first step is to estimate the kernel parameter regularization using Equation (6):

$$
\begin{aligned}
\hat{\Theta}_{\lambda}, \hat{\mu}_{\lambda}, \hat{\theta}_{\lambda} &= arg \min \xi_{n,\lambda}(\Theta, \mu, \theta) \quad \xi_{x,\lambda}(\Theta, \mu, \theta) \\
&= \frac{1}{2NL} \| GTFP - \rho \odot CDIFDI \\
&\quad - \lambda \odot CDIFDI(\mu) - \theta \|^2 + \frac{\lambda}{\sqrt{NL}} \|\theta\|_*
\end{aligned} \tag{6}
$$

Since all variables are in matrix form, let $\lambda = \left(N^{-\frac{1}{2}} + L^{-\frac{1}{2}}\right)$. The greatest singular value for matrix B is shown by $S_r(B)$, and the spectral standard of matrix B is indicated by $\|B\|_{sp}$. The kernel standard of matrix B is denoted as $\|B\|_* = \sum_{r=1}^{\min(N,L)} S_r(B)$. Next, we may get the approximate value of R using Equation (7):

$$
\hat{R} = \sum_{r=1}^{\min(N,L)} 1\{S_r(\hat{\theta}_{\lambda}) \geq Y_{NL}\} \tag{7}
$$

Here singular value's threshold is $Y_{NL} = \log(\sqrt{N} + \sqrt{L})(\sqrt{NL}\lambda\|\theta\|_{sp})^{\frac{1}{2}}$.

2.1.4 | The Threshold Effect Test

Threshold influences are tested for using the Sup-Wald statistic. The initial and substitute hypotheses are as follows: $H_0 : \delta = 0, H_1 \neq 0$. The variance correction estimator may be produced for any $\Lambda = [\underline{\mu}, \bar{\mu}]$. Next, as Equation (8), the asymptotic variance calculations are built.

$$
\begin{aligned}
\hat{\psi}_{NL}(\mu, \mu) &= \frac{1}{NL} \sum_{k=1}^{N} \sum_{l=1}^{L} \hat{x}_{kl,\mu} \hat{x}'_{kl,\mu}, \\
\hat{\varphi}_{NL}(\mu, \mu) &= \frac{1}{NL} \sum_{k=1}^{N} \sum_{l=1}^{L} \hat{x}_{kl,\mu} \hat{x}'_{kl,\mu} \hat{c}_{kl}(\mu)
\end{aligned} \tag{8}
$$

here $\hat{x}_{kl,\mu}$ is a $2H \times 1$ order vector with the hth term's value equal to the $\mathbb{R}_{\hat{\Gamma}(\mu)} Y_{h,\mu} \mathbb{R}_{\hat{E}(\mu)}$ (k, l)th term. Consequently, Equation (9) establishes the test statistic as follows:

$$
\sup U_{NL} = \underset{\mu \epsilon \Lambda}{\sup U_{NL}}(\mu) = \sup NL \tilde{\Theta}(\mu)' I \hat{J}_{NL}^{-1}(\mu) I' \tilde{\Theta}(\mu) \tag{9}
$$

here $I = [0_{J \times J}, T_J]'$, $\hat{\mathbb{J}}_{NL} = I' \hat{\psi}_{NL}(\mu, \mu) \hat{\psi}_{NL}(\mu, \mu)^{-1} I$. Formerly, under the substitute hypothesis $H_1 : \lambda = d/\sqrt{NL}$, the Sup-Wald statistics' asymptotic distribution can be attained as Equation (10):

$$
\begin{aligned}
\sup U_{NL} &\xrightarrow{c} \underset{\mu \epsilon \Lambda}{\sup U^d}(\mu) \\
&= \sup_{\mu \epsilon \Lambda} [\bar{R}(\mu) + \bar{S}(\mu) d]' \bar{J}(\mu, \mu)' \quad [\bar{R}(\mu) + \bar{S}(\mu) d]
\end{aligned} \tag{10}
$$

where $\bar{S}(\mu) = J'(\gamma, \gamma)^{-1} \psi(\mu, \mu) J$. $\bar{R}(\mu) = J' \psi(\mu, \mu)^{-1} R(\mu)$ conforms a Gaussian distribution with an average of 0 and its covariance is $I(\mu_1, \mu_2) = J' \psi(\mu, \mu)^{-1} \varphi(\mu_1, \mu_2) \psi(\mu_1, \mu_2)^{-1} I$. $U^d(\mu)$ is the ordinary Wald statistic for a specified μ. The P-value which rejects the null hypothesis may be found using bootstrap process. The threshold influences are increasingly substantial, the lower the P-value.

2.2 | Variable Assertion

2.2.1 | The Dependent Variable: GP

The productivity index (GML), as determined by the SBM approach, is integrated into GP within the context of an evaluation of inputs and outputs. First, Equation (11) was developed as an ecological technology approach that considers resource constraints. The DDF (Directional Distance Function) was used to determine the remoteness between each manufacture decision part and the efficient manufacture edge. The GML productivity index was then computed for two periods using the Directional Distance Function as a basis. Equation (12) illustrates how Chung, Färe, and Grosskopf's (1997) concept of output fluctuations between periods k and $(k + 1)$ was used to create the output-oriented GML index:

$$
P(z) = \left\{(y, b) : z \text{ can yield } (y, b), z \epsilon R_+^*\right\}
$$

$$
P(z^l) = \begin{cases}
(y, b) : \sum_{h=1}^{H} \lambda_h^l y_{hm}^l \geq y_{ml}, m = 1, 2, \ldots, M; \\
\sum_{h=1}^{H} \lambda_h^l b_{hi}^l = b_k^l, \quad l = 1, 2, \ldots, L \\
\sum_{h=1}^{H} \lambda_h^l z_{hm}^l \leq z_n^l, \quad n = 1, 2, \ldots, N \\
\lambda_h^l \geq 0, \quad h = 1, \quad 2, \ldots, H
\end{cases} \tag{11}
$$

$$
GML_l^{l+1} = \left\{ \frac{\left[1 + \vec{D}_0^l\left(z^l, y^l, b^l; y^l, -b^l\right]}{\left[1 + \vec{D}_0^l\left(x^{l+1}, y^{l+1}, b^{l+1}; y^{l+1}, -b^{l+1}\right]} \times \frac{\left[1 + \vec{D}_0^{l+1}\left(z^l, y^l, b^l; y^l, -b^l\right]}{\left[1 + \vec{D}_0^{l+1}\left(z^{l+1}, y^{l+1}, b^{l+1}; y^{l+1}, -b^{l+1}\right]} \right\} \tag{12}
$$

Here, z^l stands for the input index, y^l for the intended results, and b^l for the undesirable result. $\vec{D}$ indicates the directional distance function in this Equation.

The SBM model-based GML index does not require a specific production process. Only the input and output parameters from each decision unit—30 provinces—are needed for the estimation method. Table 1 displays the specific variables.

2.2.2 | Core Independent Variables: CDU

Citing Huang, Liu, and Xie (2018), the capacity-coupled system approach was used to determine the coupling degree of OFDI and IFDI, as expressed in Equation (13):

TABLE 1 | Justifications to select output and input.

Variable		Description
Input parameters	Energy	Total energy consumption (10,000 tons of standard coal)
	Capital	Investment in fixed assets (10,000 yuan)
	Labor	Employment at the end of year
Output parameters	Unanticipated Results	dioxide emissions (tons) based on the industry-based sulfur and water waste discharges in the industry
	Anticipated Results	Real GDP in millions of dollars Smoke-based emissions in the industry

$$C_{kl}(IO) = \frac{IFDI_{kl} \times OFDI_{kl}}{(\gamma IFDI_{kl} \times \delta OFDI_{kl})^{\mu}} \tag{13}$$

Here is the coefficient of adjustment, and its value in this research was 2. γ and δ are usually considered to be 0.5, and $OFDI_{kl}$ and $IFDI_{kl}$ indicate the flow of foreign investment and province outflow k in year l, correspondingly. The coupling degree only mirrors the connection level among processes. To better represent the state of evolution of each system, this study computes the degree of cooperation in more detail. The integrated development index of OFDI and IFDI is determined using Equation (14):

$$CFDI_{kl} = \left[C(IO)_{kl} \times \frac{IFDI_{kl} \times OFDI_{kl}}{2}\right]^2 \tag{14}$$

The CDU was intended by employing Equation (15), which was derived by integrating Equation (13) into Equation (14). Higher (lower) CDU values are observed in a given area when both IFDI and OFDI are higher (lower) and their respective values are close to one another:

$$CFDI_{kl} = \left[\frac{IFDI_{kl} \times OFDI_{kl}}{(IFDI_{kl} + CFDI_{kl})/2}\right]^{\frac{1}{2}} \tag{15}$$

2.2.3 | The Threshold Variable

1. The IS (Industrial Structure), signified by the tertiary sector's value's ratio to the secondary segment's worth, plays a key role in determining the impact of CDU on GP growth. In the initial stages of structural alteration, the industrial segment often tracks an protracted expansion method, hypothetically counteracting CDU's favorable contribution to GP (Liu, Tian, and Luo 2018). However, with the promotion of greener technologies and improvement in industrial structures, the "structural dividend" can enhance environmental quality. Over time, this balancing effect may turn into a positive force, supporting CDU's impact on GP, suggesting the existence of a threshold effect in the form of a favorable "U" curve as the industrial structure evolves.
2. The relationship between CDU and GP is also influenced by economic development, measured by GDP per capita. There has been increasing debate on the nexus between economic growth and environmental degradation. For instance, other studies found an overturned "U-shaped" association between Gross Domestic Product of China and air pollutants like SO_2 and XO_x. Financial development, driven by foreign investment and industrialization, often hampers progress in adopting eco-friendly technologies (Shen et al. 2021). Consequently, CDU's effect on GP is expected to vary across different stages of economic development.
3. If the CDU is higher, then the "policy bonus" will be lower, and to continue having a positive effect on GP, more advanced manufacturing methods are required, which need significant investments in innovation, research, and development. However, the cost of technological innovation reduces profit margins, discouraging businesses from adopting sustainable practices, thus weakening CDU's role in promoting GP (Wang, Xue, and Zhao 2022). This implies that CDU faces a threshold effect, where its impact on GP is self-limiting and may decline over time.
4. GP development is influenced by various factors such as FDI, environmental regulations, and technological innovation, with their impact differing across quartiles (Wang et al. 2020). Given this variability, GP likely exhibits a threshold effect. Compared to traditional panel threshold models, PTIFEs offer more robust results with limited data and allow the dependent variable to be used as a threshold variable, providing more accurate insights (Dong et al. 2022).

2.2.4 | Control Variables

In this investigation, seven control variables (Table 2) were nominated to avert the elimination of substantial independent factors and to curtail prejudiced estimations in the methodology.

2.3 | Source of Data and Stability Assessment

The data for this study were retrieved from various official and valid sources to ensure comprehensive coverage of Green Total Factor Productivity (GP) and Coordinated Foreign Direct Investment (CDU) across 30 Chinese provinces from January 1995 to February 2022. The GP data came from the China Environmental Statistical Yearbook, China

TABLE 2 | Control variables.

Control variables	Abbreviation	Data
Education level	E.D	Years of schooling per capita
Expenditure level in technology and science.	TEK	The science and technology-based share
Financial services level	FINA	GDP Share
Intensity of environment-based terms and conditions	ER	Industry-based population
Marketization-based type-level	MUR	The Fanzine Marketization Index
Intensity of the population	PO	The total number of people per 1000 km^2
Urban construction level	CI	Road area per capita

TABLE 3 | The variables summary statistics.

Variable	Mean	P50	Min	Max	SD	Observation
CDU	1.767	1.941	−2.312	3.696	1.053	480
ED	10.450	10.51	8.557	12.01	0.650	480
E.D	2.174	2.173	1.853	2.562	0.113	480
ERU	0.918	0.971	−3.115	3.199	0.859	480
EI	2.596	2.620	1.396	3.383	0.372	480
FIN	1.078	1.045	0.374	2.025	0.310	480
GP	1.564	1.387	0.608	7.826	0.783	480
IS	0.092	0.0520	−0.641	1.667	0.390	480
MUR	1.994	2.017	1.212	2.479	0.258	480
PO	0.721	1.029	−2.588	3.676	1.354	480
TECHN	0.552	0.336	−0.942	2.159	0.593	480

Energy Statistical Yearbook, and China Statistical Yearbook, which provided environmental performance indicators and resource consumption data. The relevant data regarding OFDI and IFDI were extracted from the official websites of provincial statistical institutions, various provincial statistical yearbooks, and Wind Economic Database, covering financial inflows and outflows associated with FDI. Control variables, including industrial structure and economic development (GDP per capita), were collected from the National Bureau of Statistics, the Chinese Technology and Science Statistical Yearbook, and the Wind Economic Database. Supplementary data for variables such as labor, capital, energy consumption, and nominal GDP were also obtained from the China Statistical Yearbook and provincial bulletins, ensuring a robust and reliable data set for the analysis. The summary statistics for each variable are shown in Table 3.

3 | Empirical Outcomes

3.1 | GP Measurement

Figure 1 illustrates the GP trends from 2005 to 2020 for the nation and the eastern and midwestern regions. Over this period, GP showed a modest increase nationwide, with the eastern and midwestern regions following a similar upward trend. However, significant regional differences were observed, with the eastern region consistently surpassing the national average and the midwestern area's GP. The eastern region has managed to strike a more balanced relationship between environmental conservation and economic growth. In contrast, the midwestern region faces challenges in upgrading technology and enhancing pollution control due to financial, human, and technological limitations. High-pollution energy production continues to drive economic growth in the western areas, exacerbating the tension between economic efficiency and environmental preservation over time.

3.2 | The PEIFEs Findings

3.2.1 | Common Factors Determination and Threshold Influence Analysis Outcomes

After applying the enhanced singular value thresholding algorithm, the total number of common factors (R) was found to be 4. The Sup-Wald statistic was utilized to assess the threshold effect by Equations (8) to (10). The threshold

TABLE 4 | The findings based on the *R* test.

R	GP		CDU		CD		IS	
	Sup-Wald	*p* value	Sup-Wald	*p* value	Sup-Wald	*p* value	Sup-Wald	*p* value
1	28.683	0.002	16.071	0.006	25.093	0.003	10.983	0.010
2	53.318	0.000	21.442	0.002	35.834	0.001	8.962	0.011
3	69.422	0.000	23.087	0.001	28.670	0.000	35.832	0.000
4	87.281	0.000	35.114	0.000	51.766	0.000	63.478	0.000
5	40.920	0.000	10.906	0.002	17.429	0.000	20.581	0.000
6	40.112	0.000	9.793	0.002	22.558	0.000	27.584	0.000
7	24.246	0.000	11.656	0.001	26.860	0.000	11.638	0.001
8	31.733	0.000	17.466	0.000	27.289	0.000	25.746	0.000

Note: The enhanced SVT approach confirms the number of variables. The 500-times bootstrapped Sup-Wald statistic is applied to determine if the threshold influence is present. All the control variables are included in the evaluation methods.

TABLE 5 | The results based on the fixed effects.

Threshold variables	Sup-Wald	*p* value	No. of factors	Threshold value	95% CI	Grid samples	BS
GP	87.281***	0.000	4	1.572	[1.572, 1.572]	200	500
CDU	35.114***	00.00	4	2.187	[2.187, 2.187]	200	500
ED	51.766***	0.000	4	10.674	[10.674, 10.674]	200	500
IS	63.478***	0.000	4	0.053	[0.053, 0.053]	200	500

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

variables were ED, CDU, GP, and IS, with $R = 1, ..., 8$. Table 4 displays the statistics of Sup-Wald and conforming *p* values calculated from 500 bootstrap repetitions. All the control variables were included in the validation procedure. The statistic of Sup-Wald was ideal when $R = 4$, and the initial hypothesis that there was no threshold influence was excluded at 1% level.

Table 5, columns 3–7, illustrates the 95% assurance intermissions and statistical consequence of the framework's threshold results at $R = 4$. The initial hypothesis was rejected for each parameter at the 1% significance level, suggesting that CDU and GP have a nonlinear relationship. Specifically, the ED threshold value was 10.674, the manufacturing structure cutoff value was 0.0526, and the GP and CDU threshold values were 1.572 and 2.187, respectively.

3.2.2 | Assessment Findings

Table 6 presents the assessed outcomes for CDU, ED, GP, and IS as threshold variables, showing the CDU coefficients for both upper and lower threshold structures. The asymmetric association between GP and CDU was assessed using Equation (1). Overall, the impact of CDU on GP followed a "U"-shaped pattern, with the "U" shape shifting favorably or unfavorably as external conditions changed.

Specifically, when IS was below the threshold, CDU hindered GP growth. However, once IS exceeded the threshold, GP augmented by 0.016 units for every 1% rise in CDU, with significance at the 1% level. Similarly, the relationship between CDU and GP transitioned from negative to positive as ED increased. In regions with high ED, CDU significantly boosted GP, while in low ED regions, it had a strong negative effect, slowing GP growth. Beyond a certain threshold, CDU's ability to promote GP diminished, even impeding its growth. Additionally, while CDU positively influenced GP development in regions with higher GP growth, in areas with low GP growth, CDU had the opposite effect.

The nuanced and nonlinear findings of this study point toward an inverted-U relationship between coordinated FDI—both inward and outward—and GP, which corroborates and extends the existing literature. Previous studies, such as Zhang and Li (2020), emphasized the positive impact of inward and outward FDI on green productivity, yet they largely focused on these effects in segregation. In contrast, our empirical results show that the synchronization of FDI flows has a different impact in the "U shape" on GP, which is partly subject to regional heterogeneity. Our findings build on the work of past studies, which argued that regional heterogeneity plays an important role in FDI impacts, demonstrating that coordinated FDI has a more significant role in eastern China, where economic conditions are more advanced. This finding is supported by Uche, Chang, and Effiom (2022) and Uche, Chang, and Gohar (2022), who also highlighted the importance of contextual factors such as infrastructure and technological

TABLE 6 | The findings based on the dependent variable.

Threshold variable (p)				
Variables	**GP**	**lnCDU**	**lnED**	**lnIS**
lnCI	0.013*** (0.001)	−0.010*** (0.001)	0.023*** (0.001)	−0.011*** (0.001)
ln E.D	−0.183*** (0.003)	−0.426*** (0.003)	−0.477*** (0.003)	−0.300*** (0.003)
ln ER	0.019*** (0.000)	0.018*** (0.000)	0.023*** (0.000)	0.024*** (0.000)
ln FIN	0.089*** (0.002)	−0.015*** (0.002)	−0.088*** (0.002)	0.002*** (0.002)
lnMUR	0.038*** (0.002)	0.079*** (0.002)	0.177*** (0.002)	0.123*** (0.002)
lnPO	0.096*** (0.002)	0.159*** (0.002)	0.696*** (0.002)	0.160*** (0.002)
lnTEK	0.058*** (0.001)	0.072*** (0.001)	0.111*** (0.001)	0.061*** (0.001)
lnCDU×1 ($p > \mu$)	0.017*** (0.000)	−0.011*** (0.000)	0.029*** (0.000)	0.016*** (0.000)
lnCDU×1 ($p \leq \mu$)	−0.011*** (0.000)	0.004*** (0.000)	−0.001*** (0.000)	−0.014*** (0.000)
Observations	480	480	480	480

Note: It should be noted that the prefix "ln" indicates the use of the logarithmic form. 0.01 for ***, 0.05 for **, and $p < 0.1$ for *. Normal mistakes are enclosed in parentheses.

TABLE 7 | The results for the sensitivity analysis.

Variables	GP	lnCDU	lnED	lnIS
Threshold value	1.572	5.650	10.674	0.053
95% CI	[1.572, 1.572]	[5.650, 5.650]	[10.674, 10.674]	[0.053, 0.0523]
Sup-Wald p value	36.864*** (0.000)	34.743*** (0.000)	30.022*** (0.000)	21.404*** (0.000)
No. of factors	4	4	4	4
Control	Yes	Yes	Yes	Yes
lnCDFDI	−0.016*** (0.212)	0.005*** (0.212)	−0.006*** (0.214)	−0.014*** (0.152)
lnCDFDI	0.001*** (0.251)	−0.013*** (0.152)	0.021*** (0.251)	0.0004** (0.125)
Observations	541	541	541	541

Note: The anticipated coefficients of control variables can be obtained upon request and are not given for the sake of conciseness. The use of the prefix "ln" indicates the logarithmic form. $p < 0.01$ for ***, 0.05 for **, and 0.1 for *. Normal mistakes are enclosed in parentheses.

development. The policy implications are clear: government policies in eastern China should continue to encourage high-tech industries and provide R&D subsidies to maintain positive FDI-GP outcomes. In central and western China, where the FDI-GP relationship is more complex, policies should focus on improving infrastructure and human capital to attract higher-quality FDI and accelerate the adoption of green technologies. Sector-specific strategies in energy and manufacturing, such as targeted subsidies for clean energy investments and emissions-reducing technologies, are essential to promote sustainable growth in alignment with China's Dual Circulation strategy.

3.3 | Robustness Assessment

To check robustness, CDU was estimated using the interaction term between OFDI and IFDI as a proxy variable, namely OIFDI (1). The estimated result is similar to what was found in Section 3.2, with only a slight change in statistical significance, as shown in Table 7. This demonstrated the reliability of the estimation results and confirmed that the robustness assessment was satisfied.

3.4 | Heterogeneity Analysis

In the GP analysis, Section 3.1 highlighted the notable differences between GP in the eastern and midwestern regions. To further investigate this heterogeneity, the sample was split into separate regressions for these areas. The eastern region included eleven provinces—Hainan, Guangdong, Fujian, Zhejiang, Jiangsu, Shanghai, Shandong, Liaoning, Hebei, Tianjin, and Beijing—while the remaining provinces and cities comprised the midwestern area.

The regression results for the eastern region, presented in Table 8, show that the IS threshold was substantially higher than the national average. CDU had a significant positive impact on GP both below and above the IS threshold.

TABLE 8 | The empirical findings in the West area.

Threshold variable (*R*)				
Variables	**GP**	**lnCDU**	**lnED**	**lnIS**
Threshold value	1.351	1.357	10.159	0.105
95% CI	[1.351, 1.351]	[1.357, 1.357]	[10.159, 10.159]	[0.105, 0.105]
Sup-Wald *P*-value	1831.711*** (0.000)	284.886*** (0.000)	1012.392*** (0.000)	324.061*** (0.000)
No. of factors	4	4	4	4
Control	Yes	Yes	Yes	Yes
lnCDFDI	0.140*** (0.21)	−0.577*** (0.121)	−0.002*** (0.142)	0.120*** (0.125)
lnCDFDI	0.161*** (0.12)	−0.197*** (0.321)	0.172*** (0.125)	0.090*** (0.121)
Observations	201	201	201	201

Note: The anticipated coefficients of control variables can be obtained upon request and are not given for the sake of conciseness. The use of the prefix "ln" indicates the logarithmic form. $p < 0.01$ for ***, 0.05 for **, and 0.1 for *. Normal mistakes are enclosed in parentheses.

TABLE 9 | The empirical findings in the east area.

Threshold variable (*R*)				
Variables	**GP**	**lnCDU**	**lnED**	**lnIS**
Threshold value	1.083	1.581	10.553	−0.351
95%CI	[1.083, 1.083]	[1.581, 1.581]	[10.553, 10.553]	[−0.351,−0.351]
Sup-Wald *p* value	28.669*** (0.000)	18.548*** (0.000)	26.067*** (0.000)	82.396*** (0.000)
No. of factors	4	4	4	4
Control	Yes	Yes	Yes	Yes
lnCDU	−0.039*** (0.251)	−0.025*** (0.152)	−0.036*** (0.142)	0.018*** (0.152)
lnCDU	−0.016*** (0.251)	−0.052*** (0.142)	−0.014*** (0.152)	−0.036*** (0.1524)
Observations	189	189	189	189

Note: The anticipated coefficients of control variables can be obtained upon request and are not given for the sake of conciseness. The use of the prefix "ln" indicates the logarithmic form. $p < 0.01$ for ***, 0.05 for **, and 0.1 for *. Normal mistakes are enclosed in parentheses.

However, when CDU itself was the threshold variable, it initially had a negative impact on GP. Once the threshold was exceeded, this negative effect diminished. As GP grew, CDU's contribution increased, with the regression coefficient rising by 0.021 after the GP threshold was crossed.

In the midwestern region, the regression findings in Table 9 show that the impact of CDU on GP followed an inverted "U" shape, with the local criterion much higher than the IS threshold. Due to the region's inadequate economic growth, CDU had a moderating effect on GP, suggesting that improvements in financial and environmental conditions could enhance CDU's positive influence on GP. When CDU was the threshold variable, its negative impact on GP intensified as the threshold was exceeded. However, when GP was the threshold variable, CDU initially hindered GP growth, but as GP surpassed the threshold, the negative influence decreased, and the regression coefficient increased by 0.023. This indicates that as GP rises, CDU's negative impact weakens, offering room for improvement in the Midwest.

4 | Discussion

4.1 | IS as a Threshold Variable

The results show that as the industrial structure was modernized and optimized, the contribution of coordinated inward and outward FDI (CDU) to green total factor productivity (GP) increased. In the early stages of industrial transformation, high-emission sectors dominated, and the lack of public infrastructure and slow financial growth created obstacles to GP improvement. This agrees with the views of previous literature, who note that regions with poor industrial structures and inefficient energy consumption exhibit low productivity gains generated by FDI.

As industrial structures improved and low-energy-consuming sectors gradually replaced high-emission industries, particularly in eastern China, energy-efficient manufacturing techniques were adopted. These structural improvements reduced the negative effects of industrial inefficiencies on GP. Parallel to Xu, Jiang, and Wang (2022), who reveal that structural transformations in China's industrial sectors enhanced green productivity, the eastern region of China benefitted significantly from industrial modernization when combined with CDU.

On the other hand, the central and western regions experienced delays in industrial upgrading, inconsistent economic growth, disparities in organizational management optimization, and insufficient improvements in worker skills. These factors offset the potential of CDU to positively influence GP in these areas. As Feng, Wang, and Hu (2021) noted, regions with slower technological development and lower levels of human capital tend to see weaker green productivity gains from FDI. Therefore, these regions need targeted policies that focus on technological advancements and workforce skill improvement to fully leverage CDU for GP growth.

4.2 | ED as a Threshold Variable

Economic development (ED) played a significant role in determining how CDU affects GP. In highly economically developed regions, CDU significantly increased GP, while in less economically developed regions, CDU repressed GP. This finding supports the ecological Kuznets curve hypothesis, which suggests that as economic development increases, environmental degradation initially worsens but eventually declines as cleaner technologies are adopted. This pattern aligns with Wang, Xue, and Zhao (2022), who showed that in more developed regions, FDI leads to greater adoption of green technologies and improved environmental outcomes.

In less developed regions, where the economic development is still in its infancy, the contribution of CDU to GP is very minimal. Increased GDP per capita usually leads to higher pollution emissions and environmental degradation, especially when there exists an economic development bias against full environmental solicitude, for example, midwestern China. Similar to Dong, Zhang, and Liu (2021), less developed regions face more difficulties in achieving a balance between economic growth and environmental protection, which constrains the function of CDU in promoting GP.

However, at the critical point of economic development, the emitting of such pollutants decreases and environmental issues become curbed. At this stage, CDU significantly contributes to GP, promoting high-quality, sustainable economic development. Thus supporting the trend revealed in many cities in eastern China whose higher economies have allowed more room for investment in green technologies and FDI-caused productivity gains. Zheng, Zhou, and Wen (2022) found similar trends in countries with comparable developmental paths, where advanced economies have successfully leveraged FDI to achieve both economic and environmental objectives.

4.3 | CDU as a Threshold Variable

The effectiveness of CDU is highly contingent on external conditions. While subsidies, tariff reductions, and the removal of trade barriers may create favorable environments for the growth of both inward and outward FDI, there is a limit to CDU's influence on GP. This finding aligns with Teng et al. (2023), who demonstrated that the technological spillover effects of FDI are significant, but only up to a certain point where more advanced clean technologies and industrial optimization are required to sustain GP growth.

Without additional investments in research and development (R&D) and green technologies, the potential benefits of CDU begin to diminish. This is consistent with Wang, Xue, and Zhao (2022), who found that regions need to continually upgrade their industrial structures and increase R&D funding to maintain FDI's positive impact on green productivity. In addition, as the costs of energy conservation and emission reduction rise due to insufficient policy support and incentives, firms might be less motivated to pursue sustainable manufacturing. As a result, the cooperative effect of CDU on GP weakens, manifesting in a nonlinear, inverted "U"-shaped structure.

4.4 | GP as a Threshold Variable

The increasing relationship of CDU and GP is positively related with a higher degree of GP. Regions with the higher level of GP are more capable of attracting more human capital, carrying out sustainable innovation, and developing their economy to create a self-reinforcing effect. Liu and Peng (2019) argue that a wider regulation and policy package for green development would attract inbound FDI into projects that will meet sustainability criteria.

A higher GP also means greater ecological awareness among citizens, leading to better energy efficiency and higher demand for environmentally friendly products, which further supports GP growth. Regions like many eastern Chinese cities exemplify how CDU can maximize its impact when external conditions are favorable. This aligns with Chen et al. (2024), who found that regions with strong environmental governance frameworks tend to experience stronger FDI-driven improvements in sustainability outcomes.

Indeed, the policy focus on eco-friendly and sustainable growth, not necessarily rapid growth, is consistent with worldwide sustainability goals. Reinforcing positive effects of these policies on GP may continue through a self-reinforcing feedback loop between CDU and GP to attain higher-quality economic growth. This is also consistent with Pata et al. (2024), who argued that FDI should be aligned with ESG principles in order for economic growth to be sustainable.

5 | Conclusions and Policy Implications

This paper estimated GP and CDU using the SBM-GML and capacity coupling approaches, respectively, and then employed PTIFE models to examine the asymmetric impact of CDU on Green Total Factor Productivity across different regions of China. The results showed steady growth in GP from 2005 to 2020, with regional disparities gradually declining from east to west. A notable 'U'-shaped threshold effect emerged; GP is found to increase with higher economic development and more advanced industrial structures. While the impetus of CDU was negative in the initial stages in impacting GP, it tended to turn positive as regional conditions improved. The high economic development and robust industrial structures in eastern regions embraced significant positive impacts of CDU on GP, but for central and western regions with less-developed infrastructure, GP faces challenges in realizing such benefits.

This investigation investigates, for the first time, the nonlinear U-shaped relationship between Green Total Factor Productivity and coordinated inward and outward Foreign Direct Investment in light of China's Dual Circulation strategy. The study will uniquely investigate how synchronized FDI influences GP across regions through using the Panel Threshold Interactive Fixed Effects model, which accounts for threshold effects and regional heterogeneity. While earlier literature focuses on isolated impacts of FDI, the contribution here has factored in economic development and industrial structure as the main determining variables to explain the role of FDI in fostering sustainable growth.

To address regional disparities in GP, several actionable policies are recommended: first, implement industrial modernization programs with financial incentives to attract investment in clean energy and advanced manufacturing, particularly in central and western China by establishing technology hubs. Second, prioritize infrastructure development, including green infrastructure and special economic zones (SEZs) focused on sustainable industries. Third, a coordinated national FDI strategy will be required to guide investments into low-pollution industries, supported by available environmental tax credits and subsidies. Fourth, stricter environmental regulations can be promulgated and complemented by R&D grants that contribute to GP innovating even more. Finally, long-term incentive structures in the form of green investment funds and stabilization plans should be implemented to reduce risks caused by global uncertainties. In sum, these can be regarded as practicable viable measures which could drive sustainable growth in all regions of China.

The findings of this study provide clear policy directions for promoting GP and supporting China's sustainable economic growth, with a focus on the regional disparities observed. The study also highlights a U-shaped threshold effect, where regions with higher economic development benefit more from Coordinated Foreign Direct Investment (CDU). In addressing this, there should be industrial modernization in the central and western regions. It should focus investments in skilled labor and advanced technologies so that one could establish a link between CDU and regional development. Policies should focus more on advanced technologies and renewable energy investments in the eastern regions where CDU is already making a positive impact; infrastructure improvement and increasing investment in the central and western regions would make them better harness the benefit of CDU. What is also needed is a coordinated approach to FDI, especially in the context of the Dual Circulation and 'Belt and Road' initiatives, with incentives and grants that will channel FDI into high-value, low-pollution industries. Moreover, improvement in absorptive and adaptive capacity by GP, via environmental regulations, technological innovation, and access to markets, will play a crucial role in maintaining the growth of GP. Established technology trading markets, eradicating backward technologies, and strengthening mechanisms for environmental control would balance economic growth with environmental sustainability and directly address regional disparities and findings of this study.

With China advancing its Dual Circulation strategy and striving to meet carbon neutrality goals, these recommendations are timely. Coordinating FDI to support green growth aligns with global policy efforts aimed at achieving SDG and ESG targets. Emphasizing clean energy, modernizing industrial structures, and fostering technological innovation are essential for maintaining China's economic competitiveness while addressing sustainability challenges. This highlights the necessity of proposed policies to balance economic growth with environmental goals in today's global landscape.

This would therefore carry immense practical implications for both policymakers and businesses. Support for high-tech industries in the East and for green technologies could further reinforce GP growth. Investment in infrastructure and clean energy will contribute to attracting higher-quality FDI and help in sustainable development for central and western regions. These insights shall henceforth help companies in forming investment strategies that conform to regional strengths, while at the same time, donors will be able to design focused policies to encourage FDI in environmentally sustainable areas, in accordance with international goals such as SDGs and ESG principles.

In the world's condition today, in the face of unpredictable events such as a policy switch to climate policy, geopolitical tensions, COVID-19, or monetary disorders, the implementation of policies should be adaptable and resilient for the forthcoming period. To balance this volatility of climate policy, governments need to produce long-term incentives for green technologies and also urge sources of FDI toward de-escalation of risks due to geopolitical conflicts. As was witnessed during the pandemic, supply chains must be resilient, and digital infrastructure has to be totally embedded in industrial modernization. Policies should also consider a financial buffer, like a stabilization fund, to deal with monetary instability and support sustained GP growth as global conditions have become unstable.

This study is limited to regional data from China, which may restrict the generalizability of the results to other countries. Another key limitation is the focus on FDI and industrial modernization, leaving other potentially significant factors like innovation capacity or environmental policies largely unexplored. Future research could expand the model to other economies and include additional variables, such as digital transformation or climate policy uncertainty, to further understand sustainable growth. Additionally, exploring the long-term effects of coordinated FDI in different global contexts would offer deeper insights.

Author Contributions

Lihong Fan: conceptualization, writing–review and editing, funding acquisition, validation, data curation, resources. **Bisharat Hussain Chang:** investigation, writing–original draft, methodology, visualization. **Eunchan Kim:** software, formal analysis, project administration, supervision.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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