International Journal of Sustainable Development and Planning
Vol. 20, No. 12, December, 2025, pp. 5031-5042
Journal homepage: http://iieta.org/journals/ijsdp

Foreign Direct Investment Inflows and Green Technology Innovation: The Role of Institutional Quality

Thi Thu Giang Dang[1], Thi Dong Nguyen[2*]

[1] Faculty of Political Theory Studies, Academy of Finance, Hanoi 100000, Vietnam
[2] Training Department, Academy of Policy and Development, Hanoi 100000, Vietnam

Corresponding Author Email: dongnt@apd.edu.vn

https://doi.org/10.18280/ijsdp.201201

Received: 27 October 2025
Revised: 4 December 2025
Accepted: 11 December 2025
Available online: 31 December 2025

Keywords:
ASEAN, GTI, FDI, institutional quality, technology spillover effect

ABSTRACT

In the context of emerging economies facing the dual challenge of economic growth and environmental protection, foreign direct investment (FDI) is expected to be a crucial channel for green technology transfer. However, empirical evidence on the impact of FDI on green technology innovation (GTI) remains divided between the "Pollution Halo" and "Pollution Haven" hypotheses. Existing studies primarily view institutional quality (IQ) as a factor that enhances an already positive impact of FDI, rather than examining whether institutions are a prerequisite for that positive impact to emerge. This study, conducted in five ASEAN countries (ASEAN-5), aims to test the impact of FDI on GTI and, specifically, to analyze the moderating role of IQ. Using panel data for the period 2002-2021 with 88 observations, applying the System GMM estimation method combined with an FDI × IQ interaction term model, and identifying the institutional threshold through marginal effect analysis. The results show that FDI has no statistically significant direct impact on GTI (β_1 = -0.015, $p > 0.1$), while the positive and highly significant interaction term coefficient (β_3 = 0.150, $p < 0.01$) implies that IQ plays a decisive moderating role. Concurrently, the IQ threshold is identified at IQ = 0.1, indicating that FDI only promotes green innovation when IQ surpasses the global average. The study reconciles the two opposing hypotheses by demonstrating that IQ is the decisive variable determining which scenario prevails, while also implying that ASEAN countries must prioritize comprehensive institutional reforms to enhance their technological absorptive capacity and transform FDI into a true driver of green growth.

1. INTRODUCTION

The world is facing a dual challenge of our time: sustaining economic growth while confronting the increasingly severe consequences of climate change and environmental degradation. Landmark international commitments such as the Paris Agreement on climate change and the United Nations' Sustainable Development Goals (SDGs) have created a global impetus, pushing nations to transition towards a green and sustainable economic model [1, 2]. In this transition, green technology innovation (GTI) is considered a foundational solution, expected to break the historical link between economic growth and resource depletion, allowing economies to develop without environmental costs [3, 4].

For emerging economies, particularly those in the Association of Southeast Asian Nations (ASEAN), this challenge is even more pressing. The ASEAN-5 region (comprising Indonesia, Malaysia, Philippines, Thailand, and Vietnam) has been witnessing impressive economic growth, largely driven by abundant foreign direct investment (FDI) inflows [5]. However, this growth trajectory has also been accompanied by severe environmental pressures, from air and water pollution to the depletion of natural resources [6, 7]. This raises a core policy question: how can these nations leverage external resources, especially FDI, to "green" their development paths and achieve sustainable prosperity?

Theoretically, FDI inflows are seen as a vital conduit, bringing not only capital but also advanced technology and managerial knowledge to host countries. In the environmental sphere, the academic debate on the impact of FDI on GTI is divided into two main schools of thought. On one hand, the "Pollution Halo Hypothesis" posits that FDI from developed countries often brings cleaner, more energy-efficient production technologies and higher environmental management standards than those of domestic firms [8-10]. The presence of these multinational corporations (MNCs) can create green technology spillover effects through competition, supply chain linkages, and the mobility of skilled labor, thereby boosting the green innovation capacity of the entire economy [11].

On the other hand, the "Pollution Haven Hypothesis" presents a contrasting scenario. This hypothesis argues that, to evade stringent environmental regulations in their home countries, MNCs tend to relocate resource-intensive and polluting industries to countries with laxer environmental regulations [12, 13]. In this case, FDI not only fails to promote but may even hinder the process of GTI and exacerbate environmental problems in the host country. The coexistence of these two hypotheses, along with conflicting empirical results in previous studies, suggests that the relationship between FDI and GTI is a complex and context-dependent interaction.

This inconsistency suggests that the impact of FDI is deeply dependent on the specific conditions of the host country, with institutional quality (IQ) being considered a key moderating factor. Based on institutional theory, the formal (e.g., laws, regulations) and informal (e.g., social norms) "rules of the game" strongly shape the incentives and behaviors of economic agents, including MNCs [14]. A sound institutional environment—characterized by the rule of law, strong protection of intellectual property rights, low levels of corruption, and government effectiveness—reduces transaction costs and risks for economic activities, thereby encouraging MNCs to make long-term investments, transfer advanced technology, and engage in R&D activities in the host country [15-17]. Conversely, weak institutions create an unstable environment, encouraging short-term, resource-extractive investments and rent-seeking behaviors that are detrimental to the environment.

However, existing studies examining the role of institutions have predominantly viewed it as an amplifying factor—a mechanism that enhances an assumed pre-existing positive impact of FDI [18]. This study challenges that traditional "amplification" view by asking a more fundamental question: what if IQ is not merely a factor that adjusts the intensity of FDI's impact, but a prerequisite that determines whether a positive impact can emerge in the first place? Instead of just asking *how much* institutions affect green technology transfer, we investigate *whether* the expected green benefits from FDI can be realized in the absence of a sufficiently strong institutional framework.

Based on the identified research gap and the theoretical foundation analyzed, this paper sets two specific research objectives:

(i) To re-examine the direct impact of FDI inflows on GTI in the ASEAN-5 countries.

(ii) To analyze the moderating role of IQ in the relationship between FDI and GTI, specifically testing the hypothesis that high-quality institutions are a prerequisite for activating the positive impact of FDI.

By addressing these objectives, this study expects to contribute new empirical evidence that clarifies the complex role of IQ within the specific context of the ASEAN-5 economies. These findings will not only have academic significance but also provide important implications for ASEAN policymakers in their efforts to forge a sustainable development path.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

2.1 Theoretical foundation

This study is built upon a combination of three core theoretical pillars that interact to explain the complex relationship between FDI, IQ, and GTI.

Technology spillover theory provides the mechanism explaining the transmission channel from FDI to the innovative capacity of the host country. According to Blomström and Kokko [19], MNCs bring with them knowledge capital, advanced technology, and managerial capabilities, thereby creating spillover effects through competition, supply chain linkages, and the mobility of skilled labor. However, studies also indicate that this spillover effect is not automatic but depends on the absorptive capacity of the host economy [20]. Absorptive capacity is defined as the ability to recognize, assimilate, and apply new external knowledge, which is governed by foundational factors such as human capital, research infrastructure, and especially the institutional environment.

Institutional theory, as articulated by North [14], adds explanatory depth to this relationship by asserting that institutions, including both formal and informal rules, shape the behavior and incentives of economic agents. A high-quality institutional environment, characterized by the rule of law, protection of intellectual property rights, and effective control of corruption, reduces transaction costs and risks for foreign investors [21, 22]. This encourages MNCs to undertake long-term investments, transfer core technology, and engage in research and development activities in the host country, rather than merely exploiting cheap labor or evading environmental regulations.

The combination of these three theories forms an integrated analytical framework: technology spillover theory explains the *potential* of FDI to promote green innovation; absorptive capacity theory indicates that this potential is only realized when the host country has sufficient capacity to receive it; and institutional theory identifies IQ as the key factor determining that absorptive capacity. Therefore, IQ is not just a contextual factor but acts as a prerequisite for realizing the positive link between FDI and GTI.

2.2 Hypothesis development

2.2.1 FDI and GTI

Theoretically, the presence of MNCs can generate green technology spillover effects through three main mechanisms: a competition effect that forces domestic firms to upgrade their technology; a vertical linkage effect where local suppliers must meet the environmental standards of their foreign partners; and a labor mobility effect as employees carry knowledge and skills to other firms [23, 24].

However, empirical evidence on this relationship is inconsistent. Some studies find a positive impact of FDI on green innovation in developed and emerging economies [25, 26]. Conversely, many other studies report insignificant or even negative impacts, especially in countries with lax environmental regulations [13, 27]. An analysis of Chinese cities shows that inward FDI has an inhibitory effect on GTI, whereas outward FDI exhibits a promotional effect [28]. This finding challenges the assumption that FDI universally promotes green innovation and suggests that the direction and quality of investment flows matter significantly. In the ASEAN context, Shabir et al. [5] indicate that FDI is associated with increased carbon emissions, suggesting that these capital inflows are not yet truly oriented towards green objectives. This inconsistency indicates that the impact of FDI is deeply dependent on the context and specific conditions of the host country, rather than being an automatic effect. Therefore, this study proposes:

H1. *FDI inflows do not have a direct positive impact on GTI in the ASEAN-5 countries when considered independently.*

2.2.2 The moderating role of IQ

In the relationship between FDI and green innovation, IQ acts as a moderating mechanism through two channels. First, a strong institutional environment with strict protection of intellectual property rights encourages MNCs to transfer advanced technology rather than just obsolete technology [16]. Second, high-quality institutions are often accompanied by effectively enforced environmental regulations, compelling all firms to compete based on efficiency and innovation rather than exploiting legal loopholes [16, 29].

Empirical studies have provided evidence supporting this moderating role. Wang et al. [18] and Udo et al. [30] demonstrate that IQ enhances the positive impact of FDI on economic growth and environmental quality in African countries. Furthermore, research on green FDI in European countries shows that the positive impact of green FDI on environmental innovation is greater in countries with highly developed institutional systems [31]. This finding suggests that IQ not only facilitates the attraction of environmentally beneficial FDI but also enhances its effectiveness in promoting green innovation. This moderating effect is particularly pronounced in the context of digital innovation and environmental outcomes. The study by Ren et al. [32] indicates that the institutional environment can amplify the positive impact of technological innovation on environmental quality, especially in regions with well-developed institutional environments.

However, existing studies primarily view institutions as a factor that enhances an already positive impact of FDI, rather than testing whether institutions are a prerequisite for that impact to emerge. Based on the above reasoning, this study proposes:

H2. *IQ positively moderates the relationship between FDI and GTI, whereby the impact of FDI on green innovation becomes more positive as IQ improves.*

3. RESEARCH METHODOLOGY

3.1 Econometric model

To examine the moderating role of IQ (Hypothesis H2) in the relationship between FDI and GTI (Hypothesis H1), we construct a dynamic panel regression model that incorporates an interaction term. The baseline model is specified as follows:

$$GTI\_log_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 IQ_{it} + \beta_3(FDI_{it} \times IQ_{it}) + \beta_4 GDP\_Growth_{it} + \beta_5 Trade\_Openness_{it} + \beta_6 HC_{it} + \beta_7 RD_{it} + \mu_i + \nu_t + \varepsilon_{it}$$

where,

- *i* and *t* are the indices for country (i = 1,...,5) and year (t = 2002,...,2021), respectively.
- GTI_log_{it}: The dependent variable, which is the natural logarithm of the total number of patents in environmental technology fields plus one for country *i* in year *t*.
- FDI_{it}: The main independent variable, measured as net FDI inflows as a percentage of GDP.
- IQ_{it}: The moderating variable, a composite index of IQ constructed using Principal Component Analysis (PCA).
- $FDI_{it} \times IQ_{it}$: The interaction term between FDI and IQ. The coefficient β_3 is the primary interest of this study, representing how the impact of FDI on GTI changes at different levels of IQ. A positive and statistically significant β_3 coefficient would support the hypothesis that good institutions activate or amplify the positive impact of FDI on GTI.
- A vector of control variables (Z_{it}), including:
  - GDP_Growth_{it}: Annual real GDP growth rate (%).
  - $Trade\_Openness_{it}$: Trade openness, measured as the sum of exports and imports as a percentage of GDP (%).
  - HC_{it}: Human capital, measured by the average years of schooling.
  - RD_{it}: Research and Development (R&D) expenditure as a percentage of GDP (%).
- μ_i: Unobserved and time-invariant country-fixed effects (e.g., geography, culture), which control for the unique characteristics of each country.
- ν_t: Time-fixed effects, which control for common shocks affecting all countries in the sample at a given time (e.g., the 2008 global financial crisis, the COVID-19 pandemic).
- ε_{it}: The random error term, assumed to be independently and identically distributed.

3.2 Data and variable measurement

This study uses a panel dataset for 5 ASEAN countries, including Indonesia, Malaysia, the Philippines, Thailand, and Vietnam, over a 20-year period from 2002 to 2021.

Rationale for the period (2002-2021): This period was chosen based on two main reasons. First, it ensures the availability and consistency of data on IQ from the Worldwide Governance Indicators (WGI) dataset, which has been published annually since 2002. Second, this 20-year span is long enough to observe changes in policies, FDI flows, and innovation outcomes, while also covering significant socio-economic events like the 2008 financial crisis and the initial phase of the COVID-19 pandemic, allowing the model to control for common macroeconomic shocks.

Rationale for the sample (ASEAN-5): The focus on the ASEAN-5 group is deliberate. These are the five largest and most dynamic economies in the ASEAN bloc, and leading destinations for FDI inflows in the region. Although they belong to the same economic bloc, these 5 countries exhibit significant differences in their levels of development, economic structure, and especially IQ. This diversity within homogeneity creates a suitable context for testing the moderating role of institutions on the impact of FDI.

Data processing procedure: Data were compiled from various reputable sources (see Table 1). After removing observations with missing critical data (mainly the R&D expenditure variable in some early years), the final dataset is an unbalanced panel data with a total of 93 country-year observations. However, in the System GMM models, the sample size decreases to 88 observations. This reduction of 5 observations is due to two reasons. First, including the lagged dependent variable GTI_log(t-1) in the model results in the loss of the first year of observation for each country (5 observations). Second, the difference equation in System GMM requires continuous data for at least two consecutive periods, leading to the additional removal of some scattered missing data points.

Table 1. Description of variables and data sources

Variable	Symbol	Measurement and Calculation	Data Source
		Dependent variable	
Green technology innovation	GTI_log	Natural logarithm of (Total number of patents in environment-related technologies + 1).	OECD Statistics (OECD.Stat)
		Independent & moderating variables	
Foreign direct investment	FDI	Net inflows of Foreign Direct Investment as a percentage of GDP.	World Bank - World Development Indicators (WDI)
Institutional quality	IQ	The first principal component (PC1) from PCA on the six WGI indicators (VA, PV, GE, RQ, RL, CC).	World Bank - Worldwide Governance Indicators (WGI)
		Control variables	
Economic growth	GDP_Growth	Annual growth rate of real GDP (%).	World Bank - WDI
Trade openness	Trade_Openness	(Exports + Imports of goods and services) / GDP (%).	World Bank - WDI
Human capital	HC	Average years of schooling for the population aged 25 and over (data are linearly interpolated for missing years).	Barro-Lee Educational Attainment Dataset (2013)
R&D expenditure	RD	Gross expenditure on research and development (% of GDP).	World Bank - WDI & UNESCO Institute for Statistics

Note: The six WGI used to construct the IQ index are: VA = Voice and Accountability; PV = Political Stability and Absence of Violence/Terrorism; GE = Government Effectiveness; RQ = Regulatory Quality; RL = Rule of Law; CC = Control of Corruption.
Sources: Data are compiled by the authors from the OECD Statistics database, the World Bank's World Development Indicators (WDI) and WGI databases, the Barro-Lee Educational Attainment Dataset, and the UNESCO Institute for Statistics database.

To mitigate the influence of outliers that could bias the regression results, all continuous variables in the model were winsorized at the 1st and 99th percentiles. Winsorizing at the 1% and 99% levels affects a maximum of 2 observations at each tail of the distribution for each variable. Specifically, 4 observations (2 at the lower tail and 2 at the upper tail) of the FDI variable and 3 observations of the Trade_Openness variable had their values adjusted. The remaining variables did not have extreme values exceeding the winsorization threshold.

GTI (GTI_log): Following the convention in innovation studies [33], we use patent data as a proxy for the output of innovation activities. Specifically, GTI is measured by the number of patents in environment-related technology fields filed by inventors from the host country, according to the OECD classification. We acknowledge the limitations of this measure: not all innovations are patented, and the economic value of patents varies. However, it is an objective, quantifiable, and comparable measure across countries, reflecting formal inventive efforts in the green technology sector. Taking the logarithm of (number of patents + 1) is a standard technique to handle the issue of zero values and reduce the skewness of the data distribution.

IQ: IQ is a multidimensional concept. Instead of choosing a single indicator that could lead to omitted variable bias, we apply Principal Component Analysis (PCA) to construct a composite index. This method extracts common information from the six component indicators of the WGI dataset [34]. The first principal component (PC1) explains 71.3% of the total variance with an eigenvalue of 4.28, indicating that the six WGI indicators are highly correlated and that PC1 effectively captures the common dimension of IQ. The factor loadings of PC1 range from 0.35 to 0.45, specifically: Government Effectiveness has the highest value (0.45), followed by Rule of Law (0.44), Regulatory Quality (0.43), Voice and Accountability (0.42), Control of Corruption (0.41), and Political Stability (0.35). The relative uniformity of the loadings suggests that all six institutional dimensions contribute significantly to the composite index.

FDI: The FDI variable is measured as net FDI inflows as a percentage of GDP. This is a standard international measure that reflects the relative importance of FDI to the size of the host economy, allowing for a meaningful comparison of the economic significance of these capital flows across countries with different GDP sizes.

The table below summarizes the variables used in the study.

3.3 Analysis procedure and estimation strategy

The analysis procedure is designed to systematically address econometric challenges, ensuring that the estimation results are robust and reliable.

Preliminary Analysis: Before proceeding with regression, we conduct descriptive statistical analysis to grasp the basic characteristics of the data (mean, standard deviation, min, max) and correlation matrix analysis to preliminarily examine the relationships between variables and detect potential signs of multicollinearity.

Static Panel Estimations and the Issue of Cross-Sectional Dependence: We begin with traditional static panel models, including Pooled OLS, Fixed Effects (FE), and Random Effects (RE) models. The Hausman test is used to choose between FE and RE. However, a potential concern in panel data analyses, especially with country-level samples, is the presence of cross-sectional dependence. This occurs when macroeconomic shocks or specific events simultaneously affect all countries in the sample. If not controlled for, this phenomenon can lead to biased standard error estimates. Therefore, we will use the Pesaran (2004) test to detect cross-sectional dependence. If this phenomenon exists, to thoroughly address the problems of heteroskedasticity, autocorrelation, and cross-sectional dependence, we will re-estimate the FE model using Driscoll–Kraay [35] standard errors. This method produces standard errors that are robust and consistent even in the presence of very general forms of cross-sectional dependence.

Main Estimation using System GMM developed by Arellano and Bover [36] and Blundell and Bond [37]: We recognize that applying System GMM with N = 5 countries requires special caution. However, the choice of this method remains appropriate for three reasons. First, System GMM is designed to address endogeneity in dynamic panel data, a core feature of the technological innovation process that static methods cannot handle. Second, with T = 20 years, the relatively high T/N ratio helps mitigate the standard error issues commonly found in small-N samples. Third, many macroeconomic studies have successfully applied GMM to small country samples when there is a strong theoretical basis for dynamics and endogeneity [38].

To ensure the robustness of the GMM estimates, we perform two crucial specification tests: (i) The Sargan/Hansen test: This tests the null hypothesis H_0 that the instruments are valid (uncorrelated with the error term); (ii) The Arellano-Bond test for autocorrelation: This checks for the presence of autocorrelation in the differenced errors. The model is considered well-specified if there is evidence of first-order autocorrelation (AR(1)) but no evidence of second-order autocorrelation (AR(2)). We also implement the following control measures: (i) limiting the depth of instruments to a maximum of 2 lags to avoid the problem of too many instruments; (ii) using the collapse option to reduce the instrument matrix; and (iii) including time dummies in the model to control for common shocks. The FDI variable and the FDI × IQ interaction term are treated as endogenous variables, with their lags from t-2 and earlier used as instruments in the difference equation. Additionally, we supplement with two reference estimators. The first is the bias-corrected LSDV (LSDVC) model by Bruno [39], suitable for dynamic panel data with small N. The second is a dynamic FE model with Driscoll-Kraay standard errors.

Robustness Checks: To answer the question of whether the results are sensitive to choices of model and variables, we will perform a series of robustness checks: (i) Using an alternative measure: To check if the results depend on how the key variable is measured, we will re-estimate the model using an alternative measure for IQ, such as using only the "Rule of Law" index from WGI; (ii) Changing the set of control variables: We will sequentially remove each control variable from the model to check if the coefficients of the main variables (FDI, IQ, and the interaction term) change significantly; (iii) Checking for non-linear relationships: To explore the possibility of more complex relationships, we will test for a non-linear threshold by adding the square of the FDI variable (FDI^2) to the model.

All estimations and tests in this study are performed using the specialized statistical software Stata version 17.

4. RESEARCH RESULTS

4.1 Descriptive statistics and correlation analysis

Before proceeding with the regression analysis, we conduct descriptive statistics and correlation matrix analyses to examine the overall distribution of the data and initial relationships, while also helping to check for potential issues such as multicollinearity.

Table 2 presents the descriptive statistics for all variables used in the model for the 2002-2021 period.

The descriptive statistics in Table 2 reveal several notable characteristics of the research sample. The level of GTI (GTI_log) has a mean of 1.854 with a fairly large standard deviation (1.302), reflecting a significant disparity in green innovation capacity among the 5 ASEAN countries. Average FDI inflows account for 4.621% of GDP, but are also highly volatile with a high standard deviation (2.897) and a wide range from -0.530% to 11.98%, indicating instability and competition in attracting FDI within the region. Notably, the IQ index has a negative mean (-0.211), suggesting that, as a whole, the ASEAN-5 group still has considerable room for improvement in its institutional environment compared to the global average. The institutional differences within the bloc are also very clear, with the IQ index ranging from -1.452 to 0.987. This context reinforces the suitability of selecting the ASEAN-5 sample to test the moderating role of institutions. Additionally, R&D expenditure (RD) averages only 0.398% of GDP, a relatively modest figure characteristic of many developing economies.

The correlation matrix in Table 3 provides initial clues about the relationships between the variables. First, green technology innovation (GTI_log) is positively correlated with all independent and control variables, especially with IQ (r = 0.388), Human Capital (HC) (r = 0.412), and R&D Expenditure (RD) (r = 0.351). A positive correlation between FDI and GTI_log (r = 0.215) is also noted. These correlations provide initial support for our research hypotheses, suggesting that FDI, good institutions, and a nation's internal factors could all be drivers of green innovation.

Table 2. Descriptive statistics

Variable	Symbol	Observations	Mean	Std. Dev.	Min	Max
Green technology innovation	GTI_log	93	1.854	1.302	0.000	4.796
Foreign direct investment	FDI	93	4.621	2.897	-0.530	11.98
Institutional quality	IQ	93	-0.211	0.655	-1.452	0.987
Economic growth	GDP_Growth	93	5.033	3.104	-2.780	8.950
Trade openness	Trade_Openness	93	124.67	45.81	61.25	210.43
Human capital	HC	93	8.876	1.059	7.120	10.74
R&D expenditure	RD	93	0.398	0.312	0.080	1.430

Source: Authors' calculation based on data sources mentioned in Table 1.

Table 3. Pearson correlation matrix

Variable	1	2	3	4	5	6	7
(1) GTI_log	1.000						
(2) FDI	0.215	1.000					
(3) IQ	0.388	0.342	1.000				
(4) GDP_Growth	0.109	0.287	0.156	1.000			
(5) Trade_openness	0.176	0.411	0.203	0.355	1.000		
(6) HC	0.412	0.298	0.543	0.189	0.251	1.000	
(7) RD	0.351	0.199	0.488	0.097	0.145	0.495	1.000

Source: Authors' calculation.

Second, and importantly for the subsequent regression analyses, the correlation coefficients between the explanatory variables in the model all have absolute values significantly lower than the 0.8 threshold, a commonly used benchmark to warn of severe multicollinearity. The highest correlation coefficient recorded is between IQ and Human Capital (HC) ($r = 0.543$), a relationship that is economically justifiable but still within a safe range. Therefore, it can be preliminarily concluded that multicollinearity is not a major concern, allowing us to proceed with the regression analyses reliably.

4.2 Results from static panel estimations

To establish a foundation for the analysis and diagnose potential econometric issues, we begin by estimating static panel models. Table 4 presents the results from the Pooled OLS (column 1), FE (column 2), RE (column 3), and FE with Driscoll-Kraay standard errors (FE-DK, column 4) regression models. The purpose of this analysis step is not only to compare different estimation methods but also to justify the need for the more complex dynamic models presented in the next section.

The choice between the FE and RE models is made through the Hausman test. The Hausman test result yields a p-value of 0.008 (less than 0.01), allowing us to reject the null hypothesis that individual country effects are uncorrelated with the explanatory variables. This indicates that the FE model is more appropriate and provides more consistent estimates than the RE model for our dataset. Therefore, subsequent interpretations will focus on the results of the FE model.

However, a major concern with country-level panel data, especially in an integrated region like ASEAN, is the presence of cross-sectional dependence, caused by common shocks (e.g., regional financial crises, global trade policy changes) that simultaneously affect the countries. The Pesaran [40] test, performed on the residuals of the FE model, confirms the existence of this problem at a 1% significance level (p-value = 0.002). The presence of cross-sectional dependence implies that the standard errors of the traditional FE model (column 2) may be biased and unreliable, leading to erroneous statistical inferences.

To address this issue, we re-estimate the FE model with Driscoll–Kraay (FE-DK) standard errors, presented in column (4). This method provides robust standard errors that are consistent in the presence of cross-sectional dependence, autocorrelation, and heteroskedasticity. The results from the FE-DK model show some noteworthy points. First, after controlling for country-fixed characteristics and econometric issues, the direct impact of FDI on GTI (GTI_log) is not statistically significant (coefficient = 0.021, p-value > 0.1). This suggests that, when considered independently, FDI inflows into the ASEAN-5 may not automatically translate into green innovation activities.

Second, and more importantly, the interaction term (FDI × IQ) has a positive coefficient (0.115) and is statistically significant at the 5% level. This is a key finding, providing strong preliminary evidence in support of our second research hypothesis: IQ plays a crucial moderating role. The positive sign of the interaction coefficient implies that the impact of FDI on GTI is more positive in countries with better IQ. In other words, a strong institutional environment appears to be a necessary condition to "activate" or "amplify" the potential green technology benefits from FDI inflows.

Although the results from the FE-DK model have provided important insights into the moderating role of institutions, these static models still do not fully address potential endogeneity issues, such as two-way causality between FDI and GTI, or omitted variable bias. Therefore, to obtain more robust and causally reliable estimates, we will use the System GMM estimation method in the next section of the analysis.

Table 4. Regression results from static panel models

Variable	(1) Pooled OLS	(2) FE	(3) RE	(4) FE-DK
FDI	0.058**	0.021	0.043*	0.021
	(0.025)	(0.031)	(0.024)	(0.029)
IQ	0.485***	0.315**	0.401***	0.315**
	(0.131)	(0.140)	(0.128)	(0.135)
FDI × IQ	0.092**	0.115**	0.103**	0.115**
	(0.041)	(0.048)	(0.043)	(0.051)
GDP_Growth	0.013	0.009	0.011	0.009
	(0.010)	(0.012)	(0.010)	(0.013)
Trade_Openness	0.004*	0.005	0.004*	0.005
	(0.002)	(0.003)	(0.002)	(0.004)
HC	0.351***	0.289*	0.327***	0.289*
	(0.098)	(0.151)	(0.105)	(0.166)
RD	0.512**	0.407*	0.459**	0.407*
	(0.210)	(0.235)	(0.208)	(0.221)
Constant	-2.876***	-1.998*	-2.514***	-1.998*
	(0.850)	(1.105)	(0.912)	(1.154)
Observations	93	93	93	93
Number of countries	5	5	5	5
R^2 (within)		0.684		0.684
R^2 (overall)	0.457		0.449	
Hausman test (p-value)			0.008	
Pesaran CD test (p-value)				0.002

Source: Authors' calculation.

Notes: Values in parentheses () are standard errors. Column (4) uses Driscoll-Kraay (1998) robust standard errors, which are robust to cross-sectional dependence, autocorrelation, and heteroskedasticity. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.3 Main estimation results: System GMM

To thoroughly address potential endogeneity issues such as the dynamic nature of the innovation process, two-way causality, and omitted variable bias that static models cannot handle, we employ the System Generalized Method of

Moments (System GMM) estimation. This is our main estimation method, providing the core and most reliable results to answer the two proposed research hypotheses. Table 5 presents the estimation results from the System GMM model.

Table 5. System GMM estimation results on the impact of FDI and IQ on GTI

Variable	(5) System GMM
GTI_log(t-1)	0.512***
	(0.108)
FDI	-0.015
	(0.028)
IQ	0.254***
	(0.089)
FDI × IQ	0.150***
	(0.050)
GDP_Growth	0.007
	(0.009)
Trade_openness	0.003
	(0.003)
HC	0.188**
	(0.081)
RD	0.305***
	(0.102)
Constant	-1.542*
	(0.833)
Observations	88
Number of countries	5
Number of instruments	28
Hansen test (p-value)	0.254
AR(1) test (p-value)	0.021
AR(2) test (p-value)	0.318

Source: Authors' calculation.

Notes: Values in parentheses are robust standard errors. The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is GTI_log.

GMM Specification Details: The model is estimated using two-step System GMM with Windmeijer [41] finite-sample corrected standard errors. Variable treatment: GTI_log(t-1), FDI, and FDI × IQ are treated as endogenous variables, instrumented with their own lags dated t-2 and earlier (GMM-style instruments). IQ is treated as predetermined, instrumented with lags dated t-1 and earlier. GDP_Growth, Trade_Openness, HC, and RD are treated as exogenous (IV-style instruments). The collapse option is applied to limit instrument proliferation. The maximum lag depth for instruments is restricted to 2. Year dummies are included but not reported. The instrument count (28) is kept below the number of cross-sectional units times time periods to avoid instrument proliferation bias.

Before analyzing the coefficients, we validate the GMM model. The p-value of the Hansen test is 0.254 (greater than 0.1), indicating that the null hypothesis of the validity of the instruments used cannot be rejected. Furthermore, the Arellano-Bond test for autocorrelation shows the presence of first-order autocorrelation (AR(1) with p-value = 0.021) and no evidence of second-order autocorrelation (AR(2) with p-value = 0.318), fully meeting the requirements of a well-specified GMM model. The coefficient of the lagged variable GTI_log(t-1) is positive and highly statistically significant, confirming the dynamic and cumulative nature of GTI.

Analysis of results related to Hypothesis H1: The results from the System GMM model (Table 5) show that the coefficient of the FDI variable is -0.015 and is not statistically significant. This finding, after controlling for endogeneity issues, provides strong evidence to conclude that FDI inflows, when considered independently, do not generate a direct positive impact on GTI in the ASEAN-5 countries. This challenges the "Pollution Halo Hypothesis" in the absence of supportive conditions and suggests that merely attracting FDI is insufficient to promote a green transition.

Analysis of results related to Hypothesis H2: Conversely, the most important finding of this study lies in the interaction term. The coefficient of the FDI × IQ variable is 0.150, positive, and statistically significant at the 1% level. This strongly supports our second research hypothesis: IQ plays a pivotal moderating role. More specifically, the impact of FDI on GTI is positively dependent on the level of IQ in the host country. Good institutions not only amplify but are also a prerequisite for activating the positive impact of FDI. This finding suggests that in a weak institutional environment, FDI may not yield green technology benefits and may even pose a risk of a "Pollution Haven."

Threshold Effect Analysis: To further clarify this "activation" role, we calculate the marginal effect of FDI on GTI ($\partial GTI\_log/\partial FDI = \beta_1 + \beta_3 IQ$) and determine the threshold value of IQ at which this effect turns from negative/insignificant to positive.

Based on the results in Table 5, the marginal effect is calculated as follows:

$$\partial GTI\_log / \partial FDI = -0.015 + 0.150 \times IQ$$

Setting the marginal effect to zero, we find the threshold value of IQ:

$$0 = -0.015 + 0.150 \times IQ \Longrightarrow IQ = 0.015 / 0.150 = 0.1$$

This implies that only when a country reaches a certain level of institutional "maturity" (an IQ index exceeding the 0.1 threshold) do FDI inflows begin to contribute positively to green innovation efforts. Given the sample's average IQ of -0.211 (from Table 2), this result implies that for an "average" ASEAN-5 country during the study period, the overall impact of FDI on green innovation was still negative. Only those countries with outstanding institutional reform efforts that achieve an IQ index above the 0.1 threshold can truly leverage the green technology spillover effects from FDI.

To assess the uncertainty of the IQ = 0.1 threshold, we use the delta method to calculate the standard error for the ratio $-\beta_1/\beta_3$. With $\beta_1 = -0.015$ (SE = 0.028) and $\beta_3 = 0.150$ (SE = 0.050), the 95% confidence interval for the IQ threshold is estimated to be [-0.28, 0.48]. This relatively wide confidence interval reflects the inherent uncertainty in estimations with a small sample, but importantly, the entire interval lies within the observable range of the IQ variable in the sample (from -1.452 to 0.987), indicating that the threshold is practically meaningful.

The Johnson-Neyman analysis identifies the range of IQ values where the marginal effect of FDI on GTI is statistically significant. The results show that the marginal effect of FDI becomes positive and statistically significant at the 5% level when $IQ \geq 0.35$. Conversely, the marginal effect is negative and statistically significant when $IQ \leq -0.52$. In the IQ range from -0.52 to 0.35, the marginal effect is not statistically different from zero.

Figure 1 presents a graph of the marginal effect of FDI on GTI at different levels of IQ, accompanied by a 95% confidence interval.

Figure 1 shows that the marginal effect of FDI on green innovation is conditionally dependent on IQ. Specifically, in the Negative Effect Zone (IQ < 0.1), FDI does not promote green innovation. Most ASEAN-5 countries fall in this zone. In the Positive Effect Zone (IQ > 0.1), FDI promotes green innovation when IQ exceeds the threshold.

4.4 Robustness checks

To ensure that the main estimation results are not spurious due to specific model or variable choices, but are indeed robust and reliable findings, we conducted a series of robustness checks. The detailed results are presented in Table 6.

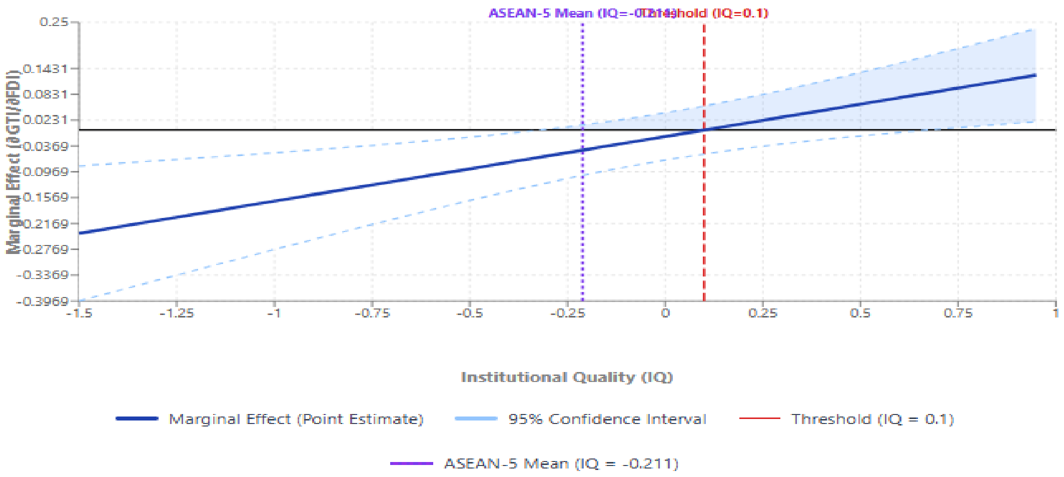

Figure 1. Marginal effect of FDI on GTI across IQ levels

Notes: This figure plots the marginal effect of FDI on GTI (∂GTI_log/∂FDI = -0.015 + 0.150 × IQ) across the range of IQ values observed in the sample. The solid line represents the point estimate, and the dashed lines with shaded area represent the 95% confidence interval calculated using the delta method. The vertical dashed line at IQ = 0.1 indicates the threshold where the marginal effect turns positive. The vertical dotted line at IQ = -0.211 indicates the sample mean. The figure is generated using Stata 17's margins and marginsplot commands based on the System GMM estimates from Table 5.

Table 6. Robustness check results from the system GMM model

Variable	(6) Alternative IQ Measure (RL)	(7) Excluding HC	(8) Excluding Trade_Openness	(9) Non-linear Relationship Test
GTI_log(t-1)	0.498***	0.505***	0.518***	0.510***
	(0.115)	(0.105)	(0.110)	(0.109)
FDI	-0.021	-0.011	-0.018	-0.025
	(0.030)	(0.027)	(0.029)	(0.035)
FDI²				0.002
				(0.004)
IQ		0.270***	0.259***	0.251***
		(0.095)	(0.091)	(0.090)
FDI × IQ		0.145***	0.153***	0.148***
		(0.051)	(0.049)	(0.052)
RL (Rule of Law)	0.288***			
	(0.098)			
FDI × RL	0.142**			
	(0.061)			
GDP_Growth	0.008	0.006	0.008	0.007
	(0.010)	(0.009)	(0.009)	(0.009)
Trade_Openness	0.004	0.002		0.003
	(0.003)	(0.003)		(0.003)
HC	0.195**		0.185**	0.186**
	(0.088)		(0.083)	(0.082)
RD	0.299***	0.315***	0.301***	0.303***
	(0.109)	(0.100)	(0.104)	(0.103)
Constant	-1.785**	-2.011**	-1.603*	-1.535*
	(0.890)	(0.954)	(0.841)	(0.838)
Observations	88	88	88	88
Number of countries	5	5	5	5
Number of instruments	28	27	27	29
Hansen test (p-value)	0.281	0.305	0.266	0.249
AR(1) test (p-value)	0.025	0.023	0.022	0.021
AR(2) test (p-value)	0.345	0.331	0.325	0.320

Notes: The dependent variable is GTI_log. Values in parentheses () are robust standard errors.
The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
Column (6): Re-estimates the baseline model by replacing the composite institutional quality index (IQ) with a specific component, 'Rule of Law' (RL), from the WGI dataset. The corresponding interaction term is FDI × RL.
Column (7): Re-estimates the baseline model after excluding the 'Human Capital' (HC) control variable to check if the results are driven by this variable.
Column (8): Re-estimates the baseline model after excluding the 'Trade Openness' (Trade_Openness) control variable.

Column (9): Re-estimates the baseline model by adding the squared term of FDI (FDI^2) to test for a potential non-linear (U-shaped or inverted U-shaped) relationship between FDI and green innovation.
Source: Authors' calculation.

The results from Table 6 show:

Using an alternative measure of institutions (Column 6): To test the sensitivity of the results to the measurement of institutions, we replaced the composite IQ index with the 'Rule of Law' (RL) index, a core aspect of institutions related to the protection of property rights and contract enforcement. The result in column (6) shows that the coefficient of the new interaction term (FDI × RL) is 0.142, still positive and statistically significant at the 5% level. This reaffirms our main conclusion that a good institutional environment, specifically the rule of law, is a crucial moderating factor that helps activate the positive impact of FDI.

Changing the set of control variables (Columns 7 & 8): We re-estimated the baseline model by sequentially removing the Human Capital (HC) variable in column (7) and the Trade Openness (Trade_Openness) variable in column (8). In both cases, the coefficients and significance levels of the main variables of interest remained very stable. The coefficients of the FDI × IQ interaction term are 0.145 and 0.153, respectively, both statistically significant at the 1% level. The direct impact of FDI remains statistically insignificant. This indicates that the study's results are not driven by any specific control variable and that the main findings are robust.

Checking for a non-linear relationship (Column 9): We added the squared term of FDI (FDI^2) to the model to test for a potential non-linear (U-shaped or inverted U-shaped) relationship, such as the hypothesis that at very high levels, FDI may yield diminishing returns. The result in column (9) shows that the coefficient of FDI^2 is 0.002 and is not statistically significant. Meanwhile, the coefficient of the FDI × IQ interaction term remains positive (0.148) and highly statistically significant. This suggests that the linear interaction model between FDI and IQ is a suitable specification and that there is no evidence of a more complex non-linear relationship in our dataset.

To reinforce the reliability of the results, we supplement with two reference estimators. The first is the bias-corrected LSDV (LSDVC) model by Bruno [39], suitable for dynamic panel data with small N. The second is a dynamic FE model with Driscoll-Kraay standard errors. The results from both of these methods are presented in Table 7 and show high consistency with the main GMM results.

Table 7. Sensitivity analysis with alternative estimators

Variable	(10) LSDVC (Bruno)	(11) Dynamic FE-DK
GTI_log(t-1)	0.489*** (0.095)	0.501*** (0.112)
FDI	-0.018 (0.031)	-0.012 (0.033)
IQ	0.241** (0.098)	0.262*** (0.091)
FDI × IQ	0.138** (0.055)	0.147*** (0.053)
GDP_Growth	0.008 (0.011)	0.006 (0.010)
Trade_Openness	0.004 (0.004)	0.003 (0.003)
HC	0.175* (0.092)	0.191** (0.085)
RD	0.288** (0.115)	0.312*** (0.098)
Observations	88	88
Number of countries	5	5

Notes: Column (10) uses the bias-corrected LSDV estimator (Bruno, 2005) with Blundell-Bond initial estimator and 200 bootstrap replications. Column (11) uses the dynamic FE model with Driscoll-Kraay standard errors. Values in parentheses are standard errors. ***, **, * denote significance at 1%, 5%, 10% levels.
Source: Authors' calculation.

5. DISCUSSION

5.1 Discussion of the main results

The first core finding of this study is the absence of a statistically significant direct impact of FDI inflows on GTI in the ASEAN-5 countries during the 2002-2021 period. The results from the System GMM model (Table 5) show that the coefficient of the FDI variable is not only statistically insignificant but also has a slight negative sign. This finding directly challenges the optimistic assumption of the "Pollution Halo Hypothesis," which posits that FDI is inherently a conduit for clean technology and advanced environmental standards [8, 9]. Our results suggest that the mere act of attracting FDI is not a sufficient condition to generate the expected positive technological impacts. These benefits do not arise automatically but require catalytic factors from the host country's institutional environment.

Conversely, this result provides a more fitting perspective with the 'Pollution Haven Hypothesis,' but with a more complex nuance. It does not necessarily assert that all FDI into ASEAN-5 is polluting, but suggests that in an average institutional environment, FDI flows tend not to prioritize green innovation objectives. This aligns with previous studies that found negative or insignificant impacts of FDI on the environment in developing countries with lax regulations [13, 27].

The difference between our results and some studies that found a direct positive impact [18] can be explained by the specific context of the ASEAN-5. Unlike developed economies (OECD) where similar studies are often conducted, the ASEAN-5 countries during the study period were still in the process of refining their legal frameworks for the environment and intellectual property. In many cases, the main drivers for attracting FDI to this region were low labor costs, large market size, and favorable access to resources, rather than an innovative environment. Consequently, MNCs may lack sufficient incentive to transfer their most advanced green technologies, which require high investment costs and a sufficiently secure legal environment to protect intellectual property. Instead, they might only apply technology that just meets the minimum environmental standards of the host country, leading to negligible green technology spillover effects.

5.2 Discussion of the moderating role of IQ and the significance of the threshold

The most important finding and also the most outstanding contribution of this study is the robust demonstration that IQ acts as a determinant moderator. The positive and highly statistically significant coefficient of the FDI × IQ interaction term (0.150, $p < 0.01$) shifts the research question from "Does FDI promote GTI?" to "Under what institutional conditions does FDI promote GTI?". This result extends North's [14] institutional theory into the field of environmental economics, affirming that the "rules of the game" not only shape general economic behavior but also determine the quality and technological orientation of foreign investments.

The mechanism behind this moderating role can be explained as follows:

(i) Reducing risk and transaction costs: A good institutional environment, characterized by the Rule of Law, effective control of corruption, and strict protection of intellectual property rights, significantly reduces the risks for MNCs when transferring core, expensive, and sensitive technologies. They will be more confident that their intellectual assets will not be stolen and that contracts will be enforced, thereby encouraging long-term investments in R&D and green technology.

(ii) Creating a level playing field and compliance pressure: High-quality institutions are often accompanied by clear environmental regulations and effective enforcement mechanisms. This eliminates the "competitive advantage" of polluting firms, forcing all companies, including MNCs, to compete based on efficiency and innovation. This compliance pressure encourages MNCs to adopt the cleaner technologies they already use in their home countries, creating a positive spillover effect.

The core point of the study is the identification of a threshold value for IQ (IQ ≈ 0.1). This is not just a statistical figure; it carries profound economic meaning. Since the WGI index is standardized with a global mean of 0, the threshold of 0.1 implies that an ASEAN-5 country needs to build a sufficiently strong institutional foundation that surpasses the world average. Only then can the country effectively absorb and leverage the green technology spillover effects from FDI.

For instance, in countries with IQ < 0.1 (e.g., an IQ index of -0.5), the marginal effect of FDI on GTI would be: $-0.015 + 0.150 \times (-0.5) = -0.09$. In this case, an MNC might decide to build a factory in this country to take advantage of cheap labor. However, due to concerns about copyright infringement and lax environmental regulations, they only transfer an older, more energy-intensive, and polluting production line. FDI flows in, GDP increases, but the nation's green innovation capacity not only fails to improve but may even be stifled.

Or, for countries with IQ > 0.1 (e.g., an IQ index of 0.8, equivalent to countries like Malaysia in recent years), the marginal effect of FDI on GTI would be: $-0.015 + 0.150 \times (0.8) = +0.105$. In this country, MNCs perceive that laws are strictly enforced and intellectual property rights are well-protected. To meet rising environmental standards and compete in the market, they decide to invest in an R&D center and apply the most advanced green production technology. Local engineers and suppliers gain access to and learn from this technology, creating a spillover effect that boosts the entire nation's green innovation ecosystem.

The fact that the average IQ of the research sample (-0.211) lies below the 0.1 threshold explains why the average direct impact of FDI was not statistically significant. It implies that, for most of the study period, the "typical" ASEAN-5 country had not yet met the necessary institutional conditions to turn FDI into a driver for green innovation. The robustness check result in column (6), using the "Rule of Law" (RL) index instead of the composite IQ, further strengthens this argument. It shows that legal assurance is one of the most core aspects of institutions for attracting high-quality FDI.

5.3 Discussion of the non-linear relationship test results

The study also tested for the possibility of a non-linear (U-shaped or inverted U-shaped) relationship between FDI and GTI by adding the FDI^2 term to the model, but the results showed that the coefficient of this term was not statistically significant (Table 6, column 9). The failure to find this non-linear relationship in the ASEAN-5 context can be explained by several reasons.

First, it is possible that the ASEAN-5 economies have not yet reached a sufficiently large scale of FDI for non-linear effects to become apparent. Hypotheses about non-linear relationships often suggest that after a certain FDI threshold, benefits may diminish (due to excessive competition weakening domestic firms) or accelerate (due to reaching a critical mass to create innovative industrial clusters). It may be that FDI inflows into the region, though large in absolute terms, are still not sufficient in terms of GDP share and quality to trigger these complex dynamics.

Second, and more importantly, this result further reinforces the main argument of the study: the decisive factor is not the "quantity" of FDI, but the "interaction" between FDI and IQ. The linear interaction model has captured the main dynamic governing this relationship very well. This means that, instead of the impact of FDI changing with its own scale, the impact of FDI changes consistently with the improvement of IQ. The fundamental relationship is a function of IQ, not a function of FDI scale. Therefore, adding the FDI^2 term did not bring significant additional explanatory power to the model. This suggests that for ASEAN policymakers, the focus should not be on "attracting more FDI at all costs" but on "improving institutions to enhance the quality of existing and future FDI flows".

5.4 Limitations and future research directions

Despite achieving its proposed research objectives, we acknowledge that our study still has some limitations. Specifically, the use of aggregate data at the national level for both FDI and patent counts may obscure important differences in the nature of capital flows (e.g., FDI by industry) and the true value of each innovation.

Future research could delve deeper by disaggregating FDI by sector to identify which types of investment truly deliver green benefits. Furthermore, shifting to an industry- or firm-level analysis would allow for a direct test of technology spillover mechanisms and the exploration of more diverse measures of green innovation beyond patent data. These directions would provide a more detailed picture of how to build an effective institutional framework to optimize the benefits from FDI.

6. CONCLUSION AND IMPLICATIONS

This study was conducted to address a critical paradox in development economics: the true role of FDI inflows in the process of GTI in the ASEAN-5 countries. The study questions whether FDI is a self-evident driver of green growth, or if its impact is contingent on the foundational conditions of the host country.

The main conclusions of the study offer a clear affirmation. First, the study refutes the notion that FDI is, in itself, an agent for promoting green innovation. Robust empirical analyses from the System GMM model show that, when considered independently, FDI inflows have no direct positive impact on GTI in the ASEAN-5. This indicates that merely attracting FDI is insufficient to generate the expected technology spillover effects.

Second, and as its core contribution, the study demonstrates that IQ is not just an amplifying factor, but a decisive prerequisite. The most significant finding is the existence of an institutional threshold (IQ ≈ 0.1). Only when a country builds a sufficiently strong institutional framework, surpassing the global average, do FDI inflows begin to "activate" and contribute positively to green innovation efforts. Below this threshold, FDI brings no benefits and may even pose the risk of stifling the nation's environmental technology capacity.

These conclusions carry profound implications, both theoretically and practically. Theoretically, this study reconciles the two opposing hypotheses of the "Pollution Halo" and "Pollution Haven." It shows that both scenarios are possible, and that IQ is the variable that determines which scenario will prevail. In doing so, the study extends North's [14] institutional theory into the field of environmental economics, affirming that the "rules of the game" not only shape general economic behavior but also determine the quality and technological orientation of foreign investments.

Practically, the study shows that policymakers in the ASEAN-5 cannot rely solely on attracting FDI at all costs to "green" their economies. Instead, the strategic focus must shift towards comprehensive and deep institutional reform. Top priorities should include: strengthening the rule of law, rigorously protecting intellectual property rights, enhancing government effectiveness, and resolutely combating corruption. These are the foundational investments needed to enhance the economy's technological absorptive capacity, thereby transforming FDI from a mere source of capital into a true engine for sustainable development.

Ultimately, this study demonstrates that the path to sustainable prosperity cannot be built on the financial strength of FDI alone but must be underpinned by the foundation of strong institutions. For ASEAN, building that foundation is not an option, but an imperative for a green future.

REFERENCES

[1] Sachs, J.D., Schmidt-Traub, G., Mazzucato, M., Messner, D., Nakicenovic, N., Rockström, J. (2019). Six transformations to achieve the Sustainable Development Goals. Nature Sustainability, 2(9): 805-814. https://doi.org/10.1038/s41893-019-0352-9

[2] Haberl, H., Wiedenhofer, D., Pauliuk, S., Krausmann, F., Müller, D.B., Fischer-Kowalski, M. (2019). Contributions of sociometabolic research to sustainability science. Nature Sustainability, 2(3): 173-184. https://doi.org/10.1038/s41893-019-0225-2

[3] Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D. (2012). The environment and directed technical change. American Economic Review, 102(1): 131-166. https://doi.org/10.1257/aer.102.1.131

[4] Georgeson, L., Maslin, M. (2019). Estimating the scale of the US green economy within the global context. Palgrave Communications, 5(1): 121. https://doi.org/10.1057/s41599-019-0329-3

[5] Shabir, M., Gill, A.R., Ali, M. (2022). The impact of transport energy consumption and foreign direct investment on CO2 emissions in ASEAN countries. Frontiers in Energy Research, 10. https://doi.org/10.3389/fenrg.2022.994062

[6] Pao, H.T., Tsai, C.M. (2011). Modeling and forecasting the CO2 emissions, energy consumption, and economic growth in Brazil. Energy, 36(5): 2450-2458. https://doi.org/10.1016/j.energy.2011.01.032

[7] Bhakta, B., Maiti, S. (2025). Economic growth and environmental degradation in ASEAN-10 countries: An econometric descriptive analysis. South Asian Journal of Social Studies and Economics, 22(2): 73-81. https://doi.org/10.9734/sajsse/2025/v22i2958

[8] Elliott, R.J.R., Zhou, Y. (2012). Environmental regulation induced foreign direct investment. Environmental and Resource Economics, 55(1): 141-158. https://doi.org/10.1007/s10640-012-9620-0

[9] To, A.H., Ha, D.T.T., Nguyen, H.M., Vo, D.H. (2019). The impact of foreign direct investment on environment degradation: Evidence from emerging markets in Asia. International Journal of Environmental Research and Public Health, 16(9): 1636. https://doi.org/10.3390/ijerph16091636

[10] Qamruzzaman, M., Karim, S., Kor, S. (2024). Nexus between innovation-openness-natural resources-environmental quality in N-11 countries: What is the role of environmental tax? Sustainability, 16(10): 3889. https://doi.org/10.3390/su16103889

[11] Vilema-Escudero, S.F., Ruiz-Martínez, M., Manya-Orellana, M., Arguello-Núñez, L. (2024). Energy intensity and employment: Evidence from Latin American countries. IOP Conference Series: Earth and Environmental Science, 1434(1): 012013. https://doi.org/10.1088/1755-1315/1434/1/012013

[12] Brucal, A., Javorcik, B., Love, I. (2019). Good for the environment, good for business: Foreign acquisitions and energy intensity. Journal of International Economics, 121: 103247. https://doi.org/10.1016/j.jinteco.2019.07.002

[13] Singhania, M., Saini, N. (2021). Demystifying pollution haven hypothesis: Role of FDI. Journal of Business Research, 123: 516-528. https://doi.org/10.1016/j.jbusres.2020.10.007

[14] North, D.C. (1990). Institutions, Institutional Change and Economic Performance. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511808678

[15] Buchanan, B.G., Le, Q.V., Rishi, M. (2012). Foreign direct investment and institutional quality: Some empirical evidence. International Review of Financial Analysis, 21: 81-89. https://doi.org/10.1016/j.irfa.2011.10.001

[16] Globerman, S., Shapiro, D. (2002). Global foreign direct investment flows: The role of governance infrastructure. World Development, 30(11): 1899-1919. https://doi.org/10.1016/s0305-750x(02)00110-9

[17] Behera, B., Behera, P., Sethi, N. (2023). Decoupling the role of renewable energy, green finance and political stability in achieving the Sustainable Development Goal 13: Empirical insight from emerging economies. Sustainable Development, 32(1): 119-137. https://doi.org/10.1002/sd.2657

[18] Wang, M.L., Sarkodie, N.V., Yang, J., Zheng, Q., Geng, L. (2022). Effect of institutional quality and foreign direct investment on economic growth and environmental quality: Evidence from African countries. Economic Research-Ekonomska Istraživanja, 35(1): 4065-4091. https://doi.org/10.1080/1331677X.2021.2019639

[19] Blomström, M., Kokko, A. (1998). Multinational corporations and spillovers. Journal of Economic Surveys, 12(3): 247-277. https://doi.org/10.1111/1467-

6419.00056
[20] Cohen, W.M., Levinthal, D.A. (1990). Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 35(1): 128. https://doi.org/10.2307/2393553
[21] Hung, P.H. (2023). The influence of cultural, legal and institutional factors on auditors' roles, responsibilities and perceptions of audit quality. European Journal of Theoretical and Applied Sciences, 1(5): 1131-1145. https://doi.org/10.59324/ejtas.2023.1(5).99
[22] Thuy Pham, T., Hung Pham, H. (2025). The impact of green governance and the moderating role of institutional ownership on financial reporting quality in VN-Allshare listed companies. Management (Montevideo), 3: 337. https://doi.org/10.62486/agma2025337
[23] Javorcik, B.S. (2004). Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages. American Economic Review, 94(3): 605-627. https://doi.org/10.1257/0002828041464605
[24] Castellani, D., Marin, G., Montresor, S., Zanfei, A. (2022). Greenfield foreign direct investments and regional environmental technologies. Research Policy, 51(1): 104405. https://doi.org/10.1016/j.respol.2021.104405
[25] Luo, Y., Salman, M., Lu, Z. (2021). Heterogeneous impacts of environmental regulations and foreign direct investment on green innovation across different regions in China. Science of the Total Environment, 759: 143744. https://doi.org/10.1016/j.scitotenv.2020.143744
[26] Ali, N., Phoungthong, K., Khan, A., Abbas, S., Dilanchiev, A., Tariq, S., Sadiq, M.N. (2023). Does FDI foster technological innovations? Empirical evidence from BRICS economies. PLoS ONE, 18(3): e0282498. https://doi.org/10.1371/journal.pone.0282498
[27] Cole, M.A., Elliott, R.J.R. (2003). Do environmental regulations influence trade patterns? Testing old and new trade theories. The World Economy, 26(8): 1163-1186. https://doi.org/10.1111/1467-9701.00567
[28] Cheng, P., Wang, X., Choi, B., Huan, X. (2023). Green finance, international technology spillover and green technology innovation: A new perspective of regional innovation capability. Sustainability, 15(2): 1112. https://doi.org/10.3390/su15021112
[29] Chen, L., Hu, L., He, F., Zhang, H. (2024). Environmental regulation, foreign direct investment, and green total factor productivity: An empirical test based on Chinese city-level panel data. Sustainability, 16(13): 5620. https://doi.org/10.3390/su16135620
[30] Udo, E.S., Ekwunife, F.C., Ibobo, B.I., Idamoyibo, H.R., Atakpa, O.E., Stephen, O.U. (2025). Green finance development, governance quality, and environmental sustainability: Evidence from Sub-Saharan Africa. Southern African Business Review. https://doi.org/10.25159/1998-8125/15782
[31] Nhuong, B.H., Bao, H.D., Linh, V.M., Ha, L.T. (2024). Do green foreign direct investments promote environmental innovation in European countries? International Journal of Renewable Energy Development, 14(1): 10-24. https://doi.org/10.61435/ijred.2025.60421
[32] Ren, H., Huang, J., Ren, J. (2025). Digital innovation, institutional environment and air quality improvement. Frontiers in Environmental Science, 13. https://doi.org/10.3389/fenvs.2025.1658767
[33] Griliches, Z. (1998). Patent statistics as economic indicators: A survey. In R&D and Productivity: The Econometric Evidence, pp. 287-343.
[34] Kaufmann, D., Kraay, A., Mastruzzi, M. (2011). The worldwide governance indicators: Methodology and analytical issues. Hague Journal on the Rule of Law, 3(2): 220-246. https://doi.org/10.1017/s1876404511200046
[35] Driscoll, J.C., Kraay, A.C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. Review of Economics and Statistics, 80(4): 549-560. https://doi.org/10.1162/003465398557825
[36] Arellano, M., Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68(1): 29-51. https://doi.org/10.1016/0304-4076(94)01642-d
[37] Blundell, R., Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1): 115-143. https://doi.org/10.1016/s0304-4076(98)00009-8
[38] Roodman, D. (2009). How to do Xtabond2: An introduction to difference and system GMM in Stata. The Stata Journal: Promoting communications on statistics and Stata, 9(1): 86-136. https://doi.org/10.1177/1536867x0900900106
[39] Bruno, G.S.F. (2005). Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models. Economics Letters, 87(3): 361-366. https://doi.org/10.1016/j.econlet.2005.01.005
[40] Pesaran, M.H. (2020). General diagnostic tests for cross-sectional dependence in panels. Empirical Economics, 60(1): 13-50. https://doi.org/10.1007/s00181-020-01875-7
[41] Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics, 126(1): 25-51. https://doi.org/10.1016/j.jeconom.2004.02.005