Revisiting the FDI, Industrialization and Environmental Pollution Nexus: The Conditional Role of Renewable Energy in Developing Economies

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Abstract: This study examines how foreign direct investment (FDI) and industrialization (IND) affect carbon dioxide (CO_2) and nitrous oxide (N_2O) emissions and whether renewable energy (REN) alters these relationships. Using a balanced panel of 101 developing countries from 2002 to 2022, the analysis applies two-way fixed effects with Driscoll–Kraay standard errors, two-step System GMM, and Lewbel IV–2SLS. The results consistently show that FDI and IND increase both pollutants, supporting the Pollution Haven Hypothesis, whereas REN directly reduces emissions. The negative interaction effects indicate that REN significantly weakens the adverse environmental effects of FDI and IND. Marginal-effects analysis shows that these effects remain positive at low and median REN levels but become small and generally statistically insignificant at the 75th percentile. The estimated zero-crossing thresholds range from approximately 66.6% to 78.6% of total final energy consumption, suggesting that substantial REN penetration is required to neutralize the pollution effects of foreign investment and industrial expansion. Institutional-quality heterogeneity analysis further reveals that stronger institutions reduce the emission intensity of FDI and IND and enhance the direct and moderating benefits of REN. These findings reconcile the Pollution Haven and Pollution Halo hypotheses by demonstrating that the environmental consequences of economic expansion depend on energy structure and institutional capacity. Developing countries should therefore coordinate renewable-energy expansion with environmental regulation, green-investment screening, and cleaner industrial policies.

Keywords: Foreign Direct Investment; Industrialization; Renewable Energy; Institutional Quality; Environmental Pollution; Sustainable Development

1. Introduction

Environmental degradation has become a central constraint on sustainable development, with climate change intensifying exposure to sea-level rise, floods, droughts, acid rain, and heatwaves (Ahmad and Hussain, 2024; Lan et al., 2025a). Developing economies are particularly vulnerable because growth imperatives often coexist with limited technological capacity, weak institutions, and carbon-intensive production structures (Lan et al., 2025b; Ali et al., 2022). The resulting environmental burden extends beyond ecological damage: it raises healthcare demand, reduces labor productivity, and increases households' exposure to climate-related risks (Amin et al., 2023; World Health Organization, 2024). Understanding how major drivers of structural transformation affect different greenhouse gases is therefore important for designing growth strategies that do not compromise environmental sustainability.

Foreign direct investment (FDI) is an important source of capital, employment, managerial knowledge, and technological upgrading in developing countries. Its environmental effect, however, is theoretically ambiguous. Growth-oriented governments may relax or weakly enforce environmental standards to attract foreign capital, allowing pollution-intensive activities to relocate to jurisdictions with lower compliance costs (Nkemgha et al., 2024; Aquilas et al., 2024; Shahbaz et al., 2019). This mechanism is consistent with the Pollution Haven Hypothesis (PHH) and is especially plausible where production relies heavily on fossil energy (Ho et al., 2026). Conversely, multinational firms may transfer cleaner technologies, advanced management practices, and energy-efficient production processes, consistent with the Pollution Halo Hypothesis (PHaH) (Kurniawan et al., 2024). As illustrated in Figure 1, the long-term expansion of FDI flows from developed to developing economies makes it necessary to identify the conditions under which foreign capital produces a pollution-haven or pollution-halo outcome.

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Industrialization (IND) presents a related economic–environmental trade-off. Industrial expansion supports employment, productivity, structural transformation, and machinery upgrading, but it also increases demand for energy and material inputs (Huang et al., 2025). Where fossil fuels dominate the energy mix and environmental regulation and technological capabilities remain limited, rising industrial output tends to increase emissions (Munir and Ameer, 2020; Mahmood et al., 2020; Nasrollahi et al., 2020). By contrast, cleaner energy, efficient production technologies, and stronger regulatory enforcement can reduce the emission intensity of industrial activity. Thus, the environmental consequences of FDI and IND should not be treated as predetermined; rather, they depend partly on the energy and institutional structures within which economic activities take place.

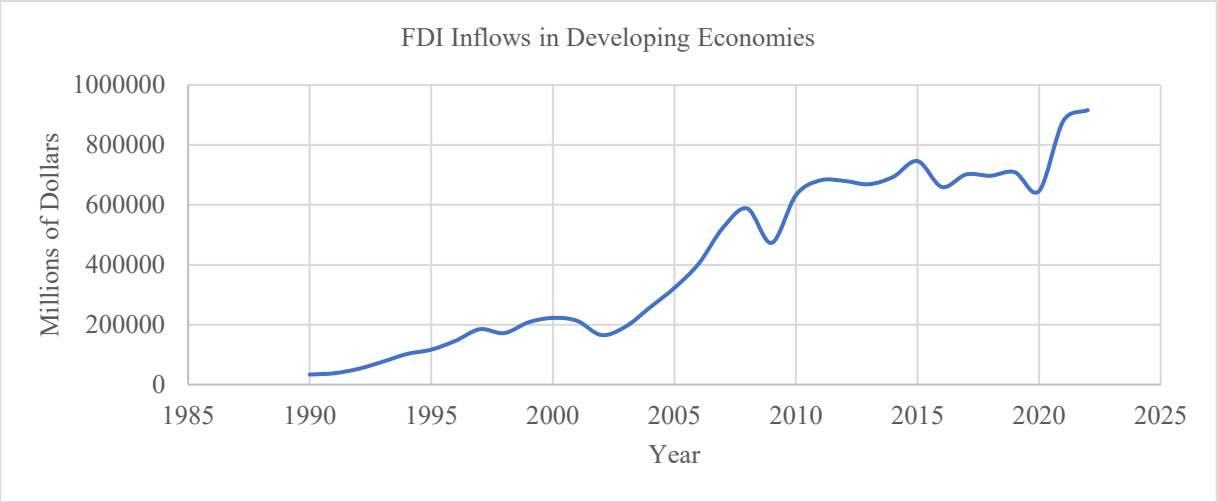


Figure 1. FDI flows from developed to developing countries. *Source:* Author's construction using UNCTAD (2023).

Renewable energy (REN), including solar, wind, hydro, geothermal, and modern bioenergy, can alter these relationships by replacing fossil energy and facilitating cleaner production. Greater REN use can directly reduce emissions, improve energy security, and help decouple economic expansion from environmental pressure (Rahman and Alam, 2021). It may also operate as a conditioning mechanism: the environmental costs of additional FDI and IND should decline as renewable-energy penetration increases (Mentel et al., 2022a; Osei, 2025). This conditional perspective implies a transition along the REN continuum. At low levels of REN, fossil-fuel dependence may allow the PHH mechanism to dominate. Beyond a sufficiently high REN threshold, cleaner energy and technology spillovers may weaken or reverse the marginal pollution effects of FDI and IND, making a PHaH-type outcome more likely.

The use of both carbon dioxide (CO_2) and nitrous oxide (N_2O) emissions is deliberate because these indicators capture related but non-interchangeable dimensions of environmental pressure. CO_2 emissions are driven primarily by fossil-fuel combustion in electricity generation, transportation, manufacturing, and other energy-intensive activities. By contrast, N_2O emissions arise more strongly from agricultural soil management, fertilizer use, biomass burning, chemical production, and selected industrial processes. FDI and IND may therefore affect CO_2 more immediately through their influence on energy demand, whereas their effects on N_2O may operate through changes in agro-industrial production, input intensity, waste management, and industrial processes. Estimating separate models for the two pollutants permits a comparison of these mechanisms rather than assuming that CO_2 and N_2O are interchangeable measures of the same underlying environmental process.

Despite a growing body of literature on the environmental effects of FDI, IND, and REN, three important gaps remain. First, many studies estimate the direct effects of economic activities on a single pollutant and consequently provide limited evidence on whether FDI and IND influence energy-related CO_2 and process- and agriculture-related N_2O emissions differently. Second, REN is commonly treated only as an additional determinant of emissions, with less attention given to its capacity to change the marginal environmental effects of FDI and IND or to the REN levels at which those effects become neutral or beneficial. Third, limited cross-country evidence examines whether these conditional relationships differ according to institutional quality, even though regulatory capacity influences environmental enforcement, technological adoption, and the sectoral composition of foreign and industrial investment. These omissions prevent a clear reconciliation of the PHH and PHaH within the broader logic of ecological modernization. Accordingly, this study addresses the following research questions:

RQ1: How do FDI and IND affect CO_2 and N_2O emissions in developing economies, and do their effects differ between the two pollutants?

RQ2: Does REN directly reduce CO_2 and N_2O emissions, and does it weaken the adverse environmental effects of FDI and IND?

RQ3: At what levels of REN do the estimated marginal effects of FDI and IND on CO_2 and N_2O emissions cross zero?

RQ4: Do the environmental effects of FDI, IND, and REN differ between developing countries characterized by relatively low and high institutional quality?

To answer these questions, the study uses a balanced panel of 101 developing countries covering the period 2002–2022. Separate models are estimated for CO_2 and N_2O emissions. Fixed-effects estimation with robust inference is employed to account for time-invariant country characteristics and panel-data disturbances, while dynamic System GMM addresses emission persistence and potential endogeneity. Lewbel IV–2SLS provides an additional endogeneity and robustness assessment. Marginal-effects and threshold analyses are subsequently used to identify how the environmental effects of FDI and IND change across the REN distribution, while subsample analysis examines whether these relationships differ between countries with low and high institutional quality.

This study makes three contributions. First, it develops a pollutant-specific account of the FDI–IND–environment nexus by comparing energy-related CO_2 emissions with N_2O emissions associated more strongly with agricultural and industrial processes. This approach provides a more nuanced assessment than studies that treat different emission indicators as interchangeable measures of environmental pollution. Second, the study moves beyond the direct REN–emissions relationship by conceptualizing REN as both an independent environmental determinant and a structural condition that can change the marginal effects of FDI and IND. The estimation of REN transition thresholds provides a testable reconciliation of the PHH and PHaH and connects these competing perspectives to ecological modernization. Third, the study introduces institutional-quality heterogeneity into this conditional framework, thereby examining whether regulatory capacity strengthens the ability of REN to transform foreign investment and industrial development into cleaner growth. The resulting evidence provides a foundation for differentiated investment, industrial, and energy policies across developing countries at different stages of renewable-energy penetration and institutional development.

2. Literature Review

2.1. Foreign Direct Investment, Industrialization, and Environmental Pollution

FDI and IND support capital formation, employment, technological upgrading, and structural transformation in developing economies. However, their environmental effects depend on production composition, energy structure, technological capacity, and environmental regulation. The PHH suggests that multinational enterprises may relocate pollution-intensive activities to countries with weak environmental standards and low compliance costs. Conversely, the PHaH argues that FDI can improve environmental quality through cleaner technologies, efficient production processes, and superior environmental-management practices.

Empirical evidence on FDI remains mixed. Shahbaz et al. (2015) found that FDI increased CO_2 emissions in low-income economies, reduced them in high-income economies, and produced an inverted U-shaped relationship in middle-income countries. Naz et al. (2019) documented an emissions-increasing effect in Pakistan, while Shahbaz et al. (2019) validated the PHH in Middle Eastern and North African (MENA) economies. Opoku and Boachie (2020) similarly reported that FDI increased environmental degradation across 36 African countries. Although Nepal et al. (2021) found a short-run environmental benefit of FDI in India, Ahmed et al. (2022) showed that it increased CO_2 and methane emissions in the Asia-Pacific region. Balsalobre-Lorente et al. (2022) and Awan et al. (2022) also identified emissions-increasing effects of foreign investment. Recent evidence shows that the effect of FDI is conditional. Ho et al. (2026) identified a persistent association between FDI and environmental degradation in Asian economies and emphasized green-technology transfer. Xuan (2025) found that FDI increased pollution in Japan because of fossil-fuel dependence, but greater REN use could reverse this effect. Supporting the PHaH, Deng and Liu (2025) showed that the environmental costs of FDI decline when foreign investment facilitates cleaner technologies. Kurniawan et al. (2024) likewise found that FDI improved environmental quality in Association of Southeast Asian Nations (ASEAN) economies. Thus, fossil-fuel dependence, weak regulation, and limited absorptive capacity may produce pollution-haven outcomes, whereas REN, technological capability, and effective regulation can facilitate pollution-halo effects.

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IND creates a comparable trade-off. It supports productivity, employment, exports, and structural transformation, but poorly regulated industrial expansion intensifies energy consumption, resource use, and emissions (Aquilas et al., 2024). Opoku and Boachie (2020) found an insignificant environmental effect of IND in African countries, whereas Opoku and Aluko (2021) showed that it worsened environmental quality at lower emission quantiles but improved it at higher quantiles. These differences indicate that the effect of IND varies with production structures, technological efficiency, and development levels. Most regional studies nevertheless associate IND with greater environmental pressure. Mahmood et al. (2020) found that industrial expansion raised CO_2 emissions in Saudi Arabia, while Nasrollahi et al. (2020) reported adverse effects in MENA and OECD economies. Munir and Ameer (2020) identified a similar relationship in Pakistan. Hassan et al. (2025) documented environmental deterioration in South Asia, while Ahmed et al. (2022) reported a weakly positive effect in the Asia-Pacific region. Nkemgha et al. (2024) showed that industrial and manufacturing activities increased environmental degradation in Sub-Saharan Africa, although stronger environmental-policy stringency mitigated the damage. Aquilas et al. (2024) similarly found that REN weakened the adverse environmental effects of IND in Africa.

A limitation of this literature is its predominant focus on CO_2, which is closely associated with fossil-fuel combustion in electricity generation, transportation, and manufacturing. Accordingly, FDI and IND affect CO_2 mainly through production scale, energy demand, fuel composition, and technological efficiency. N_2O involves different mechanisms. Agriculture is the largest source of anthropogenic N_2O through fertilizer application, manure management, and intensified production, while additional emissions arise from chemical manufacturing, combustion, wastewater treatment, and other industrial processes (Tian et al., 2020). FDI and IND may therefore affect N_2O through fertilizer-intensive agro-industrial production, chemical industries, food processing, waste generation, and industrial nitrogen use. The environmental effects observed for CO_2 cannot automatically be assumed to apply to N_2O with the same magnitude or significance.

2.2. Renewable Energy and the Environmental Effects of FDI and Industrialization

REN can reduce fossil-fuel dependence, improve energy security, and support cleaner production. Assi et al. (2021) found that REN reduced environmental degradation in Asian economies, while Amin et al. (2024) identified bidirectional causality between REN and environmental quality in ASEAN countries. Rahman and Alam (2021) similarly reported that clean-energy use improved environmental quality in Bangladesh. Hasanov et al. (2021) found that REN and technological progress reduced emissions in BRICS economies, and Pata (2021) documented environmental benefits in the United States. Chen et al. (2023) showed that REN reduced air pollution and carbon emissions in China, particularly when accompanied by technological innovation. Comparable emissions-reducing effects were reported by Wang et al. (2021), Nguyen and Le (2024), and Amin et al. (2023).

Nevertheless, the benefits of REN may not emerge immediately. Pata and Caglar (2021) found an insignificant environmental effect during the earlier stages of REN adoption in China, suggesting that clean energy must reach a sufficient share before producing measurable benefits. Yi et al. (2023) identified a positive association between REN and pollution in the United States, indicating that infrastructure construction, supply-chain emissions, fossil-fuel backup, and an insufficient deployment scale may initially offset environmental gains. Therefore, the REN–environment relationship may depend on the scale, maturity, efficiency, and integration of clean-energy systems, implying a possible transition threshold. REN may also change the environmental consequences of FDI. Under fossil-fuel dependence, foreign investment expands energy demand and emissions; with greater REN penetration, the same investment can be supported by cleaner electricity and more efficient production. Osei (2025) showed that REN reduced the carbon intensity of FDI-related activity. Kurniawan et al. (2024) found that REN and FDI jointly improved environmental quality in ASEAN economies, while Xuan (2025) showed that REN could reverse the adverse environmental effect of FDI. Pan et al. (2025) similarly documented a synergistic relationship between FDI and REN in developing countries. REN can therefore determine whether foreign investment produces pollution-haven or pollution-halo outcomes.

A similar mechanism applies to IND. Mentel et al. (2022a) found that renewable electricity weakened the effect of IND on CO_2 emissions in SSA. Mentel et al. (2022b) showed that the environmental consequences of IND in Europe and Central Asia depended on REN-sector development, while Aquilas et al. (2024) reported comparable evidence for Africa. Greater REN penetration can therefore facilitate green industrialization by supporting manufacturing, infrastructure, and technological upgrading with lower emission intensity. The moderating effect may differ between CO_2 and N_2O. Because CO_2 is strongly linked to fossil-fuel combustion, renewable-energy substitution can directly reduce the carbon intensity of FDI and IND. The N_2O effect may be weaker because much of this pollutant originates from fertilizer use, soil management, livestock waste, and chemical production. Nevertheless, REN can reduce combustion-related N_2O and support cleaner fertilizer production, electrified industrial processes, and improved waste treatment. These differences justify separate estimations for the two pollutants and an examination of REN thresholds rather than reliance on average interaction effects.

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2.3. Institutional Quality and Technological Innovation, and Research Gap

Institutional quality shapes environmental outcomes through regulatory design, enforcement, and firms' compliance with environmental standards. Weak institutions may attract pollution-intensive FDI, whereas effective regulation can encourage cleaner investment and technology transfer (Birdsall and Wheeler, 1993; Eskeland and Harrison, 2003; Cole, 2004; Copeland and Taylor, 2004). Environmental-policy stringency and governance can also mitigate the damage associated with industrial and other economic activities (Nkemgha et al., 2024; Wang et al., 2024; Si et al., 2025). Strong institutions additionally support REN through policy consistency, transparent investment procedures, effective grid integration, and environmental screening.

Technological innovation improves energy efficiency, cleaner production, and the environmental benefits of REN. Hasanov et al. (2021), Chen et al. (2023), and Nguyen and Le (2024) showed that technological progress and REN can jointly reduce environmental pressure. Technological capacity also determines whether host countries can absorb cleaner technologies transferred through FDI. Technological innovation is therefore included as a control, while institutional quality is used as both a control and a basis for heterogeneity analysis.

Recent decision-science research highlights the importance of data-driven planning and environmental management. Su et al. (2025) demonstrated the value of mixed-frequency information for production planning, while Zheng and Shao (2022) and Shao et al. (2025) applied complex-network and forecasting methods to port and logistics systems. Shao and Zhang (2026) extended this perspective to AI-supported environmental early-warning and coordinated responses. Although the present study uses macro-panel methods, this literature illustrates how technological and institutional capabilities improve the monitoring of industrial, trade, and environmental systems.

Several gaps remain. Existing studies focus primarily on CO_2, examine FDI, IND, and REN separately, and generally treat REN only as an independent determinant. Few identify the REN levels at which the environmental effects of FDI and IND become insignificant or change direction, while limited evidence examines differences between weak- and strong-institutional environments. This study addresses these gaps by analyzing CO_2 and N_2O separately, incorporating REN as both an independent variable and moderator, estimating REN thresholds, and assessing heterogeneity between low- and high-institutional-quality developing countries.

3. Theoretical Framework and Hypothesis Development

3.1. Integrated Theoretical Framework

The PHH and PHaH offer competing explanations for the environmental consequences of FDI. The PHH argues that multinational enterprises may relocate pollution-intensive activities to developing countries where environmental regulations, enforcement capacity, and compliance costs are relatively weak (Eskeland and Harrison, 2003; Copeland and Taylor, 2004). Countries with fossil-fuel-dependent energy systems and limited regulatory capacity may consequently become pollution havens, as FDI and industrial expansion increase energy demand and pollution-intensive production. Under these conditions, FDI and IND are expected to increase environmental degradation (Cole, 2004; Shahbaz et al., 2019; Ho et al., 2026).

In contrast, the PHaH proposes that FDI can improve environmental quality through the transfer of cleaner technologies, efficient production methods, managerial expertise, and stronger corporate environmental standards (Birdsall and Wheeler, 1993; Zarsky, 1999). These technological and managerial spillovers may reduce emissions when host countries possess adequate absorptive capacity, effective institutions, and supportive environmental policies (Kurniawan et al., 2024; Deng and Liu, 2025). Thus, the environmental effect of FDI is not inherently positive or negative. The PHH is more likely to prevail under weak regulation, fossil-fuel dependence, and limited technological capacity, whereas the PHaH becomes more plausible when clean energy, regulatory enforcement, and technological capabilities are sufficiently developed.

Ecological Modernization Theory (EMT) provides a broader framework for reconciling these competing perspectives. It argues that industrial development and environmental protection can be achieved simultaneously through technological innovation, institutional reform, cleaner energy, and effective environmental policies (Mol et al., 2013; Ali et al., 2022; Pan et al., 2025). Unlike conventional arguments that associate IND automatically with environmental degradation, EMT emphasizes that environmental outcomes depend on how production and energy systems are organized. The adoption of efficient technologies, cleaner inputs, and sustainable production methods can reduce the environmental intensity of FDI and IND (Nguyen et al., 2021; Mentel et al., 2022b; Aquilas et al., 2024). This perspective is particularly relevant to developing countries, where early industrial

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expansion frequently relies on fossil fuels but may gradually shift toward cleaner production as technological and institutional capacities improve.

Within this integrated framework, REN serves as the principal conditioning mechanism. At low levels of REN, additional FDI and IND are largely supported by fossil-fuel-based energy, strengthening the pollution-enhancing mechanism predicted by the PHH. As REN penetration increases, cleaner electricity, production electrification, and energy-efficient technologies reduce the emission intensity of foreign investment and industrial output. Beyond a sufficiently high transition threshold, the marginal pollution effects of FDI and IND may become insignificant or negative, making PHaH-type outcomes and ecological modernization more likely. REN therefore operates both as an independent factor reducing emissions and as a moderator that changes the environmental effects of FDI and IND. This conditioning process may differ between CO_2 and N_2O. Because CO_2 is primarily associated with fossil-fuel combustion, REN can directly weaken the effects of FDI and IND by replacing carbon-intensive energy. For N_2O, the mechanism is less direct because emissions arise substantially from fertilizer use, agricultural soils, chemical production, waste treatment, and other industrial processes. Nevertheless, REN may reduce combustion-related N_2O and support cleaner fertilizer production, electrified industrial processes, and improved waste-management technologies. The transition threshold and the magnitude of the moderating effect may therefore differ across the two pollutants.

Institutional quality and technological innovation strengthen this theoretical mechanism. Effective institutions enforce environmental standards, screen the environmental quality of FDI, and support the implementation of REN policies. Technological capacity enables domestic firms and industries to absorb cleaner technologies and translate REN expansion into lower emission intensity. Accordingly, countries with stronger institutions are expected to realize greater environmental benefits from REN than countries where regulatory enforcement and implementation capacity remain weak. Figure 2 presents the integrated framework linking FDI, IND, and REN to environmental pollution, including REN threshold effects and institutional-quality heterogeneity.

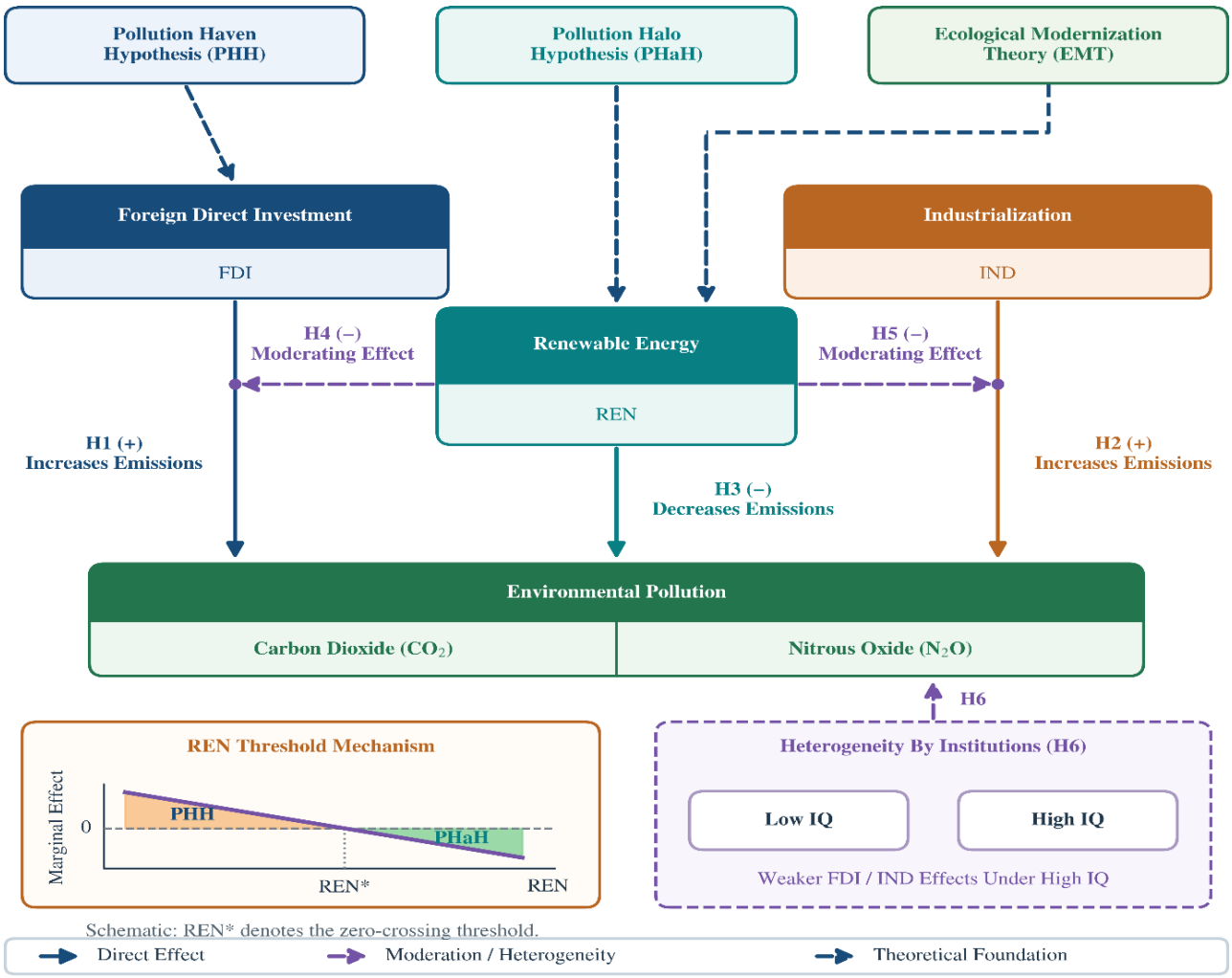


Figure 2. Conceptual Framework of the Study

3.2. Hypothesis Development

The PHH predicts that FDI increases environmental pollution when multinational enterprises relocate pollution-intensive production to countries with weak environmental regulations and low compliance costs (Eskeland and Harrison, 2003; Shahbaz et al., 2019). This effect is particularly likely in developing countries where foreign-invested production depends on fossil fuels and environmental enforcement remains limited (Ho et al., 2026). FDI may increase CO_2 through energy consumption, transportation, and manufacturing, while its effect on N_2O may arise through fertilizer-intensive agriculture, chemical production, waste generation, and agro-industrial processes. Accordingly:

H1: FDI increases CO_2 and N_2O emissions in developing countries.

IND promotes structural transformation but also expands energy consumption, resource use, and pollution-intensive production. Its environmental consequences are particularly harmful where industrial activity relies on fossil fuels, inefficient technologies, and weak regulatory enforcement (Mahmood et al., 2020; Nasrollahi et al., 2020). IND can increase CO_2 through energy-intensive manufacturing and combustion, whereas its effect on N_2O may operate through chemical industries, fertilizer production, food processing, and waste treatment. Previous evidence generally indicates that rapid industrial expansion increases environmental pressure in developing economies (Aquilas et al., 2024). Therefore:

H2: IND increases CO_2 and N_2O emissions in developing countries.

REN can directly improve environmental quality by substituting fossil fuels, reducing the emission intensity of electricity generation, and supporting cleaner production. Its expansion can reduce CO_2 emissions through lower dependence on coal, oil, and natural gas (Rahman and Alam, 2021; Hasanov et al., 2021). Although its relationship with N_2O is less direct, REN can reduce combustion-related emissions and support cleaner fertilizer manufacturing, electrified production processes, and improved waste-management systems. These environmental benefits may be strengthened by technological innovation and efficient energy infrastructure (Chen et al., 2023). This leads to the following hypothesis:

H3: REN reduces CO_2 and N_2O emissions in developing countries.

The environmental effect of FDI is expected to vary with REN penetration. Under a fossil-fuel-intensive energy structure, additional FDI may expand pollution-intensive production, consistent with the PHH. As REN increases, foreign-invested firms can access cleaner electricity, adopt efficient technologies, and reduce their dependence on carbon-intensive production. Evidence suggests that REN can weaken or reverse the adverse environmental effects of FDI (Kurniawan et al., 2024; Osei, 2025; Pan et al., 2025). REN may therefore shift the FDI–environment relationship from a pollution-haven toward a pollution-halo outcome. Accordingly:

H4: REN weakens the positive effects of FDI on CO_2 and N_2O emissions in developing countries.

A similar conditional mechanism applies to IND. Industrial expansion generally raises energy demand, but its environmental intensity depends on the energy source supporting production. At low REN levels, additional industrial output is likely to rely on fossil fuels and increase emissions. Greater REN penetration allows manufacturing and industrial infrastructure to operate with cleaner energy, thereby lowering their emission intensity. Previous studies demonstrate that REN mitigates the environmental damage associated with industrial development (Mentel et al., 2022a; Mentel et al., 2022b; Aquilas et al., 2024). Therefore:

H5: REN weakens the positive effects of IND on CO_2 and N_2O emissions in developing countries.

Institutional quality can further condition the environmental effects of FDI and IND. Strong institutions improve environmental monitoring, enforce emission standards, screen pollution-intensive investment, and encourage firms to adopt cleaner technologies. Conversely, weak institutions may allow foreign and domestic producers to avoid environmental compliance, increasing the likelihood of pollution-haven outcomes (Cole, 2004; Copeland and Taylor, 2004). Evidence also shows that stronger governance and environmental-policy stringency can mitigate the ecological damage associated with industrial and other economic activities (Nkemgha et al., 2024; Wang et al., 2024; Si et al., 2025). Effective institutions may additionally strengthen the environmental benefits of REN through policy continuity, transparent investment procedures, and effective implementation. Therefore, the adverse environmental effects of FDI and IND should be more pronounced under weak institutional quality.

H6: The positive effects of FDI and IND on CO_2 and N_2O emissions are weaker in countries with high institutional quality than in countries with low institutional quality.

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These hypotheses reflect the study's integrated theoretical framework. H1 and H2 capture the pollution-enhancing mechanisms predicted by the PHH, while H3 represents the direct environmental benefits of REN. H4 and H5 test whether REN changes the environmental consequences of FDI and IND, and H6 examines whether these relationships differ according to institutional quality. The marginal-effects and threshold analyses subsequently identify the REN level at which the adverse effects of FDI and IND become statistically insignificant or change direction, while the heterogeneity analysis compares the estimated relationships across low- and high-institutional-quality countries.

4. Materials and Methods

4.1. Data, Variables, and Measurement

This study employs a balanced panel of 101 developing countries covering 2002–2022, providing 2,121 country-year observations. The initial sample was drawn from low-, lower-middle-, and upper-middle-income economies classified by the World Bank. High-income economies were excluded because their regulatory, technological, and production structures differ from those of the developing countries examined in this study. Countries were retained when consistent annual observations were available for the variables required in the empirical models. The study period begins in 2002 because this is the first year for which annual institutional-quality data are consistently available. The period ends in 2022 because it is the latest common year providing adequate and comparable coverage across the dependent, explanatory, moderating, and control variables when the dataset was compiled.

The dependent variables are CO_2 and N_2O emissions, which are estimated separately rather than combined into a composite environmental-pollution measure. CO_2 reflects emissions associated with fossil-fuel combustion, electricity generation, transportation, manufacturing, and other energy-intensive activities. N_2O captures emissions associated mainly with agricultural soils, fertilizer use, livestock and manure management, biomass burning, chemical production, combustion, and other industrial processes. Using separate dependent variables makes it possible to identify whether energy-related and agriculture- or process-related emissions respond differently to FDI, IND, and REN. Both indicators have been employed in previous environmental studies (Ahmad and Hussain, 2024; Wang et al., 2024; Si et al., 2025; Huang et al., 2025).

FDI may increase emissions by expanding pollution-intensive production or reduce them by transferring cleaner and more energy-efficient technologies (Huang et al., 2025). IND captures the relative importance of industrial and manufacturing activities. Its expected environmental effect is positive because industrial expansion typically increases energy demand and fossil-fuel use, although the magnitude depends on technological efficiency and production structure (Nasrollahi et al., 2020; Opoku and Aluko, 2021). REN was included both as an independent explanatory variable and as a moderator of the effects of FDI and IND. Higher REN penetration is expected to reduce emissions directly and lower the pollution intensity of foreign investment and industrial production. The interaction terms FDI × REN and IND × REN are constructed using mean-centered values of their component variables. Mean-centering improves interpretation of the constituent coefficients and reduces nonessential multicollinearity without changing the substantive interaction effects.

The models include five controls. GDP growth (GDPG) captures the scale effect of economic expansion and is expected to increase emissions when additional output relies on pollution-intensive energy and production (Munir and Ameer, 2020). Population Density (POPD) controls for demographic pressure on energy demand, transportation, land use, and infrastructure (Rahman and Alam, 2021). The expected effect of Trade Openness (TRO) is ambiguous because trade may expand pollution-intensive production or facilitate access to cleaner technologies (Pata and Caglar, 2021). Institutional quality (IQ) is represented by the regulatory quality estimate. IQ is expected to reduce emissions by strengthening environmental regulation, investment screening, and policy implementation. It is also used for the heterogeneity analysis, in which countries are divided into low- and high-IQ groups according to the median of their period-average IQ values. Technological innovation (TI) controls for countries' capacity to develop, absorb, and apply cleaner and more energy-efficient technologies. Table 1 summarizes the variable definitions, measurements, expected signs, and data sources.

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Table 1. Variable Definitions, Measurements, and Sources

Variable	Symbol	Measurement	Expected Sign	Source
Dependent variables				
Carbon Dioxide Emissions	CO_2	CO_2 emissions per capita, measured in metric tons		WDI, WB
Nitrous Oxide Emissions	N_2O	N_2O emissions per capita, measured in metric tons of CO_2 equivalent		WDI, WB
Core explanatory variables				
Foreign Direct Investment	FDI	FDI, net inflows as a % of GDP	+	WDI, WB
Industrialization	IND	Industry value added as a % of GDP	+	WDI, WB
Moderating variable and independent main effect				
Renewable Energy	REN	Renewable energy consumption as a % of total final energy consumption	−	WDI, WB
FDI–Renewable Energy Interaction	FDI × REN	Interaction between mean-centered FDI and mean-centered REN	−	Authors' calculation
Industrialization–Renewable Energy Interaction	IND × REN	Interaction between mean-centered IND and mean-centered REN	−	Authors' calculation
Control variables				
GDP Growth	GDPG	Annual percentage growth rate of gross domestic product	+	WDI, WB
Population Density	POPD	Natural logarithm of the number of people per square kilometre of land area	+	WDI, WB
Trade Openness	TRO	Sum of exports and imports of goods and services as a percentage of GDP	+/−	WDI, WB
Institutional Quality	IQ	Regulatory Quality estimate, ranging approximately from −2.5 (weak) to 2.5 (strong)	−	WGI, WB
Technological Innovation	TI	Natural logarithm of one plus scientific and technical journal articles per million people	−	Authors' calculation using WDI, WB

4.2. Model Specification

The empirical models are specified based on the theoretical framework and previous studies examining FDI, IND, REN, and environmental pollution (Ahmed et al., 2022; Amin et al., 2024; Mentel et al., 2022b; Awan et al., 2022; Aquilas et al., 2024; Huang et al., 2025). Separate equations are estimated for CO_2 and N_2O to account for their different emission sources and transmission mechanisms. The baseline models examining the direct effects of FDI, IND, and REN are specified as:

$$CO2_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 IND_{it} + \beta_3 REN_{it} + \beta' Z_{it} + v_i + \omega_t + \mu_{it} \quad (1)$$

$$N2O_{it} = \infty_0 + \infty_1 FDI_{it} + \infty_2 IND_{it} + \infty_3 REN_{it} + \infty' Z_{it} + v_i + \omega_t + \mu_{it} \quad (2)$$

where i and t represent country and year, respectively. Z_{it} is the vector of control variables comprising GDPG, POPD, TRO, IQ, and TI. Country-specific effects are represented by v_i, common year effects by ω_t, and the idiosyncratic error term by μ_{it}. Based on H1-H3, the expected signs are β_1, $\infty_1 > 0$, β_2, $\infty_2 > 0$, and β_3, $\infty_3 < 0$.

To examine the moderating role of REN, the models include the main effects of FDI, IND, and REN together with their respective interaction terms:

$$CO2_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 IND_{it} + \beta_3 REN_{it} + \beta_4 (FDI_{it} \times REN_{it}) + \beta_5 (IND_{it} \times REN_{it}) + \beta' Z_{it} + v_i + \omega_t + \mu_{it} \quad (3)$$

$$N2O_{it} = \infty_0 + \infty_1 FDI_{it} + \infty_2 IND_{it} + \infty_3 REN_{it} + \infty_4 (FDI_{it} \times REN_{it}) + \infty_5 (IND_{it} \times REN_{it}) + \infty' Z_{it} + v_i + \omega_t + \mu_{it} \quad (4)$$

REN is included independently in both moderation models to adhere to the hierarchical principle of interaction-model specification. The interaction terms are constructed using mean-centered FDI, IND, and REN. Consequently, the coefficients on FDI and IND represent their effects at the sample mean of REN, while the coefficient on REN captures its effect when FDI and IND are at their respective sample means. Mean-centering also reduces nonessential multicollinearity without changing the interaction effects. Negative coefficients on FDI×REN and IND×REN indicate that greater REN penetration weakens the pollution-enhancing effects of FDI and IND. Accordingly, H4 and H5 imply and β_4, $\infty_4 < 0$ and β_5, $\infty_5 < 0$. Because interaction coefficients alone

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do not reveal the effects of FDI and IND at specific REN levels, the corresponding marginal effects are calculated as:

$$\frac{\partial(CO2_{it})}{\partial(FDI_{it})} = \beta_1 + \beta_4 \widetilde{REN}_{it} \tag{5}$$

$$\frac{\partial(CO2_{it})}{\partial(IND_{it})} = \beta_2 + \beta_5 \widetilde{REN}_{it} \tag{6}$$

$$\frac{\partial(N2O_{it})}{\partial(FDI_{it})} = \infty_1 + \infty_4 \widetilde{REN}_{it} \tag{7}$$

$$\frac{\partial(N2O_{it})}{\partial(IND_{it})} = \infty_2 + \infty_5 \widetilde{REN}_{it} \tag{8}$$

where $\widetilde{REN}_{it} = REN_{it} - \overline{REN}$. The marginal effects are evaluated at the 25th percentile, median, and 75th percentile of REN to compare countries at different stages of energy transition. The REN transition thresholds are obtained by setting each marginal effect equal to zero. Because REN is mean-centered in the interaction models, the thresholds expressed on the original REN scale are:

$$REN^*_{FDI,CO_2} = \overline{REN} - \frac{\beta_1}{\beta_4}, \qquad REN^*_{IND,CO_2} = \overline{REN} - \frac{\beta_2}{\beta_5} \tag{9}$$

$$REN^*_{FDI,N_2O} = \overline{REN} - \frac{\infty_1}{\infty_4}, \qquad REN^*_{IND,N_2O} = \overline{REN} - \frac{\infty_2}{\infty_5} \tag{10}$$

These thresholds indicate the REN levels at which the estimated effects of FDI and IND change from pollution-increasing to pollution-reducing. We assess their empirical relevance by verifying that each threshold lies within the observed REN distribution and by examining the confidence intervals of the corresponding marginal effects.

Finally, H6 is assessed through institutional-quality heterogeneity analysis. Countries are classified into low- and high-institutional-quality groups according to the median of their period-average IQ values. Equations (3) and (4) are then estimated separately for both groups. Cross-group coefficient-difference tests are used to determine whether the effects of FDI, IND, REN, and their interactions differ significantly between the two institutional regimes.

4.3. Estimation Methods

The study employs an estimation strategy consisting of two-way Fixed Effects (FE), two-step System GMM, and Lewbel instrumental-variable two-stage least squares (Lewbel IV–2SLS). These estimators address different econometric concerns, including unobserved country heterogeneity, cross-sectional dependence, emission persistence, reverse causality, and the potential endogeneity of FDI, IND, and REN. Consistency across the three estimators provides stronger evidence than reliance on a single estimation method. The analysis begins with FE estimation. The FE estimator controls for unobserved country characteristics that remain relatively stable over time, including geography, natural-resource endowments, historical production structures, and persistent institutional differences. Year effects are also included to account for common shocks such as global economic crises, changes in international energy prices, environmental agreements, and technological developments. The selection of FE over random effects is guided by the Hausman specification test, which examines whether country-specific effects are correlated with the explanatory variables (Hausman, 1978).

Panel-data errors may exhibit heteroskedasticity, serial correlation, and cross-sectional dependence because developing countries are exposed to common economic, energy, trade, and environmental shocks. Conventional FE standard errors may therefore produce unreliable statistical inference. The FE models are consequently estimated with Driscoll–Kraay standard errors, which are robust to heteroskedasticity, temporal dependence, and general forms of cross-sectional correlation (Driscoll and Kraay, 1998). The two-way FE estimates with Driscoll–Kraay standard errors serve as the baseline results for the direct and moderating effects. Although FE controls for time-invariant heterogeneity, it relies on a strict-exogeneity assumption that may not hold for the core explanatory variables. Reverse causality may arise because environmental pollution can affect foreign investment decisions, industrial policies, and the transition toward REN. Simultaneity and omitted time-varying factors may also bias the FE estimates (Wooldridge, 2010). In addition, CO_2 and N_2O emissions exhibit temporal persistence because energy systems, industrial structures, and environmental conditions adjust gradually.

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To address these concerns, the study applies two-step System GMM, developed by Arellano and Bover (1995) and Blundell and Bond (1998), based on the difference-GMM framework of Arellano and Bond (1991). The dynamic models include the first lag of the respective dependent variable to capture emission persistence. System GMM jointly estimates equations in first differences and levels, using lagged values of the variables as internal instruments. This estimator is appropriate for the present panel, which has a relatively large cross-sectional dimension of 101 countries and a shorter time dimension of 21 years. The instrument strategy is specified to reflect the potential endogeneity of the study variables. The lagged dependent variable, FDI, IND, REN, and the interaction terms are treated as endogenous because they may be jointly determined with emissions. Their second and third lags are used as internal instruments. GDPG, POPD, and TRO are treated as predetermined because feedback from environmental outcomes may occur over time. IQ and TI are treated as exogenous controls. The interaction terms are instrumented using their own available lags to ensure consistency with the treatment of their component variables.

Instrument proliferation may overfit endogenous variables and weaken the Hansen test. Therefore, the instrument matrix is collapsed, and the lag range is restricted following Roodman (2009a, 2009b). The two-step estimates use robust standard errors with the finite-sample correction developed by Windmeijer (2005), which addresses the downward bias commonly found in uncorrected two-step standard errors. The validity of the System GMM estimates is evaluated using several diagnostics. The Wald χ^2 statistic assesses the joint significance of the explanatory variables. The Arellano–Bond tests examine first- and second-order serial correlation in the differenced residuals. Significant AR(1) is expected after first differencing and does not invalidate the estimator. In contrast, the absence of significant AR(2) is necessary because second-order correlation would undermine the validity of the lagged instruments. The Hansen test evaluates the joint validity of the instrument set under heteroskedasticity (Hansen, 1982). The reported AR(2) and Hansen probabilities indicate whether the dynamic models satisfy the required specification and instrument-validity conditions. The instrument count is considered jointly with the Hansen results because excessive instruments can weaken the test's diagnostic power (Roodman, 2009b).

System GMM relies primarily on internal lagged instruments and may remain sensitive to instrument selection. Therefore, Lewbel IV–2SLS is employed as an additional endogeneity robustness test. Conventional external instruments that satisfy both relevance and exclusion restrictions are difficult to identify consistently for a large and heterogeneous sample of developing countries. The Lewbel approach generates internal instruments from heteroskedasticity in the first-stage residuals and can provide identification when credible external instruments are unavailable or insufficient (Lewbel, 2012). Country and year effects are retained in all Lewbel specifications. In the Lewbel models, FDI, IND, REN, and the interaction terms are treated as potentially endogenous. The lagged dependent variable is also included to maintain consistency with the dynamic specification. Instrument relevance and model identification are assessed through the Kleibergen–Paap LM and Wald F statistics. The Kleibergen–Paap LM test examines whether the model is underidentified, while the Wald F-statistic evaluates potential weak-instrument concerns. The Hansen J-test assesses the validity of the overidentifying restrictions, and the Durbin–Wu–Hausman test determines whether the regressors treated as endogenous can instead be considered exogenous. Lewbel IV–2SLS is interpreted as complementary evidence rather than as a replacement for FE or System GMM.

For the moderation analysis, the marginal effects of FDI and IND are evaluated at the 25th percentile, median, and 75th percentile of REN. Confidence intervals are calculated to determine whether the effects remain statistically different from zero at each REN level. The transition thresholds identify the REN levels at which the estimated effects of FDI and IND become neutral or change direction. Thresholds are interpreted only when they fall within the observed REN range. Institutional-quality heterogeneity is assessed by estimating the interaction models separately for low- and high-institutional-quality countries and testing whether the corresponding coefficients differ significantly across the two groups.

5. Results

5.1. Descriptive Statistics and Preliminary Diagnostics

Table 2 presents descriptive statistics. CO_2 emissions have a mean of 2.184 metric tons per capita and a standard deviation (SD) of 2.463, with values ranging from 0.031 to 14.762. The SD exceeding the mean indicates cross-country variation in carbon-intensive production and energy use. N_2O emissions average 0.094 metric tons of CO_2 equivalent per capita and range from 0.004 to 0.487, also showing variation across the sample. FDI averages 4.126% of GDP, although it ranges from −3.241% to 21.735% indicates that some country-year observations experienced net capital outflows while others received substantial foreign investment. IND represents an average of 25.684% of GDP, with values ranging from 6.318% to 59.476%, reflecting marked differences in economic structure. REN also exhibits dispersion: its mean is 38.572%, while its 25th and 75th percentiles are 12.684% and

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63.941%, respectively. This wide distribution supports the examination of moderation and transition thresholds across countries at different stages of energy transition.

Table 2. Descriptive statistics

Variable	Obs.	Mean	SD	Min	P25	Median	P75	Max
CO_2	2,121	2.184	2.463	0.031	0.624	1.438	3.012	14.762
N_2O	2,121	0.094	0.081	0.004	0.038	0.071	0.124	0.487
FDI	2,121	4.126	4.382	−3.241	1.284	2.917	5.486	21.735
IND	2,121	25.684	10.127	6.318	17.842	24.136	32.264	59.476
REN	2,121	38.572	28.416	0.107	12.684	31.527	63.941	97.826
GDPG	2,121	4.218	4.672	−15.842	2.137	4.326	6.714	17.638
POPD	2,121	4.386	1.447	0.284	3.416	4.481	5.392	8.974
TRO	2,121	78.463	37.219	18.527	50.328	70.814	97.365	218.472
IQ	2,121	−0.526	0.684	−2.184	−0.984	−0.491	−0.038	1.427
TI	2,121	2.136	1.312	0.000	1.073	2.026	3.062	6.184

The pairwise correlations reported in Table A1 in the appendix provide preliminary support for the expected relationships. FDI and IND are positively correlated with both pollutants, whereas REN, IQ, and TI are negatively correlated with CO_2 and N_2O. However, these associations are descriptive and do not account for country heterogeneity, time effects, or endogeneity. The largest absolute correlation among the explanatory variables is 0.438 between IQ and TI, which remains well below conventional multicollinearity thresholds.

Table A2 confirms that multicollinearity is not a serious concern. The maximum VIF is 1.42 in the baseline specification and 1.57 in the moderation specification. The corresponding mean VIF values are 1.27 and 1.34, respectively. All tolerance values remain well above commonly applied minimum levels. The modest increase after adding the interaction terms indicates that mean-centering effectively limits nonessential multicollinearity. These diagnostics support including the explanatory, moderating, interaction, and control variables in subsequent estimations.

5.2. Baseline Fixed-Effects Results

Tables 3 and 4 report the two-way FE estimates with Driscoll–Kraay standard errors for CO_2 and N_2O emissions, respectively. The models are estimated sequentially. Model 1 includes FDI, IND, and the conventional controls; Model 2 introduces the independent effect of REN; and Model 3 adds IQ and TI. This progression assesses whether the estimated effects of FDI and IND remain stable after accounting for differences in energy structure, regulatory capacity, and technological capability.

Table 3 shows that FDI has a positive and statistically significant relationship with CO_2 across all three specifications. Its coefficient declines from 0.052 in Model 1 to 0.042 in Model 3 but remains significant at the 1% level. The Model 3 estimate indicates that a one-percentage-point increase in FDI inflows is associated with an increase of 0.042 metric tons of CO_2 per capita, holding the other factors constant. The decline in magnitude after adding REN, IQ, and TI suggests that part of the FDI-related environmental effect operates through countries' energy, institutional, and technological conditions. IND also remains positive and significant at the 1% level. Its coefficient decreases from 0.044 in Model 1 to 0.037 in Model 3. Thus, a one-percentage-point increase in industry value added is associated with an additional 0.037 metric tons of CO_2 per capita in the fully specified model. The stability of the sign and significance across the specifications supports the view that industrial expansion increases carbon emissions even after controlling for REN, institutional quality, and technological innovation. REN has a negative and statistically significant coefficient in Models 2 and 3. In the complete specification, a one-percentage-point increase in the REN share is associated with a reduction of 0.014 metric tons of CO_2 per capita. IQ and TI also have significant negative coefficients, indicating that stronger regulatory capacity and greater technological capability are associated with lower CO_2 emissions. By contrast, GDPG, POPD, and TRO are positively related to CO_2. The within-(R2) increases from 0.392 in Model 1 to 0.512 in Model 3, indicating improved explanatory power after incorporating REN, IQ, and TI.

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Table 3. Fixed-Effects Estimates for CO_2 Emissions

Variables	Model 1	Model 2	Model 3
FDI	0.052***	0.047***	0.042***
	(0.011)	(0.010)	(0.009)
IND	0.044***	0.041***	0.037***
	(0.010)	(0.009)	(0.008)
REN		−0.016***	−0.014***
		(0.004)	(0.004)
GDPG	0.021***	0.019***	0.017***
	(0.007)	(0.007)	(0.006)
POPD	0.186***	0.169***	0.143***
	(0.052)	(0.049)	(0.046)
TRO	0.004***	0.003**	0.002**
	(0.001)	(0.001)	(0.001)
IQ			−0.224***
			(0.058)
TI			−0.118***
			(0.034)
Constant	−0.826***	−0.471**	−0.184
	(0.285)	(0.239)	(0.226)
Obs.	2,121	2,121	2,121
Countries	101	101	101
Within R^2	0.392	0.456	0.512
F-stat	41.73***	48.26***	45.91***
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Driscoll–Kraay SEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4 presents the results of N_2O emissions. FDI is positive and significant at the 1% level in every specification, although its coefficient decreases from 0.0019 in Model 1 to 0.0015 in Model 3. This indicates that a one-percentage-point increase in FDI is associated with an increase of 0.0015 metric tons of CO_2 equivalent per capita in N_2O emissions.

Table 4. Fixed-Effects Estimates for N_2O Emissions

Variables	Model 1	Model 2	Model 3
FDI	0.0019***	0.0017***	0.0015***
	(0.0005)	(0.0005)	(0.0004)
IND	0.0014***	0.0012***	0.0010***
	(0.0004)	(0.0004)	(0.0003)
REN		−0.0005***	−0.0004***
		(0.0001)	(0.0001)
GDPG	0.0008***	0.0007***	0.0006***
	(0.0003)	(0.0002)	(0.0002)
POPD	0.0072***	0.0064***	0.0055***
	(0.0021)	(0.0019)	(0.0018)
TRO	0.0003***	0.0002**	0.0002**
	(0.0001)	(0.0001)	(0.0001)
IQ			−0.0087***
			(0.0026)
TI			−0.0043***
			(0.0013)
Constant	0.0321***	0.0458***	0.0576***
	(0.0105)	(0.0097)	(0.0092)
Obs.	2,121	2,121	2,121
Countries	101	101	101
Within R^2	0.348	0.407	0.461
F-stat	34.28***	40.75***	39.62***
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Driscoll–Kraay SEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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IND also remains positive and significant, with its coefficient declining from 0.0014 to 0.0010 across the three models. REN is negatively associated with N_2O emissions. Its coefficient is −0.0005 in Model 2 and −0.0004 in Model 3, with both estimates significant at the 1% level. Although the magnitude is smaller than that observed for CO_2 because the pollutants are measured on different scales, the result indicates that REN also contributes to reducing agriculture- and process-related emissions. IQ and TI have significant negative coefficients, whereas GDPG, POPD, and TRO remain positive and significant. The within-(R2) rises from 0.348 to 0.461 across the specifications. The baseline results are consistent across both pollutants and model specifications. FDI and IND increase CO_2 and N_2O emissions, supporting H1 and H2, while REN reduces both pollutants, supporting H3. However, the coefficients should not be compared directly across CO_2 and N_2O because the two dependent variables have different measurement scales and emission-generating mechanisms.

5.3. Moderating Role of Renewable Energy

Tables 5 and 6 examine whether REN changes the environmental effects of FDI and IND. Model 1 introduces the FDI × REN interaction, Model 2 includes the IND × REN interaction, and Model 3 estimates both interaction terms simultaneously. Because the constituent variables are mean-centered, the coefficients on FDI and IND represent their estimated effects at the sample mean of REN.

Table 5 reports the results for CO_2 emissions. FDI, IND, and REN retain their expected signs and remain statistically significant across all specifications. In Model 3, the coefficients on FDI and IND are 0.037 and 0.032, respectively, indicating that both variables continue to increase CO_2 emissions at the average level of REN. The REN coefficient is −0.013 and significant at the 1% level, confirming its direct emissions-reducing effect. More importantly, both interaction coefficients are negative and statistically significant. The coefficient on FDI × REN is −0.0012, indicating that each one-percentage-point increase in REN reduces the marginal CO_2 effect of FDI by 0.0012 metric tons per capita. Similarly, the IND × REN coefficient of −0.0009 shows that greater REN penetration reduces the CO_2 intensity of industrial expansion. The interaction effects remain significant when entered separately and jointly, demonstrating that the moderating role of REN is not dependent on a particular model specification.

Table 5. Moderating Role of Renewable Energy in the FDI–Industrialization–CO_2 Nexus

Variables	Model 1	Model 2	Model 3
FDI	0.039***	0.041***	0.037***
	(0.009)	(0.009)	(0.008)
IND	0.036***	0.034***	0.032***
	(0.008)	(0.008)	(0.007)
REN	−0.015***	−0.014***	−0.013***
	(0.004)	(0.004)	(0.003)
FDI × REN	−0.0013***		−0.0012***
	(0.0003)		(0.0003)
IND × REN		−0.0009***	−0.0009***
		(0.0002)	(0.0002)
GDPG	0.016***	0.016***	0.015***
	(0.006)	(0.006)	(0.005)
POPD	0.137***	0.139***	0.128***
	(0.044)	(0.045)	(0.043)
TRO	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
IQ	−0.216***	−0.218***	−0.205***
	(0.056)	(0.057)	(0.054)
TI	−0.113***	−0.115***	−0.107***
	(0.033)	(0.033)	(0.032)
Constant	−0.152	−0.161	−0.094
	(0.221)	(0.224)	(0.218)
Obs.	2,121	2,121	2,121
Countries	101	101	101
Within R^2	0.536	0.529	0.558
F-stat	47.82***	46.91***	49.37***
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Driscoll–Kraay SEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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Table 6 presents the corresponding results for N_2O. In Model 3, FDI and IND remain positive and significant, with coefficients of 0.0014 and 0.0010, respectively. REN retains a negative coefficient of −0.0004, confirming that greater renewable-energy use is also associated with lower N_2O emissions. The FDI × REN coefficient is −0.00005, while the IND × REN coefficient is −0.00003; both are significant at the 1% level. These results indicate that REN weakens the effects of FDI and IND on N_2O, although the relevant mechanisms may operate through cleaner industrial energy, fertilizer production, agro-industrial processing, and waste-treatment systems rather than only through fossil-fuel substitution.

The negative interaction coefficients demonstrate that the environmental consequences of FDI and IND depend on the level of REN. Greater REN penetration reduces the pollution intensity of both foreign investment and industrial expansion, supporting H4 and H5. However, the interaction coefficients alone do not establish the REN level at which these effects become statistically insignificant or change direction. This issue is examined through the marginal-effects and threshold analyses in Section 5.5.

Table 6. Moderating Role of Renewable Energy in the FDI–Industrialization–N_2O Nexus

Variables	Model 1	Model 2	Model 3
FDI	0.0016***	0.0015***	0.0014***
	(0.0004)	(0.0004)	(0.0004)
IND	0.0011***	0.0011***	0.0010***
	(0.0003)	(0.0003)	(0.0003)
REN	−0.0005***	−0.0005***	−0.0004***
	(0.0001)	(0.0001)	(0.0001)
FDI × REN	−0.00005***		−0.00005***
	(0.00001)		(0.00001)
IND × REN		−0.00003***	−0.00003***
		(0.00001)	(0.00001)
GDPG	0.0006***	0.0006***	0.0005***
	(0.0002)	(0.0002)	(0.0002)
POPD	0.0052***	0.0053***	0.0048***
	(0.0017)	(0.0017)	(0.0016)
TRO	0.0002*	0.0002**	0.00034*
	(0.00012)	(0.0001)	(0.0002)
IQ	−0.0084***	−0.0085***	−0.0079***
	(0.0025)	(0.0025)	(0.0024)
TI	−0.0041***	−0.0042***	−0.0038***
	(0.0013)	(0.0013)	(0.0012)
Constant	0.0584***	0.0579***	0.0617***
	(0.0091)	(0.0091)	(0.0089)
Obs.	2,121	2,121	2,121
Countries	101	101	101
Within R^2	0.482	0.475	0.503
F-stat	42.76***	41.93***	44.58***
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Driscoll–Kraay SEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.4. Dynamic System GMM Results

Table 7 presents the two-step System GMM estimates for the baseline and moderation models. The dynamic specifications include the first lag of the dependent variable to capture persistence in environmental outcomes and address potential endogeneity through restricted and collapsed internal instruments. The lagged dependent variables are positive and statistically significant in all specifications. For CO_2, the coefficients are 0.721 in the baseline model and 0.704 in the moderation model. The corresponding N_2O coefficients are 0.683 and 0.661. These estimates indicate significant persistence in both pollutants, reflecting the gradual adjustment of energy systems, industrial structures, and environmental conditions.

FDI and IND retain positive and statistically significant coefficients. In the CO_2 moderation model, the coefficients on FDI and IND are 0.031 and 0.028, respectively. In the N_2O moderation model, the corresponding estimates are 0.0012 and 0.0008. Although these coefficients are moderately smaller than the FE estimates, their directions and significance remain unchanged. The results therefore confirm that the positive environmental

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effects of FDI and IND are not explained solely by unobserved country heterogeneity, reverse causality, or emission persistence. REN remains negative and significant at the 1% level in all four models. Its coefficient is −0.011 in the CO_2 moderation model and −0.0004 in the N_2O moderation model, confirming its direct emissions-reducing effect. The interaction coefficients also remain negative. For CO_2, FDI × REN and IND × REN have coefficients of −0.0010 and −0.0007, respectively, both significant at the 1% level. For N_2O, the FDI × REN coefficient is −0.00004 and significant at the 1% level, while the IND × REN coefficient is −0.00002 and significant at the 5% level. These results confirm that REN continues to weaken the environmental effects of FDI and IND after accounting for endogeneity and dynamic adjustment.

The control variables remain broadly consistent with the FE results. GDPG, POPD, and TRO are positively associated with both pollutants, whereas IQ and TI have significant negative coefficients. This stability across static and dynamic specifications strengthens confidence in the estimated relationships. The diagnostic tests support the validity of the System GMM models. The AR(1) tests are significant in all specifications, as expected for first-differenced residuals. In contrast, the AR(2) p-values range from 0.364 to 0.536, indicating that the null hypothesis of no second-order serial correlation cannot be rejected. The Hansen p-values range from 0.291 to 0.406, suggesting that the joint validity of the instrument sets cannot be rejected. The instrument counts range from 26 to 33 and remain substantially below the 101 countries, reducing concerns about instrument proliferation. The Wald statistics are also significant at the 1% level, confirming the joint explanatory power of the models. The dynamic evidence therefore continues to support H1–H5 while addressing concerns related to persistence, simultaneity, and endogeneity.

Table 7. Dynamic Two-Step System GMM Estimates

Variables	CO_2 Baseline (1)	CO_2 Moderation (2)	N_2O Baseline (3)	N_2O Moderation (4)
Lagged dependent variable	0.721***	0.704***	0.683***	0.661***
	(0.041)	(0.039)	(0.046)	(0.044)
FDI	0.035***	0.031***	0.0013***	0.0012***
	(0.009)	(0.008)	(0.0004)	(0.0003)
IND	0.031***	0.028***	0.0009***	0.0008***
	(0.008)	(0.007)	(0.0003)	(0.0002)
REN	−0.012***	−0.011***	−0.0004***	−0.0004***
	(0.003)	(0.003)	(0.0001)	(0.0001)
FDI × REN		−0.0010***		−0.00004***
		(0.0003)		(0.00001)
IND × REN		−0.0007***		−0.00002**
		(0.0002)		(0.00001)
GDPG	0.014**	0.013**	0.0005**	0.0004**
	(0.006)	(0.006)	(0.0002)	(0.0002)
POPD	0.119***	0.108***	0.0046***	0.0042***
	(0.041)	(0.039)	(0.0015)	(0.0014)
TRO	0.002**	0.0032**	0.00021**	0.0003***
	(0.001)	(0.0014)	(0.0001)	(0.0001)
IQ	−0.182***	−0.174***	−0.0071***	−0.0068***
	(0.052)	(0.050)	(0.0022)	(0.0021)
TI	−0.091***	−0.086***	−0.0034***	−0.0032***
	(0.029)	(0.028)	(0.0011)	(0.0011)
Constant	−0.124	−0.086	0.018**	0.021**
	(0.181)	(0.174)	(0.009)	(0.009)
Obs.	2,020	2,020	2,020	2,020
Countries	101	101	101	101
Instruments	29	33	26	31
Wald χ^2	684.27***	731.46***	592.38***	641.72***
AR(1), p-value	0.000	0.000	0.000	0.000
AR(2), p-value	0.417	0.536	0.364	0.482
Hansen test, p-value	0.328	0.291	0.406	0.347
Country effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

Notes: Robust SEs in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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5.5. Marginal Effects and Renewable-Energy Thresholds

Tables 8 and 9 report the marginal effects of FDI and IND at the 25th percentile, median, and 75th percentile of REN. Unlike the interaction coefficients, these estimates show the magnitude and statistical significance of the environmental effects at specific stages of renewable-energy penetration.

Table 8 presents the CO_2 results. At the 25th percentile of REN, corresponding to a renewable-energy share of 12.684%, the marginal effect of FDI is 0.068 under FE and 0.057 under System GMM. Both estimates are positive and significant at the 1% level. At the median REN level of 31.527%, the effect declines to 0.045 under FE and 0.038 under System GMM but remains significant. At the 75th percentile of 63.941%, the effect falls to 0.007 under FE and 0.006 under System GMM, with both confidence intervals including zero. Thus, the adverse CO_2 effect of FDI becomes statistically insignificant at high REN penetration. A similar pattern is observed for IND. Its marginal CO_2 effect declines from 0.055 under FE and 0.046 under System GMM at the 25th percentile to 0.038 and 0.033 at the median. At the 75th percentile, the FE estimate falls to 0.009 and becomes statistically insignificant. The System GMM estimate is 0.010 and is only weakly significant at the 10% level; its 95% confidence interval includes zero. Therefore, the evidence indicates that the CO_2 effect of IND becomes economically small and approaches statistical neutrality at high REN levels.

Table 8. Marginal Effects of FDI and Industrialization on CO_2 at Different Levels of Renewable Energy

Variable	REN Level	REN Value	FE Marginal Effect	FE 95% CI	GMM Marginal Effect	GMM 95% CI
FDI	P25	12.684	0.068***	[0.044, 0.092]	0.057***	[0.035, 0.079]
FDI	P50	31.527	0.045***	[0.028, 0.063]	0.038***	[0.022, 0.054]
FDI	P75	63.941	0.007	[−0.009, 0.022]	0.006	[−0.008, 0.019]
IND	P25	12.684	0.055***	[0.034, 0.077]	0.046***	[0.027, 0.066]
IND	P50	31.527	0.038***	[0.023, 0.054]	0.033***	[0.019, 0.047]
IND	P75	63.941	0.009	[−0.004, 0.023]	0.010*	[−0.002, 0.022]

Notes: P25, P50, and P75 denote the 25th percentile, median, and 75th percentile of renewable energy consumption, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 9 confirms the same declining pattern for N_2O. The marginal effect of FDI decreases from 0.00269 under FE and 0.00224 under System GMM at the 25th percentile to 0.00175 and 0.00148 at the median. At the 75th percentile, the estimates decline to 0.00013 and 0.00019 and become statistically insignificant. The marginal N_2O effect of IND similarly decreases from 0.00178 and 0.00132 at the 25th percentile to 0.00121 and 0.00094 at the median. At the 75th percentile, both estimates are close to zero and statistically insignificant.

Table 9. Marginal Effects of FDI and Industrialization on N_2O at Different Levels of Renewable Energy

Variable	REN Level	REN Value	FE Marginal Effect	FE 95% CI	GMM Marginal Effect	GMM 95% CI
FDI	P25	12.684	0.00269***	[0.00162, 0.00377]	0.00224***	[0.00128, 0.00319]
FDI	P50	31.527	0.00175***	[0.00107, 0.00244]	0.00148***	[0.00087, 0.00209]
FDI	P75	63.941	0.00013	[−0.00040, 0.00066]	0.00019	[−0.00029, 0.00066]
IND	P25	12.684	0.00178***	[0.00090, 0.00266]	0.00132***	[0.00055, 0.00208]
IND	P50	31.527	0.00121***	[0.00064, 0.00178]	0.00094***	[0.00045, 0.00143]
IND	P75	63.941	0.00024	[−0.00015, 0.00063]	0.00029	[−0.00006, 0.00065]

Notes: P25, P50, and P75 denote the 25th percentile, median, and 75th percentile of renewable energy consumption, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 10 identifies the REN levels at which the estimated marginal effects cross zero. For CO_2, the FDI threshold is 69.405% under FE and 69.572% under System GMM. The corresponding IND thresholds are 74.128% and 78.572%. For N_2O, the estimated FDI thresholds are 66.572% under FE and 68.572% under System GMM, while the IND thresholds are 71.905% and 78.572%, respectively. All thresholds lie above the sample's 75th percentile of 63.941% but within the observed REN range of 0.107%–97.826%. Their confidence intervals also remain within the observed distribution. These findings indicate a gradual transition rather than an immediate reversal. At low and moderate REN levels, FDI and IND continue to increase both pollutants. At high REN penetration, their marginal effects become substantially smaller and generally statistically indistinguishable from zero. The estimated thresholds identify the points at which the predicted effects change sign; however, they should not automatically be interpreted as evidence of a statistically significant pollution-reducing effect beyond the threshold.

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The close correspondence between the FE and System GMM estimates demonstrates that the core conclusion does not change after accounting for endogeneity. The marginal-effects and threshold results provide additional support for H4 and H5 and show that a substantial renewable-energy share is required to neutralize the environmental consequences of FDI and IND.

Table 10. Renewable-Energy Transition Thresholds

Dependent Variable	Explanatory Variable	Estimator	REN Threshold (%)	95% Confidence Interval	Observed REN Range	Position in Distribution
CO_2	FDI	FE	69.405	[62.418, 78.326]	0.107–97.826	Above P75
CO_2	IND	FE	74.128	[65.836, 85.914]	0.107–97.826	Above P75
CO_2	FDI	System GMM	69.572	[61.842, 80.617]	0.107–97.826	Above P75
CO_2	IND	System GMM	78.572	[68.914, 93.486]	0.107–97.826	Above P75
N_2O	FDI	FE	66.572	[59.638, 76.824]	0.107–97.826	Above P75
N_2O	IND	FE	71.905	[63.147, 84.372]	0.107–97.826	Above P75
N_2O	FDI	System GMM	68.572	[60.528, 79.936]	0.107–97.826	Above P75
N_2O	IND	System GMM	78.572	[67.438, 95.127]	0.107–97.826	Above P75

Figure 3 shows that the marginal effects of FDI and IND decline as REN increases. Both effects remain positive and statistically significant at low and median REN levels. At the 75th percentile, they are close to zero and statistically insignificant. The estimated zero-crossing thresholds range from 69.4% to 78.6%, but do not establish a significant pollution-reducing effect beyond those levels.

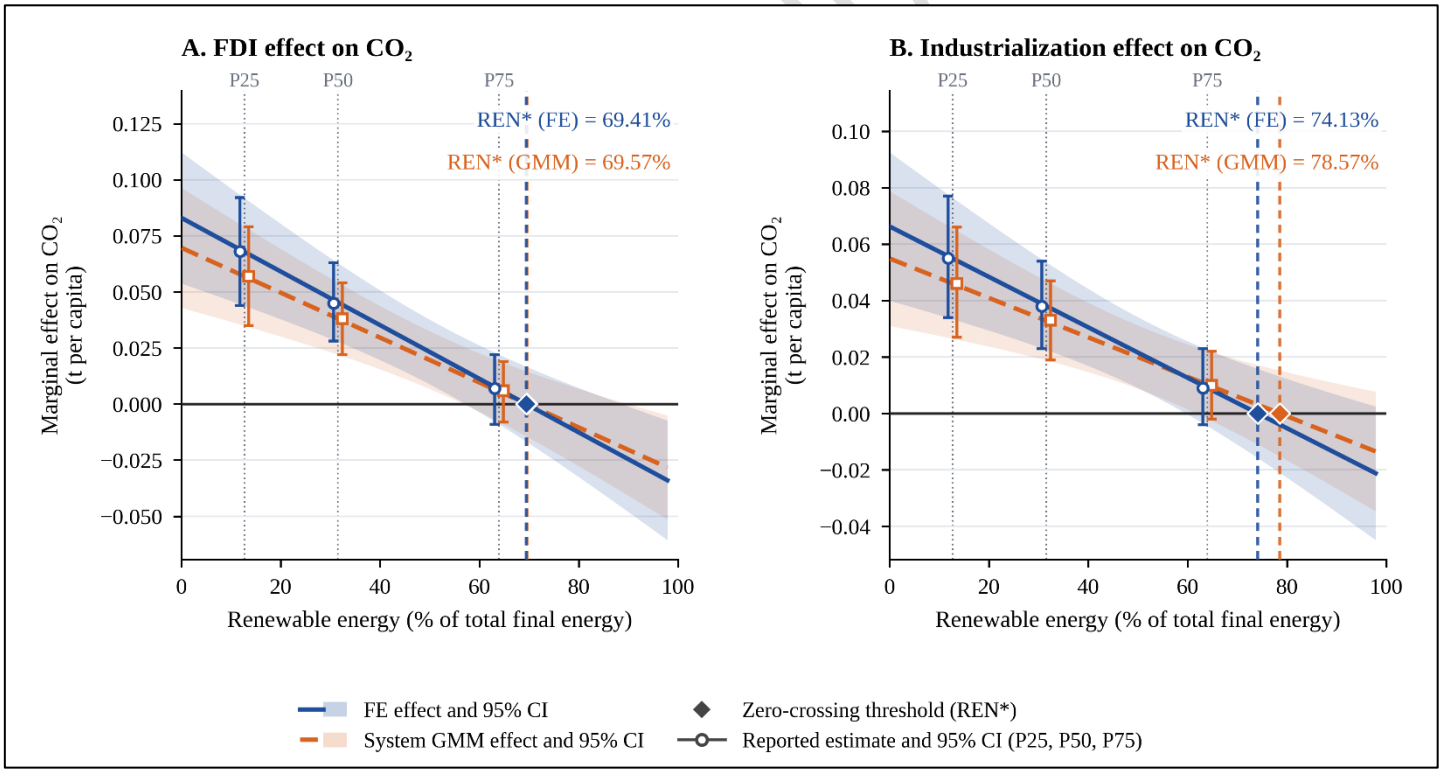


Figure 3. Marginal Effects of FDI and Industrialization on CO_2 Emissions across Renewable Energy Levels

Figure 4 shows that the marginal effects of FDI and IND on N_2O also weaken as REN increases. They are positive and significant at low and median REN levels, then become small and statistically insignificant at the 75th percentile. Estimated zero-crossing thresholds range from 66.6% to 78.6%. The similar patterns across FE and System GMM indicate that the decline is consistent across estimation methods.

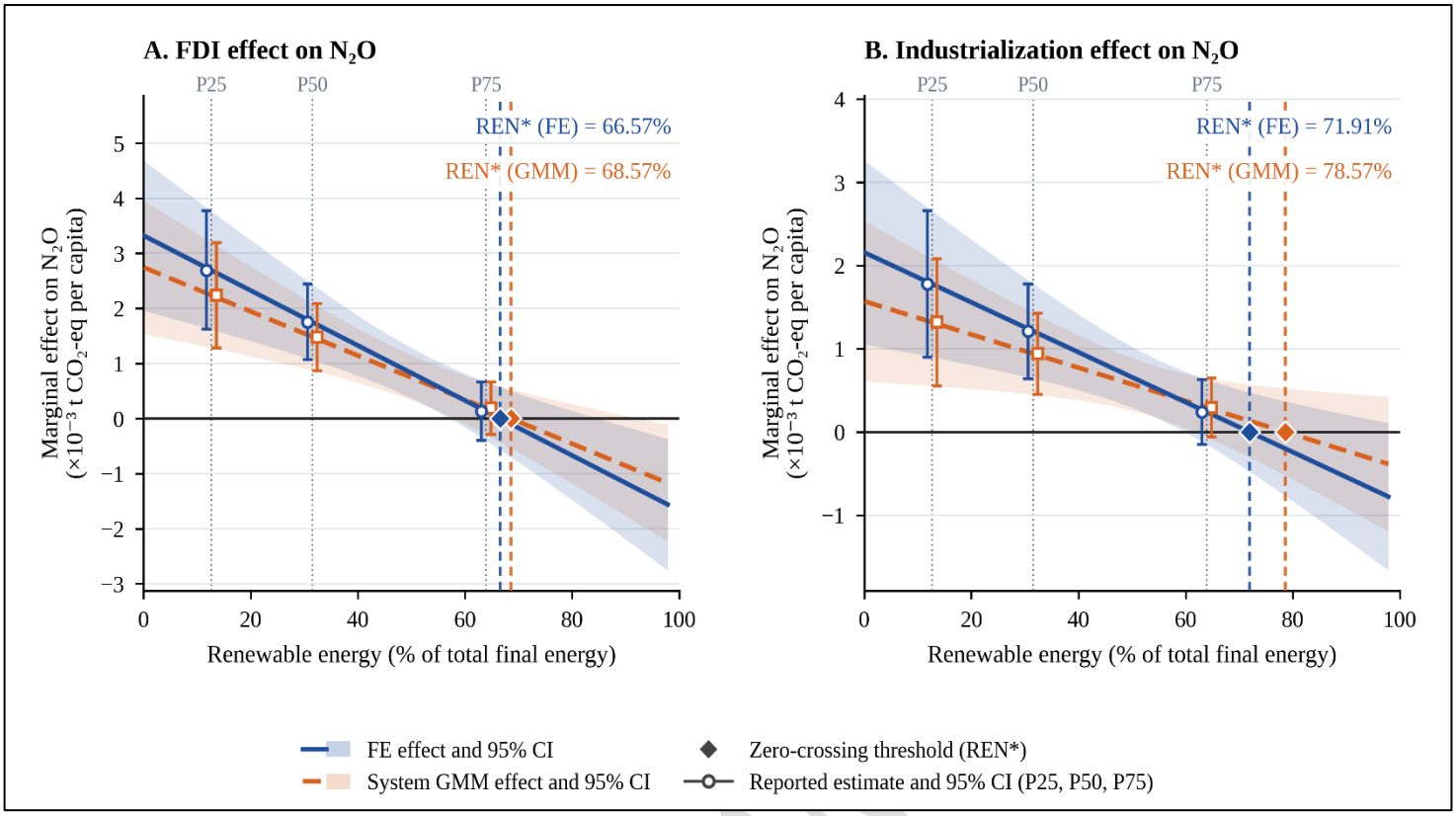


Figure 4. Marginal Effects of FDI and Industrialization on N_2O Emissions across Renewable Energy Levels

5.6. Lewbel IV–2SLS Endogeneity Analysis

Table 11 reports the Lewbel IV–2SLS estimates, which provide an additional assessment of endogeneity using heteroskedasticity-generated internal instruments. The models retain the lagged dependent variable and country and year effects to remain consistent with the dynamic specification. The lagged dependent variable is positive and significant in all four models, with coefficients ranging from 0.603 to 0.684. This finding confirms the persistence of both CO_2 and N_2O emissions. For the CO_2 model, FDI and IND remain positive and significant at the 1% level. In the moderation specification, their coefficients are 0.034 and 0.030, respectively. REN retains a negative coefficient of −0.012, while the coefficients on FDI × REN and IND × REN are −0.0011 and −0.0008, respectively. Both interaction effects are significant at the 1% level. These estimates lie between the corresponding FE and System GMM coefficients, indicating strong consistency across the three estimation approaches. The N_2O model results show the same pattern. In the moderation model, the coefficients on FDI and IND are 0.0012 and 0.0009, respectively, while the REN coefficient is −0.0004. The FDI × REN and IND × REN coefficients are −0.00004 and −0.00003, respectively. All these coefficients are statistically significant at the 1% level. The control variables also retain their previous signs: GDPG, POPD, and TRO increase emissions, whereas IQ and TI reduce them.

The identification diagnostics support the Lewbel IV specifications. The Kleibergen–Paap LM test has a p-value of 0.000 in all models, rejecting the null hypothesis of underidentification. The Kleibergen–Paap Wald F-statistics range from 17.95 to 21.46, indicating that weak instruments are unlikely to be a serious concern. The number of excluded instruments ranges from 15 to 24 across the specifications. The Hansen J-test p-values range from 0.297 to 0.418. Therefore, the null hypothesis that the overidentifying restrictions are valid cannot be rejected. By contrast, the Durbin–Wu–Hausman p-values range from 0.008 to 0.019, rejecting the exogeneity of the regressors treated as endogenous. This finding supports the use of an IV approach and confirms that relying exclusively on static FE estimates could leave endogeneity insufficiently addressed. The Lewbel IV–2SLS results closely reproduce the signs, significance levels, and relative magnitudes obtained from FE and System GMM. FDI and IND increase CO_2 and N_2O emissions, REN directly reduces both pollutants, and REN weakens the adverse environmental effects of FDI and IND. The Lewbel estimates therefore provide additional support for H1–H5 and demonstrate that the central conclusions remain robust to an alternative identification strategy.

Table 11. Lewbel IV–2SLS Endogeneity Robustness Estimates

Variables	CO_2 Baseline (1)	CO_2 Moderation (2)	N_2O Baseline (3)	N_2O Moderation (4)
Lagged dependent variable	0.684***	0.657***	0.624***	0.603***
	(0.052)	(0.049)	(0.057)	(0.054)
FDI	0.038***	0.034***	0.0014***	0.0012***
	(0.010)	(0.009)	(0.0004)	(0.0004)
IND	0.033***	0.030***	0.0010***	0.0009***
	(0.009)	(0.008)	(0.0003)	(0.0003)
REN	−0.013***	−0.012***	−0.0004***	−0.0004***
	(0.004)	(0.003)	(0.0001)	(0.0001)
FDI × REN		−0.0011***		−0.00004***
		(0.0003)		(0.00001)
IND × REN		−0.0008***		−0.00003***
		(0.0002)		(0.00001)
GDPG	0.015**	0.014**	0.0005**	0.0005**
	(0.006)	(0.006)	(0.0002)	(0.0002)
POPD	0.126***	0.114***	0.0048***	0.0044***
	(0.043)	(0.041)	(0.0016)	(0.0015)
TRO	0.0022**	0.002**	0.0004**	0.0002**
	(0.001)	(0.001)	(0.0002)	(0.0001)
IQ	−0.191***	−0.181***	−0.0074***	−0.0070***
	(0.055)	(0.052)	(0.0023)	(0.0022)
TI	−0.096***	−0.090***	−0.0036***	−0.0033***
	(0.031)	(0.029)	(0.0012)	(0.0011)
Constant	−0.139	−0.097	0.019**	0.022**
	(0.188)	(0.179)	(0.009)	(0.009)
Obs.	2,020	2,020	2,020	2,020
Countries	101	101	101	101
Excluded instruments	17	24	15	22
Kleibergen–Paap LM, p-value	0.000	0.000	0.000	0.000
Kleibergen–Paap Wald F	21.46	18.72	20.38	17.95
Hansen J, p-value	0.364	0.297	0.418	0.331
Durbin–Wu–Hausman, p-value	0.008	0.012	0.015	0.019
Country effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

Notes: Robust SEs in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.7. Institutional-Quality Heterogeneity

Tables 12 and 13 examine whether the environmental effects of FDI, IND, and REN differ between countries with low and high institutional quality. Countries are classified according to the median of their period-average IQ values, producing a low-IQ group of 50 countries and a high-IQ group of 51 countries. The reported difference tests assess whether the coefficients vary significantly between the two institutional regimes.

Table 12 presents the CO_2 results. FDI increases CO_2 emissions in both groups, but its coefficient declines from 0.052 in low-IQ countries to 0.025 in high-IQ countries. The cross-group difference is −0.027 and statistically significant at the 5% level. Similarly, the IND coefficient decreases from 0.044 to 0.021, with a significant difference of −0.023. These results indicate that stronger institutions attenuate, but do not completely eliminate, the pollution effects of foreign investment and industrial expansion. The environmental benefit of REN is also stronger under high institutional quality. Its coefficient is −0.009 in low-IQ countries and −0.019 in high-IQ countries, with a significant cross-group difference of −0.010. The FDI × REN coefficient becomes more negative, changing from −0.0009 in the low-IQ group to −0.0016 in the high-IQ group. Likewise, the IND × REN coefficient changes from −0.0006 to −0.0011. Both coefficient differences are statistically significant at the 5% level. These findings show that stronger regulatory capacity enhances both the direct and moderating effects of REN on CO_2 emissions.

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Table 12. Institutional-Quality Heterogeneity in the CO_2 Emissions Effects of FDI, Industrialization, and Renewable Energy

Variables	Low-IQ Countries	High-IQ Countries	Difference: High − Low	Difference p-value
FDI	0.052***	0.025**	−0.027**	0.041
	(0.011)	(0.010)	(0.013)	
IND	0.044***	0.021**	−0.023**	0.048
	(0.010)	(0.009)	(0.012)	
REN	−0.009**	−0.019***	−0.010**	0.036
	(0.004)	(0.005)	(0.005)	
FDI × REN	−0.0009***	−0.0016***	−0.0007**	0.049
	(0.0003)	(0.0004)	(0.0004)	
IND × REN	−0.0006**	−0.0011***	−0.0005**	0.044
	(0.0003)	(0.0003)	(0.0003)	
GDPG	0.019***	0.011*		
	(0.006)	(0.006)		
POPD	0.161***	0.093**		
	(0.052)	(0.044)		
TRO	0.003**	0.001		
	(0.001)	(0.001)		
IQ	−0.142**	−0.238***		
	(0.067)	(0.071)		
TI	−0.072**	−0.139***		
	(0.035)	(0.041)		
Obs.	1,050	1,071		
Countries	50	51		
Within R^2	0.493	0.581		
Country FE	Yes	Yes		
Year FE	Yes	Yes		

Note: Driscoll–Kraay SEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 13 reports comparable patterns for N_2O. The FDI coefficient is 0.0018 in low-IQ countries but only 0.0008 in high-IQ countries, while the IND coefficient declines from 0.0013 to 0.0006. The corresponding cross-group differences are negative and significant. Thus, institutional quality also reduces the effects of FDI and IND on agriculture- and process-related emissions. REN has a coefficient of −0.0003 in the low-IQ group and −0.0006 in the high-IQ group. Its direct N_2O-reducing effect is therefore twice as large in countries with stronger institutions. The FDI × REN coefficient changes from −0.00003 to −0.00006, while the IND × REN coefficient changes from −0.00002 to −0.00004. The differences are significant at the 5% level, confirming that stronger institutions improve the effectiveness of REN in moderating N_2O emissions. The control-variable results provide additional evidence of institutional heterogeneity. The positive effects of GDPG, POPD, and TRO are generally smaller in high-IQ countries, while the negative coefficients on IQ and TI are larger. The models also have greater explanatory power in the high-IQ group: the within-(R2) rises from 0.493 to 0.581 for CO_2 and from 0.447 to 0.526 for N_2O.

The heterogeneity results demonstrate that institutional quality shapes both the scale and composition of environmental effects. Stronger institutions reduce the pollution intensity of FDI and IND and enhance the direct and moderating benefits of REN. These findings support H6, while also showing that institutional strength attenuates rather than automatically removes the environmental costs of foreign investment and industrial development.

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Table 13. Institutional-Quality Heterogeneity in the N_2O Emissions Effects of FDI, Industrialization, and Renewable Energy

Variables	Low-IQ Countries	High-IQ Countries	Difference: High − Low
FDI	0.0018***	0.0008**	−0.001**
	(0.0005)	(0.0004)	(0.0005)
IND	0.0013***	0.0006**	−0.0007*
	(0.0004)	(0.0003)	(0.0004)
REN	−0.0003**	−0.0006***	−0.0003***
	(0.0001)	(0.0002)	(0.0001)
FDI × REN	−0.00003***	−0.00006***	−0.00003***
	(0.00001)	(0.00002)	(0.00001)
IND × REN	−0.00002**	−0.00004***	−0.00002**
	(0.00001)	(0.00001)	(0.00001)
GDPG	0.0007***	0.0004*	
	(0.0002)	(0.0002)	
POPD	0.0058***	0.0035**	
	(0.0018)	(0.0016)	
TRO	0.0002**	0.00002	
	(0.0001)	(0.00002)	
IQ	−0.0059**	−0.0098***	
	(0.0027)	(0.0031)	
TI	−0.0028**	−0.0049***	
	(0.0013)	(0.0015)	
Obs.	1,050	1,071	
Countries	50	51	
Within R^2	0.447	0.526	
Country FE	Yes	Yes	
Year FE	Yes	Yes	

Note: Driscoll–Kraay SEs in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6. Discussions

The findings demonstrate that the environmental consequences of FDI and IND in developing countries are shaped by energy structure and institutional capacity. Across FE, System GMM, and Lewbel IV–2SLS, FDI and IND increase both CO_2 and N_2O emissions, while REN directly reduces them and weakens the adverse effects of the two growth drivers. The consistency of these relationships across estimators suggests that the results are not driven solely by unobserved country heterogeneity, emission persistence, or reverse causality. The positive FDI coefficients support H1 and the PHH. Developing countries may attract pollution-intensive foreign investment because of relatively weak environmental enforcement, lower compliance costs, and continued dependence on fossil fuels. This interpretation is consistent with Shahbaz et al. (2015, 2019), Balsalobre-Lorente et al. (2022), and Ho et al. (2026), who documented emissions-increasing effects of FDI. However, this contrasts with Nepal et al. (2021) and Kurniawan et al. (2024), who found that FDI could improve environmental quality. These differences suggest that the environmental effect of foreign capital depends on its sectoral composition, technological content, host-country regulation, and energy system. FDI directed toward clean and technologically advanced sectors may generate PHaH effects, whereas investment concentrated in pollution-intensive activities reinforces the PHH.

The findings also support H2 by showing that IND increases both pollutants. This result is consistent with Mahmood et al. (2020), Munir and Ameer (2020), and Aquilas et al. (2024), who associate industrial expansion with higher energy demand and emissions. In many developing countries, industrial growth continues to rely on fossil-fuel-intensive production, inefficient technologies, and limited environmental enforcement. Nevertheless, the heterogeneous findings of Opoku and Aluko (2021) indicate that IND need not remain environmentally harmful at every development stage. Its ecological effect may decline as economies adopt efficient technologies, cleaner energy, and stronger regulation. The pollutant-specific results provide an important distinction. The positive CO_2 effects of FDI and IND are primarily consistent with greater fossil-fuel use in electricity generation, transportation, manufacturing, and other energy-intensive activities. Their N_2O effects are more likely to operate through agro-industrial expansion, fertilizer and chemical production, food processing, combustion, and waste treatment. Thus, CO_2 and N_2O capture different environmental mechanisms and should not be treated as interchangeable measures. The smaller numerical N_2O coefficients do not imply a weaker substantive effect because the two dependent variables use different scales and represent different emission processes.

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REN has a negative direct effect on both pollutants, supporting H3. For CO_2, the principal mechanism is the substitution of renewable sources for fossil fuels in electricity generation and production. For N_2O, the mechanism is less direct and may involve cleaner industrial energy, electrification of production, improved fertilizer manufacturing, and better waste-treatment systems. The negative interaction coefficients further show that REN reduces the pollution intensity of FDI and IND, supporting H4 and H5. These findings are consistent with Mentel et al. (2022a, 2022b), Osei (2025), Aquilas et al. (2024), and Pan et al. (2025), who emphasize that energy transition can improve the environmental consequences of investment and industrial activity. The marginal-effects analysis clarifies that the moderating effect of REN is gradual. At the 25th percentile and median of REN, FDI and IND continue to increase both pollutants significantly. At the 75th percentile, their effects become small and generally statistically insignificant. The estimated zero-crossing thresholds range from approximately 66.6% to 78.6% of total final energy consumption. These thresholds lie above the sample's 75th percentile but within its observed range. Therefore, limited or intermediate REN adoption may reduce pollution intensity without fully neutralizing the environmental effects of FDI and IND. A comparatively advanced energy transition is required before their predicted marginal effects reach zero.

This result provides a more precise reconciliation of the PHH and PHaH. Under low REN penetration, FDI and IND operate within fossil-fuel-intensive production systems, making PHH outcomes more likely. As REN expands, their environmental effects progressively weaken. Once REN exceeds the estimated transition threshold, the point estimates change sign, indicating the possibility of a PHaH-type outcome. However, the threshold represents the estimated zero-crossing point and should not, by itself, be interpreted as proof of a statistically significant pollution-reducing effect beyond that level. The findings therefore support a conditional transition from pollution-haven pressures toward pollution-halo potential rather than an automatic reversal. The results also support EMT. Economic modernization does not necessarily improve environmental quality unless it is accompanied by changes in energy systems, technologies, and institutions. REN reduces the emission intensity of production and strengthens the environmental value of technological spillovers from FDI. This supports the central argument of EMT that structural and technological modernization can facilitate the decoupling of economic development from environmental degradation (Mol et al., 2013; Ali et al., 2022; Pan et al., 2025). The findings extend this perspective by identifying an empirically observable REN range within which such decoupling becomes more plausible.

Institutional-quality heterogeneity further qualifies this transition. In high-IQ countries, the positive effects of FDI and IND are significantly smaller, while the direct and moderating effects of REN are stronger. This supports H6 and is consistent with evidence that environmental-policy stringency and governance reduce the ecological costs of economic activity (Nkemgha et al., 2024; Wang et al., 2024; Si et al., 2025). Stronger institutions can screen foreign investment, enforce emission standards, improve renewable-energy implementation, and encourage technology adoption. Nevertheless, FDI and IND remain positively associated with emissions even in the high-IQ group. Institutional strength therefore mitigates, but does not independently eliminate, pollution-intensive growth.

The control-variable results reinforce the importance of broader structural conditions. GDPG, POPD, and TRO generally increase emissions, reflecting the scale, demographic, and trade-related pressures accompanying economic activity. By contrast, IQ and TI reduce both pollutants, suggesting that regulatory capacity and technological capability support cleaner development. The stability of these relationships across FE, System GMM, and Lewbel IV–2SLS strengthens the overall interpretation. Taken together, the findings show that the environmental effects of FDI and IND are neither universally harmful nor automatically beneficial. They depend on whether economic expansion occurs within a fossil-fuel-intensive, weakly regulated system or within an institutional and technological environment capable of supporting substantial REN deployment. The study therefore advances the literature by demonstrating that REN thresholds and institutional capacity jointly determine whether FDI and IND reinforce pollution-haven pressures or contribute to a transition toward cleaner development.

7. Conclusions

This study examined how FDI and IND affect CO_2 and N_2O emissions and whether these relationships are conditioned by REN and institutional quality. The analysis used a balanced panel of 101 developing countries covering 2002–2022. Two-way FE estimation with Driscoll–Kraay standard errors was complemented by two-step System GMM and Lewbel IV–2SLS to address unobserved heterogeneity, emission persistence, reverse causality, and other potential sources of endogeneity. Marginal-effects, threshold, and institutional-quality heterogeneity analyses were subsequently employed to identify the conditions under which the environmental effects of FDI and IND change.

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The findings consistently show that FDI and IND increase both CO_2 and N_2O emissions, whereas REN directly reduces both pollutants. These relationships remain stable across the FE, System GMM, and Lewbel IV–2SLS estimations. The positive CO_2 effects are primarily consistent with increased fossil-fuel consumption in electricity generation, transportation, manufacturing, and other energy-intensive activities. The N_2O results indicate that FDI and IND may also create environmental pressure through fertilizer-intensive agriculture, chemical production, agro-industrial processing, combustion, and waste-treatment activities. These findings confirm that CO_2 and N_2O represent distinct emission processes and should not be treated as interchangeable indicators of environmental pollution.

The negative interaction effects demonstrate that REN significantly weakens the adverse environmental consequences of both FDI and IND. At low and median REN levels, their marginal effects remain positive and statistically significant. At the 75th percentile, however, these effects become small and generally statistically insignificant. The estimated zero-crossing thresholds range from approximately 66.6% to 78.6% of total final energy consumption. These thresholds indicate that substantial renewable-energy penetration is required to neutralize the predicted pollution effects of foreign investment and industrial expansion. Nevertheless, the zero-crossing points should not be interpreted as conclusive evidence that FDI or IND produces statistically significant environmental benefits beyond these levels.

Institutional quality further shapes these relationships. Countries with stronger institutions experience significantly smaller pollution effects from FDI and IND and stronger direct and moderating benefits from REN. However, institutional quality mitigates rather than completely eliminates the environmental costs of foreign investment and industrial development. Overall, the findings reconcile the PHH and PHaH by demonstrating that pollution-haven outcomes dominate under fossil-fuel-intensive and institutionally weak conditions, whereas greater REN penetration and stronger institutions create the conditions under which pollution-halo effects become more plausible. The results also support EMT by showing that economic modernization improves environmental outcomes only when accompanied by cleaner energy, technological capability, and effective institutions.

Several limitations should be acknowledged. The balanced-panel design improves comparability but may favor countries with more complete data, potentially limiting the generalizability of the findings to data-constrained developing economies. The use of national-level indicators may also conceal sectoral differences in FDI, industrial activity, renewable technologies, and emission sources. Moreover, the estimated thresholds are empirical transition points rather than universal engineering or policy targets. Future research could employ sector-level or firm-level data, distinguish among renewable-energy technologies and different types of FDI, incorporate more recent observations as they become available, and examine spatial spillovers and alternative quasi-experimental identification strategies.

8. Policy Implications

The findings indicate that a uniform environmental policy is unlikely to be effective across developing countries because the environmental effects of FDI and IND vary with REN penetration and institutional capacity. Policy interventions should therefore be differentiated according to countries' positions in the renewable-energy distribution. In the present sample, the 25th percentile, median, and 75th percentile of REN are approximately 12.7%, 31.5%, and 63.9%, respectively. These values provide practical reference points for policy sequencing, although they should not be treated as universal targets.

Countries below the 25th percentile require policies that simultaneously prevent the expansion of pollution-intensive activities and establish the foundations of an energy transition. Because FDI and IND have their strongest adverse effects at low REN levels, governments should not weaken environmental standards to attract foreign capital. Investment approvals should include environmental-impact assessments, sector-specific emission requirements, energy-efficiency standards, and disclosure of expected energy sources. Fiscal incentives should prioritize FDI in renewable electricity, grid infrastructure, energy-efficient manufacturing, and clean-technology supply chains. At the same time, public investment and concessional finance should be directed toward basic transmission networks, decentralized renewable systems, and reliable access to clean electricity. These measures are especially important where limited fiscal capacity and weak electricity infrastructure constrain private renewable investment.

Countries between the 25th and 75th percentiles should focus on accelerating REN deployment and integrating it into industrial production. The results show that FDI and IND continue to increase emissions at the median REN level, although their marginal effects are smaller than at the 25th percentile. Consequently, moderate REN adoption is beneficial but insufficient to neutralize the environmental costs of economic expansion. Governments

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should expand competitive renewable-energy auctions, long-term power-purchase arrangements, grid connections, energy storage, and private-sector access to renewable electricity. Fossil-fuel subsidies can be gradually redirected toward clean-energy infrastructure and industrial energy-efficiency programs. Incentives granted to foreign and domestic firms should be conditional on measurable outcomes, including renewable-electricity use, verified emission reductions, energy-efficiency improvements, and the adoption of cleaner production technologies.

For countries approaching or exceeding the 75th percentile, the priority should shift from renewable-energy expansion alone toward system integration and the decarbonization of difficult industrial processes. At this level, the marginal effects of FDI and IND become small and generally statistically insignificant. However, the estimated zero-crossing thresholds—approximately 66.6%–69.6% for FDI and 71.9%–78.6% for IND—show that substantial REN penetration is necessary before their predicted effects are neutralized. Countries near these thresholds should invest in storage, smart grids, cross-border electricity connections, industrial electrification, and demand-management systems. These thresholds should be interpreted as sample-based transition benchmarks rather than automatic policy targets because national energy systems, resource availability, and industrial structures differ.

The policies should also distinguish between CO_2 and N_2O. Reducing CO_2 requires replacing fossil-fuel electricity, electrifying industrial processes, improving energy efficiency, and strengthening fuel and emission standards. REN can directly support these objectives. N_2O mitigation requires additional sector-specific measures because a considerable proportion of these emissions originates from fertilizer use, agricultural soils, chemical production, manure management, and wastewater treatment. Governments should promote precision fertilizer application, improved soil-nutrient management, low-emission fertilizer production, emissions-control technology in nitric-acid and related industries, and improved agricultural and municipal waste treatment. REN expansion should therefore complement, rather than substitute for, direct N_2O mitigation policies.

Finally, institutional reforms are necessary to convert renewable-energy investment into measurable environmental improvements. Low-IQ countries should initially prioritize transparent licensing, standardized emission reporting, digital monitoring systems, independent inspections, and enforceable penalties. High-IQ countries can employ more advanced instruments, including carbon pricing, emissions trading, green taxonomies, and performance-based industrial support. International development institutions can assist low-income and institutionally constrained countries through blended finance, risk guarantees, technical assistance, and support for environmental monitoring. Overall, aligning energy, investment, industrial, agricultural, and institutional policies is essential for moving developing countries from pollution-intensive growth toward cleaner and more sustainable development.

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- https://databank.worldbank.org/source/world-development-indicators
- https://www.worldbank.org/en/publication/worldwide-governance-indicators

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Appendix:

Table A1. Pairwise Correlation Matrix

Variables	CO_2	N_2O	FDI	IND	REN	GDPG	POPD	TRO	IQ	TI
CO_2	1.000									
N_2O	0.462***	1.000								
FDI	0.214***	0.157***	1.000							
IND	0.481***	0.386***	0.192***	1.000						
REN	−0.516***	−0.372***	−0.083***	−0.341***	1.000					
GDPG	0.118***	0.096***	0.142***	0.087***	−0.052**	1.000				
POPD	0.307***	0.218***	0.047**	0.263***	−0.237***	0.032	1.000			
TRO	0.176***	0.124***	0.286***	0.207***	−0.104***	0.113***	0.181***	1.000		
IQ	−0.348***	−0.251***	0.168***	0.076***	0.312***	0.091***	0.219***	0.203***	1.000	
TI	−0.319***	−0.214***	0.146***	0.117***	0.268***	0.078***	0.286***	0.176***	0.438***	1.000

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A2. Variance Inflation Factor Tests

Variable	Baseline VIF	Baseline Tolerance	Moderation-Model VIF	Moderation-Model Tolerance
FDI	1.16	0.862	1.28	0.781
IND	1.35	0.741	1.49	0.671
REN	1.42	0.704	1.57	0.637
GDPG	1.08	0.926	1.09	0.917
POPD	1.22	0.820	1.23	0.813
TRO	1.20	0.833	1.21	0.826
IQ	1.38	0.725	1.40	0.714
TI	1.36	0.735	1.38	0.725
FDI × REN			1.31	0.763
IND × REN			1.43	0.699
Mean VIF	**1.27**		**1.34**	

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