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Do good neighbors lead to lower greenhouse gas emissions across countries? A spatial analysis

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ABSTRACT

This study examines how spatial interdependence helps reduce greenhouse gas (GHG) emissions across 68 countries from 1990 to 2023. The researchers hypothesized that a country's environmental policies and GHG emissions are influenced by its neighbors, and their findings support this. The study used spatial fixed effects, spatial pooled, and spatial random effects models to analyze the effects of several variables on GHG emissions. The results show that a neighbor's high GHG emissions can actually help a country lower its own. Furthermore, the study found that energy consumption increases emissions, whereas innovation (patents), renewable energy, and trade openness all decrease them. However, the study found no evidence to support the Environmental Kuznets Curve or the Pollution Haven Hypothesis. The findings emphasize the importance of regional cooperation and the diffusion of public policies and knowledge to combat climate change, aligning with the United Nations' Sustainable Development Goal 13. The study highlights the vital role of coordination between countries in addressing global warming.

Contribution/ Originality: This study tests for spatial spillover effects in greenhouse gas emissions (GHG) using a panel dataset comprising 68 countries. By integrating spatial econometrics, this study demonstrates that competition and cooperation among neighboring countries could play a vital role in mitigating GHG emissions.

1. INTRODUCTION

Countries pursue economic growth to create high-paying jobs, increase wealth, and expand the government's tax base. However, economic growth leads to deforestation, increased fossil fuel consumption, and industrialization, which in turn raise greenhouse gas (GHG) emissions and hasten climate change as GHGs absorb more of the sun's thermal energy. Countries with large populations, such as Bangladesh, Brazil, China, India, Indonesia, and Pakistan, are following the industrialization of developed countries and are likely to continue raising GHG emissions.

Economics, politics, and environmental impacts are not confined to national borders. Countries and their neighbors influence each other via labor migration, technology transfer, and trade (Radmehr, Henneberry, & Shayanmehr, 2021; Shabani, Shahnazi, & Sadati, 2025). For example, expatriates bring expertise, knowledge, and skills as they work outside their home countries (Radmehr et al., 2021). Administrators, political leaders, and regulators often emulate the successful environmental policies and strategies of their neighbors (Maddison, 2006;

Wang, Kang, Wu, & Xiao, 2013). Nevertheless, few researchers have incorporated spatial effects into their economic modeling and analysis.

The Environmental Kuznets Curve (EKC) and the Pollution Haven Hypothesis (PHH) dominate the literature. The EKC hypothesis proposes an inverted U-shaped relationship between environmental degradation and economic growth. A country typically experiences rising pollution during the early stages of development, but higher incomes create a demand for clean energy, new technologies, and stricter environmental regulations. Subsequently, pollution peaks and begins decreasing as economic growth continues. The PHH posits that companies from developed countries relocate to developing countries with weaker environmental regulations to reduce costs. The PHH could explain why pollution levels begin to fall in developed countries, as pollution is exported to developing countries. The empirical evidence for both hypotheses is mixed. Nevertheless, few researchers have explored spatial effects that could significantly impact the adoption of environmental policy.

The role of geographical relationships between countries and their neighbors still needs to be explored. For example, Shabani et al. (2025) examined how a country with good governance mitigates its CO_2 emissions while raising the emissions of its neighbors. They found support for the EKC and PHH hypotheses. Similarly, You and Lv (2018) incorporated the spatial effects of 83 countries and found evidence of the EKC between CO_2 levels and a nation's income. Furthermore, Shahzad and Aruga (2024) found support for the EKC hypothesis in 24 countries, relating the ecological footprint (a measure of degradation) to income. In addition, Maddison (2006) found no evidence of EKC in a panel of European countries while using carbon monoxide, nitrogen oxides, sulfur dioxide, and volatile organic compounds as the environmental degradation. Lastly, Wang et al. (2013) found no evidence of the EKC while using ecological footprints. These conflicting findings underscore the importance of considering the spatial interdependencies between countries and the influence that neighboring countries have on one another.

The hypothesis of this study posits that not only are a country's GHG emissions shaped by domestic factors, such as economic growth, energy consumption, and international trade, but also by the emissions and policies of neighboring countries. To test this, the research models the relationship between GHG per capita and a set of variables traditionally used to test the EKC and PHH: energy consumption, GDP, GDP squared, patents, renewable energy, and trade openness.

This study has two objectives: to test its hypothesis. First, it uses GHG emissions as a more robust proxy for environmental degradation because this metric incorporates a broader range of gases that drive climate change. For example, many studies use CO_2 as the primary driver of environmental degradation (see, for example, (Khoshnevis & Dariani, 2019; Munir, Lean, & Smyth, 2020)). However, Hao, Wu, Wang, and Huang (2018) and Zeraibi, Balsalobre-Lorente, and Murshed (2021) have utilized broader measures of environmental degradation. Even the United Nations recognizes GHG in Climate Action, which is Sustainable Development Goal 13. For example, methane absorbs the equivalent heat energy as 30 tons of CO_2, while nitrous oxide absorbs the equivalent of 273 tons (U.S. Environmental Protection Agency, 2023). Methane originates from agriculture, oil and gas systems, coal mining, and landfills, while nitrous oxide originates from fossil fuel combustion. Consequently, GHG is a better indicator of environmental degradation than CO_2 to evaluate the adverse effects on the environment.

The second objective adds a spatial lag for GHG emissions to capture spatial interdependence. This lagged variable reflects how a country's GHG emissions are influenced by its neighbors as countries adopt similar best practices, environmental regulations, and technologies (Anselin, 2022; Maddison, 2006). Countries may adopt stronger GHG mitigation measures not only for environmental reasons but also to demonstrate leadership by outperforming their neighbors. Neglecting this spatial interdependence could result in biased parameter estimates and model misspecification (Hao, Liao, & Wei, 2014; Hao et al., 2018; Maddison, 2006; Wang et al., 2013).

This study adds to the literature by analyzing how countries engage in competitive and interdependent efforts to mitigate GHG emissions. Unlike prior research that focuses only on CO_2, it employs a broader measure of environmental degradation that includes major GHGs like methane and nitrous oxide. Using data from 68 countries, the analysis integrates spatial econometric modeling to capture spatial interdependence through a lagged spatial variable for GHG emissions. This variable reflects the influence of neighboring countries' emissions on a domestic country's emissions. Thus, this approach can directly test for spatial spillover effects and also provide new insights into how cross-country interactions shape climate mitigation strategies. To the best of the authors' knowledge, this is the first study to investigate spatial spillovers in GHG emissions in a large panel dataset.

The article proceeds as follows. Section 2 reviews the literature, while Section 3 discusses the data and methodology. Section 4 discusses the results, and Section 5 concludes the study, formulates policy recommendations, and outlines the study's limitations.

2. THE LITERATURE REVIEW

The literature review encompasses the following key areas: the limited focus on greenhouse gas (GHG) emissions as a proxy for environmental degradation, the Environmental Kuznets Curve (EKC), and the Pollution Haven Hypothesis (PHH), which include the variables and countries, and the role of spatial relationships between nations.

2.1. Measure of Environmental Degradation

CO_2 emissions are a primary driver of global warming and climate change. Manabe and Wetherald (1967) pioneered CO_2 studies by using computer simulations to predict what the Earth's global temperatures would be if the atmospheric CO_2 content were to double. Burning fossil fuels leads to a buildup of atmospheric CO_2, which absorbs and radiates heat, thereby creating the greenhouse effect and contributing to global temperature rises. This increased thermal energy leads to global warming and climate change, while stressing ecosystems and wildlife.

A substantial body of literature has evolved that utilizes CO_2 as a proxy for environmental degradation. Numerous studies have found links between CO_2 emissions and energy usage, such as Cyprus (Katircioglu, Feridun, & Kilinc, 2014), Indonesia (Saboori, Sulaiman, & Mohd, 2012b; Shahbaz, Hye, Tiwari, & Leitão, 2013), Malaysia (Begum, Sohag, Abdullah, & Jaafar, 2015; Saboori, Sulaiman, & Mohd, 2012a), and the United States (Raza, Shah, & Sharif, 2019). However, the Pollution Haven Hypothesis (PHH) (Copeland & Taylor, 2004; Stern, 2004) proposes that one country's government imposing stringent environmental regulations can cause "dirty" industries to relocate to less developed countries while exporting their goods and products back. For example, the U.S. heavy manufacturing industries shifted production abroad to developing countries, while the U.S. light industrial and service-oriented industries flourished. Thus, trade liberalization led to a relocation of "dirty" industries from developed countries to developing countries (Copeland & Taylor, 2004).

Several researchers expanded their analysis to multiple countries, enabling them to test the Pollution Haven Hypothesis. For example, Chontanawat (2020) studied the connection between CO_2 emissions, economic output, and energy usage in Brunei, Indonesia, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam. Munir et al. (2020) investigated the association between economic output, energy usage, and CO_2 emissions in Indonesia, Malaysia, the Philippines, Singapore, and Thailand, finding support for the EKC. Khoshnevis and Dariani (2019) found that economic growth, energy consumption, trade openness, and urbanization raised CO_2 emissions in 18 Asian countries. Omri (2013) analyzed energy consumption, economic growth, and CO_2 emissions for 14 countries in the Middle East and North Africa (MENA). Lastly, Rehman and Rehman (2022) examined the association of economic growth, energy usage, population growth, and urbanization on CO_2 emissions in Bangladesh, China, India, Indonesia, and Pakistan. Overall, economic growth and increased energy consumption contribute to CO_2 emissions. However, the findings yielded mixed results, depending on the econometric methodology, included variables, and the group of countries being focused on.

The literature primarily focuses on CO_2 as the only driver of global warming and climate change. Our modern civilization emits an extensive range of GHGs. For example, agricultural industries emit methane and nitrous oxides; air conditioning and refrigeration systems utilize hydrofluorocarbons and perfluorocarbons, while the electronics industry emits sulfur hexafluoride. These GHGs possess much greater Global Warming Potentials than CO_2, even though CO_2 is the most abundant and prominent GHG. The Paris Agreement in 2016 recognized this and emphasized mitigating all GHG emissions and not just CO_2.

The summary of this study's novelty includes the following:

- This study adds value by combining multi-country data with spatial modeling to test environmental policy spillovers and interdependencies.
- This study broadens environmental degradation to include the major greenhouse gases (GHGs) and does not solely rely on carbon dioxide (CO_2).
- Data must include developed and developing countries to test the PHH hypothesis.

2.2. The Environmental Kuznets Curve

Kuznets (1995) introduced the Kuznets Curve, which hypothesized that income inequality would initially increase as a country develops, attain a peak, and then decrease, forming an inverted U-shape. Grossman and Krueger (1995) proposed the EKC hypothesis, which depicts a concave relationship between environmental degradation and income. Their analysis included 28 countries, and they discovered that air and water pollution initially increased as countries developed. The pollution reached a peak and began declining as higher incomes allowed the adoption of renewable energy, while industries replaced traditional, "dirty" manufacturing processes with cleaner technologies. The Pollution Haven Hypothesis (PHH) suggests that stringent environmental regulations, trade liberalization, and lower manufacturing costs lead to the outsourcing of "dirty" industries to developing countries (Cole, 2004; Copeland & Taylor, 2004). The PHH implies that countries undergo structural changes as stricter environmental regulations shift manufacturing toward 'cleaner' industries (Pasche, 2002). Despite numerous studies, researchers have yet to reach a consensus on this topic.

The research is mixed, with studies from individual countries. Researchers, however, focused on a single country to devise policy recommendations tailored to that specific country (Saboori et al., 2012b). The following studies found support for the EKC in Malaysia (Ali, Abdullah, & Azam, 2017; Saboori et al., 2012b), Thailand (Paweenawat & Plyngam, 2017), Vietnam (Tang & Tan, 2015), and the United States (Salari, Javid, & Noghanibehambari, 2021). In contrast, the following studies found no support for the EKC hypothesis in Bangladesh (Alam, 2014), Indonesia (Saboori et al., 2012b), and the United States (Dogan & Ozturk, 2017). Nevertheless, these studies overlook the influence and interconnectedness of other countries, ignoring potential cross-border environmental effects.

The literature includes extensive studies that test the EKC and PHH hypotheses across multiple countries. A panel including developed and developing countries is more likely to find evidence of the EKC. For instance, Özokcu and Özdemir (2017) discovered an N-shape EKC for CO_2 and income for 26 high-income countries and 52 emerging countries between 1980 and 2010. They included CO_2 emissions, energy usage, and income per capita. In addition, Cole (2004) did not find evidence of the EKC but found some evidence for the PHH. His study included 10 air and water pollutants across developed (i.e., Northern) and developing (i.e., Southern) countries. These findings emphasize the need to include both developed and developing countries in panels to effectively account for the PHH.

Researchers extended the EKC studies to include GHGs. The GHG studies are similar to CO_2 studies in that they focus on single-country analyses. For example, Olale, Ochuodho, Lantz, and El Armali (2018) found evidence of the EKC using GHG emissions in Canada. Freire, da Silva, and de Oliveira (2023) found evidence of the EKC in Brazil for CO_2 and nitrous oxide but not for methane. Similarly, Yang, Lou, Sun, Wang, and Wang (2017) suggested that Russia may soon reach its EKC turning point for GHG emissions if economic growth continues. However, these studies overlook the spatial dynamics by focusing on a single country.

Several researchers extended their analysis to a group of countries. For example, Adeel-Farooq, Raji, and Adeleye (2021) found the EKC for methane emissions in six Asian countries and included energy consumption, GDP, and trade openness. Lapinskienė, Tvaronavičienė, and Vaitkus (2014) observed the EKC phenomenon in 6 European countries out of 25. As noted previously, country panels should ideally include both developed and developing countries to capture the full spectrum of economic development, thereby testing for the EKC and PHH hypotheses.

These analyses, nevertheless, omit spatial interdependence. As Maddison (2006) argued, technological advancements in one country can spill over to neighboring countries, creating spatial patterns that influence GHG emissions. Excluding these spatial effects and spillovers could lead to omitted variable bias, potentially explaining the large number of conflicting results in the EKC literature.

The summary of this study's novelty includes the following:

- The analysis must include GHG emissions, a broader proxy for environmental degradation.
- The panel must include developed and developing countries to control for the PHH hypothesis.
- The analysis must include spatial interdependence and cross-border spillover effects.

2.3. Spatial Interdependence

Tobler (1970) started spatial econometrics in the 1970s by stating that “Everything is related to everything else, but near things are more related than distant things.” Moreover, Hordijk and Paelinck (1976) identified the five key characteristics of spatial econometrics, outlining the importance of spatial interdependence, the uneven influence of regions, the role of neighboring explanatory variables, spatial interactions over time, and the spatial modeling of geography.

Research started with CO_2 emissions and spatial modeling in China. Specifically, Kang, Zhao, and Yang (2016) observed an N-shaped EKC of CO_2 emissions in China and included energy consumption, income per capita, population density, trade openness, and urbanization. Wang and He (2019) found that economic relations captured and accounted for spatial effects more effectively than geography, as demonstrated by linking CO_2 emissions to economic growth. More recently, Wang, Wang, Ren, and Wen (2022) found that the development of digital financial institutions reduced CO_2 emissions in 284 prefectures but increased CO_2 emissions in neighboring prefectures. They controlled for economic growth and changes in industrial structure. Several researchers broadened their degradation measures. For instance, Hao et al. (2018) constructed an environmental quality index for 30 provinces, and they found no evidence of the EKC. Meanwhile, Liu, Cheng, and Li (2021) observed the EKC phenomenon in fertilizer and pesticide pollution in the Three Gorges region, comprising 30 provinces. In sum, these studies demonstrate the importance of increasing the explanatory power of economic modeling by incorporating spatial interdependence.

Multi-country analysis highlights the importance of spatial interdependence. You and Lv (2018) found evidence of the EKC for CO_2 emissions in 83 countries. Shabani et al. (2025) found evidence for the EKC and PHH hypotheses using a panel of 179 countries. Their research highlighted the importance of good governance in mitigating CO_2 emissions relative to their neighbors. Meanwhile, Radmehr et al. (2021) analyzed the connection between CO_2 emissions and the following variables: economic growth, energy usage, renewable energy, international trade, and urbanization for 21 European countries. Other researchers expanded their degradation proxies. For example, Shahzad and Aruga (2024) observed the EKC in 24 Asian countries by using ecological footprint as a proxy for environmental degradation. Wang et al. (2013) failed to find support for the EKC while using the ecological footprint for 150 countries. Lastly, Maddison (2006) applied spatial econometrics to multiple air pollutants in Europe. In sum, these studies highlight the significance of spatial interdependence between countries.

Omitting the spatial spillovers assumes neighboring countries do not influence a nation's GHG emissions. Failing to incorporate spatial effects could cause biased parameter estimates, misspecification of econometric models, and incorrect inferences (Hao et al., 2014; Hao et al., 2018; Maddison, 2006; Wang et al., 2013). Comprehensive econometric models should account for spatial interdependence and minimize omitted variable bias by including variables such as energy usage, economic output, renewable energy, innovation, and trade openness (Munir et al., 2020; Stern, 2004).

The summary of this study's novelty includes the following:

- The analysis must include multi-country panels to account for spatial spillovers in environmental degradation.
- The analysis must include a broad proxy for environmental degradation.
- The modeling must be comprehensive, incorporating innovation and trade as they cross and diffuse across borders.

3. DATA AND METHODOLOGY

This section develops the empirical model and explains which variables and sources are included in the analysis. It also summarizes descriptive statistics and econometric methodology.

3.1. The Empirical Model

This study employs panel estimation to account for both common and country-specific dynamics. Many researchers, including Chontanawat (2020), Grossman and Krueger (1995), Katircioglu et al. (2014), and Sharif, Afshan, and Nisha (2017), have relied on reduced forms of Equation 1 as their empirical model. They differ in their proxies used for environmental degradation and the control variables included. However, this study utilizes greenhouse gas (GHG) emissions per capita as the dependent variable, which is modeled as a function of spatial (SPA) lagged effects of GHG, energy consumption (ENE), real economic growth per capita (GDP), real economic growth squared (GDP^2), renewable energy (RE), patents (PAT), and trade openness (OPEN). The ε_{it} accounts for the spatial correlation, which equals $\varepsilon_{it} = \rho \sum_j w_{ij}\, \varepsilon_{jt-1} + \eta_{it}$. The η_{it} is the white noise process with ρ as the parameter of the spatial autocorrelation.

$$ln(GHG_{it}) = \alpha_0 + \lambda \sum_j w_{ij} ln\big(GHG_{jt-1}\big) + \alpha_1 ln(ENE_{it}) + \alpha_2 ln(GDP_{it}) + \alpha_3 [ln(GDP_{it})]^2 + \alpha_4 ln(RE_{it}) + \alpha_5 ln(PAT_{it}) + \alpha_6 \ln(OPEN_{it}) + \varepsilon_{it} \quad (1)$$

The subscript t represents the year between 1990 and 2023 for country i. The starting year was chosen because the Soviet Union and Yugoslavia split into new countries and opened their economies to the world. These nations began to develop and adopt Western technologies and business practices. The internet also rapidly developed in the 1990s and diffused into developing countries. The dataset is well-balanced, comprising 68 countries representing various stages of development. Refer to Table 1 for a complete list of countries and their regions.

Table 1. Countries by region.

Region	Number of Countries/Regions	Countries/Regions
Africa	4	Algeria, Egypt, Morocco, and South Africa
Asia	18	Azerbaijan, Bangladesh, China, Hong Kong SAR[1], India, Indonesia, Japan, Kazakhstan, Malaysia, Pakistan, Philippines, Singapore, South Korea, Sri Lanka, Thailand, Turkey, Uzbekistan, and Vietnam
Europe	32	Austria, Belarus, Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, and the United Kingdom.
Middle East	3	Iran, Israel, and Saudi Arabia
North America	3	Canada, Mexico, and the United States
Oceania	2	Australia and New Zealand
South America	6	Argentina, Brazil, Chile, Colombia, Ecuador, and Peru
Total	68	

[1] Hong Kong is a Special Administrative Region of China.

The natural logarithms are applied to all variables. All variables are normalized by scaling the mean to zero with a standard deviation equal to one. To prevent introducing perfect multicollinearity, the natural logarithm of GDP was taken. It was then normalized and squared to create the squared GDP. Accordingly, all variables are measured on the same scale, while the coefficients' magnitudes, $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5,$ and α_6 determine their relative impact on GHG emissions. Lastly, patents and trade openness have missing values. The best linear, quadratic, or cubic trend was used to interpolate these missing values. Although interpolation preserves continuity in the time series, it could smooth fluctuations and understate short-term volatility, potentially weakening the measured variability of patents and trade openness.

Our World in Data provides the dependent variable, greenhouse gas (GHG) emissions per capita. GHG emissions are calculated by multiplying country i's emission (GE) of gas j, where gas j includes carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), in year t, by their respective Global Warming Potential (GWP) in Equation 2. The GWP indicates how much thermal energy gas j can absorb. CO_2 serves as the reference gas with a GWP set to one, while methane (nitrous oxide) has a GWP of 30 (273). Subsequently, GHG per capita is divided by the country's population (POP) in year t. The per capita removes the large country effect and places all countries on equal footing when expressed per person.

$$GHG_{it} = \frac{1}{POP_{it}} \sum_j GWP_j \cdot GE_{jit} \qquad (2)$$

This study incorporates spatial interdependencies in GHG emissions by constructing a spatial lagged variable. The process begins with constructing the spatial weight matrix, where countries closer to each other have a greater influence on the country's emissions than those that are farther away. Equation 3 shows the weight matrix with a diagonal of zeros, as each country has a weight of zero for itself. Meanwhile, the weight $w_{i,j}$ between country i and its neighbor j is the inverse of the distance between them, calculated as a reciprocal. Distances, d_{ij}, are calculated using the Haversine formula, which estimates the spherical distance between each country's centroids based on their latitude and longitude coordinates. The Haversine distance assumes the Earth is a perfect sphere and is accurate at sea level. Each row of the weight matrix is standardized to ensure the row weights sum to one. This matrix is then multiplied by the lagged GHG emissions to create a vector of spatially lagged GHG emissions.

$$w_{i,j} = \begin{bmatrix} 0 & w_{1,2} & w_{1,3} & \cdots & w_{1,68} \\ w_{2,1} & 0 & w_{2,3} & \cdots & w_{2,68} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{68,1} & w_{68,2} & w_{68,3} & \cdots & 0 \end{bmatrix} \qquad (3)$$

Ordinary least squares (OLS) cannot estimate the parameters in Equation 1 because the estimates would be biased and inconsistent (Anselin, 2022; Hao et al., 2018). The spatial lagged term introduces endogeneity, as it is correlated with the error term.

3.2. The Control Variables

Control variables are included in Equation 1 to ensure that omitted factors do not confound the impact of the lagged spatial variable on GHG emissions. These control variables encompass various factors previously examined for their influence on environmental degradation. The first control variable is energy consumption, measured in kilowatt-hours (kWh) per capita. Residents of a country depend on fossil fuels for electricity generation, transportation, production, and consumption. Consequently, a society that produces and consumes products and services releases GHG emissions. This positively correlates with GHG emissions and energy consumption (ENE). Several researchers have included energy consumption, including (Chontanawat, 2020); (Khoshnevis & Dariani, 2019); Shahbaz et al. (2013), and Saboori et al. (2012b).

The second control variable includes economic growth, proxied by gross domestic product (GDP). It is defined as real GDP per capita in constant 2015 US dollars. As a country's GDP per capita increases, residents have access to more goods and services, raising fossil energy consumption and GHG emissions. Researchers such as Chontanawat (2020), Khoshnevis and Dariani (2019), Saboori et al. (2012b), and Shahbaz et al. (2013) have included GDP in their analysis.

The GDP squared is added to the model as the third control variable. Empirical support for the EKC requires GDP to be statistically significant and positive, while GDP squared must be statistically significant and negative, imparting a concave shape. Numerous researchers have incorporated GDP squared into their analyses, such as Grossman and Krueger (1995).

The fourth control variable is renewable energy (RE) consumption, measured in kilowatt-hours (kWh) per capita. Countries are increasingly turning to renewable energy (RE) as a replacement for fossil fuels. Lowering fossil fuel usage releases fewer GHGs into the atmosphere, suggesting a negative relationship between renewable energy and GHGs. Renewable energy also influences the EKC because a country can transition away from "dirty" industries, even though consumers may pay more for renewable energy (Copeland & Taylor, 2004). Lastly, the successful implementation of renewable energy often depends on technological advancements. Researchers such as Cheng, Ren, Wang, and Yan (2019); Dogan and Ozturk (2017); Hasnisah, Azlina, and Taib (2019); Radmehr et al. (2021) and Sharif, Afshan, and Nisha (2017) have included renewable energy in their analyses.

The fifth control variable is innovation (PAT), which is proxied by the number of patents filed by residents per 100,000 people. Several researchers, such as Shahbaz et al. (2013) and Zeraibi et al. (2021), have incorporated financial development into their analyses, while others, including Azam, Khan, Zaman, and Ahmad (2015) and Tang and Tan (2015), have focused on foreign investment. These studies suggest that financial development and foreign investment help a country finance innovation, especially in green technologies. However, financial development and foreign investment may be less significant since a country's renewable energy consumption already indicates its commitment to adopting green technologies.

The last control variable is trade openness (OPEN), calculated as the sum of exports and imports divided by GDP. International trade and globalization have three effects on GHG emissions. Firstly, the logistics involved in international trade typically require energy, which raises GHG emissions. Secondly, many developing countries leverage exports as an engine for economic growth by manufacturing and exporting products to developed countries. Lastly, trade fosters specialization and could boost pollution-intensive manufacturing in developing nations (Khoshnevis & Dariani, 2019). Researchers such as Azam et al. (2015); Khoshnevis and Dariani (2019); Saboori et al. (2012b), and Shahbaz et al. (2013) have included trade openness in their analyses. Table 2 summarizes the variables used in this study along with their respective sources.

Table 2. Data details, units, and sources.

Variable	Description	Units	Source
GHG	Greenhouse gas emissions per capita	CO_2 equivalent	Our World in Data
ENE	Energy consumption	kWh per capita	Our World in Data
GDP	Real GDP per capita	Constant 2015 USD	World Bank Indicator
PAT	Patent applications	The number per 100,000 residents	World Bank Indicator
RE	Renewable energy consumption	kWh per capita	Our World in Data
OPEN	Trade openness	% of exports plus imports per GDP	World Bank Indicator

3.3. Descriptive Statistics

The variable descriptive statistics are summarized in Table 3. Developed countries, i.e., Europe, North America, and Oceania, exhibit the highest means for GHG per capita, energy consumption (ENE), GDP per capita, and renewable energy (RE). Asia records the highest mean for the number of patents (PAT), followed by North America. Meanwhile, Europe has the highest mean for trade openness (OPEN), followed by Asia. Africa has the lowest means for all variables. Lastly, the lagged spatial (SPA) GHG shows the smoothing effect of utilizing a weighted average of all countries in the panel.

The skewness and kurtosis define the shape of the distributions of the variables. Europe exhibits the second-largest positive skewness in energy consumption and the largest in renewable energy, whereas Asia displays the largest skewness in energy consumption (ENE), GDP, patents (PAT), and trade openness (OPEN). Several kurtosis statistics are negative, signifying a platykurtic-shaped distribution, which means these variables and regions possess flatter peaks and thinner tails compared to a normal distribution.

The primary objective of this study is to examine the spatial effect while controlling for relevant variables commonly used in EKC studies. Figure 1 plots the GHG emissions per capita of all panel countries against their GDP per capita. A specific color represents each region, revealing a rough, inverted U-shaped pattern. European countries (red) span the entire GDP per capita range, but their points disperse after the peak. North America (brown) and Oceania (green) cluster around the plot's center, where a rough peak is located. Africa (blue), Asia (purple), the Middle East (pink), and South America (orange) are situated to the left of the peak. Overall, Figure 1 provides a rough depiction of the EKC shape, with most countries positioned to the left of the peak. This suggests that GHG emissions per capita will continue to rise if these developing countries grow economically.

Table 3. Region descriptive statistics.

Min.	Region	GHG	SPA	ENE	GDP	RE	PAT	OPEN
	Africa	2.10	7.77	3,379.33	1,680.71	4.85	0.02	29.86
	Asia	0.92	7.62	626.21	480.67	0.00	0.01	6.39
	Europe	2.09	7.48	13,671.93	1,311.59	0.00	0.01	26.26
	Middle East	6.73	7.71	14,669.33	3,448.26	0.00	0.17	29.23
	North America	5.74	8.63	15,805.21	7,970.64	745.21	0.42	19.79
	Oceania	15.33	8.25	45,347.65	24,873.01	2,477.34	6.29	32.19
	South America	3.98	7.73	4,504.21	2,640.31	1,191.02	0.01	13.75
Mean	Region	GHG	SPA	ENE	GDP	RE	PAT	OPEN
	Africa	5.60	9.69	12,999.61	3,716.65	239.32	0.75	54.05
	Asia	6.70	9.19	25,454.38	10,396.40	862.22	30.52	98.64
	Europe	10.41	10.12	46,187.22	28,195.46	9,814.52	13.97	98.85
	Middle East	14.93	9.24	51,429.76	19,961.63	265.89	10.09	59.02
	North America	17.96	10.59	71,537.39	33,619.74	12,235.43	27.04	49.74
	Oceania	25.55	9.91	60,378.45	42,376.12	11,868.86	20.99	48.94
	South America	7.96	9.57	13,754.04	7,458.37	3,245.74	1.10	41.74
Max	Region	GHG	SPA	ENE	GDP	RE	PAT	OPEN
	Africa	12.10	11.58	28,557.36	6,170.88	810.93	2.93	101.13
	Asia	22.78	11.63	176,344.12	68,218.81	5,079.97	394.75	442.62
	Europe	35.23	15.74	188,364.47	112,417.88	153,174.34	62.93	412.18
	Middle East	30.80	11.24	103,518.09	42,516.39	2,394.01	33.52	96.10
	North America	29.52	12.53	118,416.40	65,505.26	33,886.11	91.05	88.83
	Oceania	38.94	11.34	71,877.98	61,598.18	23,388.92	51.45	68.52
	South America	18.97	11.35	25,750.82	14,283.15	8,713.02	3.15	80.68
Skewness	Region	GHG	SPA	ENE	GDP	RE	PAT	OPEN
	Africa	0.69	-0.13	0.76	0.33	0.59	1.31	0.74
	Asia	1.01	0.53	2.68	1.81	1.92	2.79	1.98
	Europe	1.41	0.69	2.27	1.23	4.28	1.55	2.36
	Middle East	0.74	0.66	0.65	-0.14	2.78	0.42	0.36
	North America	-0.40	-0.24	-0.45	-0.26	0.67	0.94	-0.06
	Oceania	0.40	-0.09	-0.16	0.26	-0.02	0.67	0.14
	South America	0.95	-0.23	0.35	0.62	1.13	0.33	0.36
Kurtosis	Region	GHG	SPA	ENE	GDP	RE	PAT	OPEN
	Africa	-0.98	0.38	-0.89	-0.82	-0.89	1.19	1.13
	Asia	0.85	0.56	8.10	2.60	3.79	6.57	3.09
	Europe	3.64	1.06	6.96	1.37	19.91	2.41	9.09
	Middle East	-1.21	1.17	-1.29	-1.22	10.08	-1.05	-0.13
	North America	-1.50	-0.16	-1.52	-1.40	-1.49	-0.73	-1.45
	Oceania	-1.30	-0.84	-0.83	-1.05	-1.95	-1.09	-1.14
	South America	-0.18	-0.19	-1.13	-0.77	0.45	-1.42	-0.69

Note: The lagged spatial (SPA) GHG is calculated as a weighted average of country i with other countries using the inverse of the Haversine distance.

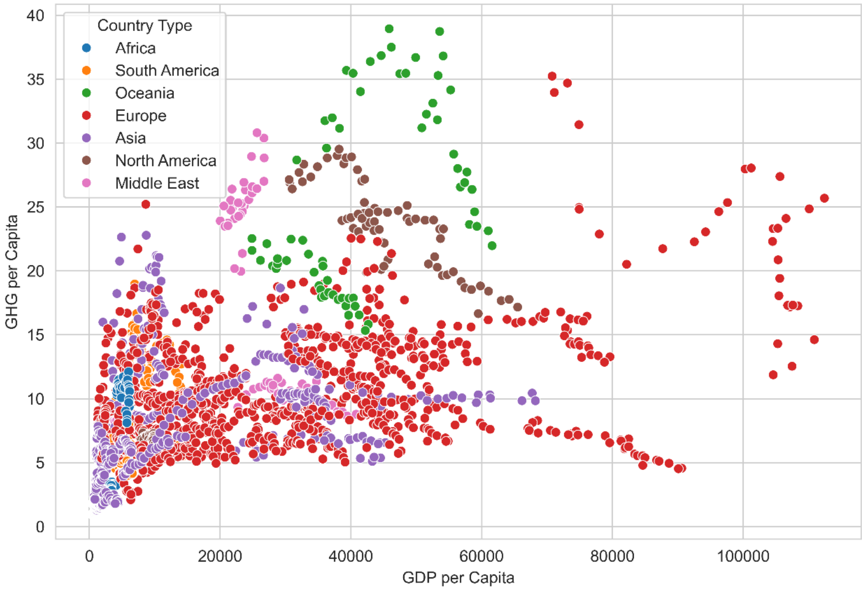

Figure 1. GHG per capita and GDP per capita.

Figure 2 presents a color matrix for the Pearson correlation. Dark reds (dark blues) indicate a strong positive (negative) correlation. The dependent variable, GHG per capita, is highly correlated with other variables. GHG is positively correlated with GDP per capita and negatively correlated with GDP squared (GDP2), suggesting the presence of the EKC phenomenon. The highest correlation is observed between GHG and energy (ENE) consumption, while GDP and GDP squared (GDP2) have the second-highest correlation of 0.84. A correlation exceeding 0.7 in magnitude suggests multicollinearity, which could pose a problem for parameter estimation because the estimation procedure cannot separate the effects of GDP and GDP squared on GHG emissions. The Variance Inflation Factor test is performed to ensure multicollinearity is not a problem. Lastly, the lagged spatial (SPA) variable shows correlations with all other variables except GDP squared (GDP2) and trade openness (OPEN), suggesting spatial interactions among countries in the sample.

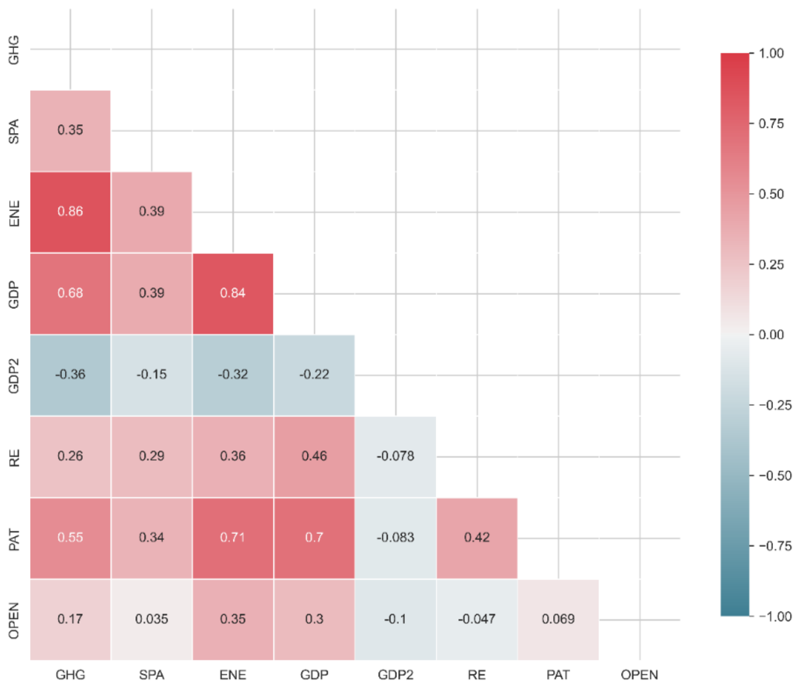

Figure 2. The Correlation Matrix (No color required for printing).

3.4. The Econometric Methodology

The analysis begins by searching for cross-sectional dependence (CD). CD arises when a shock in one country induces similar effects in other countries. Trade agreements, spillover effects, political instability, integrated financial systems, macroeconomic shocks, and omitted variables contribute to cross-section dependence, which can lead to biased parameter estimates (Munir et al., 2020). In addition, including a lagged spatial dependence variable in the analysis induces CD because it induces endogenous feedback across countries. Hence, tests and estimators must account for this dependence.

The standard fixed and random effects estimate the parameters in Equation 1. The estimators share common slope parameters, β, while each country possesses its own intercept, α_i, in Equation 4. The intercept captures individual differences between countries for fixed effects, while the intercept becomes a probability distribution for random effects. The ε_{it} defines the white noise process. Accordingly, tests can detect CD in the residuals.

$$y_{it} = \alpha_i + \beta' x_{it} + \varepsilon_{it} \quad i = 1,2 \cdots N \tag{4}$$

Pesaran (2014), and Pesaran (2021) use residuals to test CD in panel data. The null hypothesis posits that weak cross-dependence (CD) decreases as the number of cross-sections increases. Thus, any observed correlation between country residuals approaches zero as the number of countries grows, suggesting that there are no substantial feedbacks in shocks across countries (H$_0$: $\rho_{ij} = \rho_{ji} = \text{cor}(\varepsilon_{it}, \varepsilon_{jt}) = 0$ for $i \neq j$). The alternative hypothesis suggests that the cross-correlations do not vanish as the number of cross-sections increases. Instead, the correlations converge to a non-zero value, indicating the presence of strong CD (H$_a$: $\rho_{ij} = \rho_{ji} = \text{cor}(\varepsilon_{it}, \varepsilon_{jt}) \neq 0$ for some t and some i, when $i \neq j$). The Pesaran (2014), and Pesaran (2021) statistic is defined in Equation 5.

$$CD_{Pesaran} = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{5}$$

The Pesaran CD statistic ($CD_{pesaran}$) converges to a standard normal distribution under a null hypothesis of no CD as the number of cross-sections, N, is large and approaches infinity, and the time dimension T becomes sufficiently long. Specifically, $CD_{Pesaran} \xrightarrow{d} N(0,1)$ as $N \to \infty$ while T becomes sufficiently long.

The analysis proceeds to unit root tests, which determine a variable's order of integration. A unit root means that the mean and variance of the variable change over time. The cross-sectionally augmented Im-Pesaran-Shin (CIPS) (Im, Pesaran, & Shin, 2003) is a second-generation test that minimizes serial correlation and cross-sectional dependence by incorporating countries' means into the estimation. Identifying the variables' order of integration guides the subsequent analysis. The cointegration test determines if a linear combination of variables in Equation 1 exhibits a long-run relationship. Before checking for cointegration, all variables must exhibit unit roots in levels that become stationary after taking the first difference. When cointegration exists, the residuals are stationary, which Westerlund (2005) and Westerlund (2007) can test. The presence of cointegration indicates that the variables move together in a long-run, linear relationship. The pooled estimator, fixed effects, and random effects estimate the parameters in Equation 1 using maximum likelihood, the spatial Hausman test is applied to determine which estimators are consistent. Failure to reject the null hypothesis indicates that spatial random effects are preferable, while rejection implies a correlation between the random effects' explanatory variables and the error term, making the spatial fixed effects the better choice. Lastly, the Driscoll and Kraay (1998) correction adjusts standard errors and t-statistics to account for CD (including spatial interdependence), serial correlation (when the residuals are correlated over time), and heteroscedasticity (when variance changes with an explanatory variable's magnitude). For a richer discussion on spatial estimators, refer to Millo and Piras (2012).

4. RESULTS AND DISCUSSION

The analysis begins with tests for cross-sectional dependence, unit root, cointegration, and variance inflation factor to ensure no issues will affect parameter estimation. Lastly, maximum likelihood estimates the parameters using the pooled, fixed effects, and random effects models.

4.1. Diagnostic Tests

The analysis begins by checking for cross-sectional dependence (CD) among countries by applying the CD test to the residuals. The fixed and random effects estimate the parameters of Equation 1. Table 4 presents the results from the Pesaran (2014) and Pesaran (2021) CD test. The null hypothesis is rejected at the 1% level, indicating that the residuals show evidence of CD. This dependence is expected, as countries are interconnected through free trade, where economic booms and downturns can ripple across borders. Thus, a rising tide raises all boats in the same economic sea. Lastly, if CD is initially absent, including a lagged spatial dependent variable can introduce CD as it induces endogenous feedback between countries.

Table 4. The Cross-section dependency (CD) tests.

CD Test	Fixed Effects	Random Effects
Pesaran (2014) and Pesaran (2021)	**67.36*** **	**63.78*** **
	(0.0)	**(0.0)**

Note: Rejecting the null hypothesis suggests the presence of cross-sectional dependence. Reported p-values are shown in parentheses. The asterisks *** represent significance at the 1%. Coefficients with statistical significance are presented in bold type.

The cross-sectionally augmented Im-Pesaran-Shin (CIPS) test detects the presence of unit roots in both levels and first differences. The spatially lagged GHG is excluded since it is constructed from the data. Table 5 shows that all variables are stationary except GHG and GDP squared because rejecting the null hypothesis indicates stationarity. The first differences of GHG and GDP squared become stationary. Thus, the cointegration test is performed on GHG and GDP squared. The Westerlund (2005) and Westerlund (2007) tests determine whether GHG per capita and GDP2 exhibit a long-term linear relationship. Cointegration implies that the time series remains stable over time without abrupt shifts that would otherwise disrupt cointegration. If the tests indicate the absence of cointegration, the regression between these two variables would constitute spurious regression, where a relationship appears to exist but the residuals are not stationary. The other variables are excluded because they are stationary. Table 6 summarizes the results, and the results are unanimous. The two variables are cointegrated and exhibit a long-term linear relationship. The first test allows each panel to have its autoregressive term (AR), while the second imposes the same AR term for all panels, which alters the test's alternative hypothesis. Lastly, the residuals of the regressions are checked to see whether they are stationary. The cross-sectionally augmented Im-Pesaran-Shin (CIPS) test detects the presence of unit roots in both levels and first differences. The spatially lagged GHG is excluded since it is constructed from the data. Table 5 shows that all variables are stationary except GHG and GDP squared because rejecting the null hypothesis indicates stationarity. The first differences of GHG and GDP squared become stationary. Thus, the cointegration test is performed on GHG and GDP squared.

Table 5. The Panel CIPS unit root test.

Variable	Levels	First Difference
GHG	-1.444	**-5.337*** **
ENE	**-2.052***	-
GDP	**-2.850*** **	-
GDP2	-1.426	**-3.513*** **
RE	**-2.916*** **	-
PAT	**-2.093***	-
OPEN	**-2.111** **	-

Note: Rejecting the null hypothesis indicates the variable is stationary. Critical values are -2.03 for the 10% significance level, -2.1 for the 5%, and -2.2 for the 1%. The asterisks ***, **, and * represent significance at the 1%, 5%, and 10%, respectively. Coefficients with statistical significance are presented in bold type.

Table 6. The Cointegration Tests.

The Westerlund test	AR specific	AR same
Variance ratio	**-3.6912*** **	**-3.5051*** **
	(0.0)	**(0.0)**

Note: Rejecting the null hypothesis indicates that a linear combination of the variables exhibits cointegration. The AR-specific (same) suggests that some (or all) panels are cointegrated. Reported p-values are shown in parentheses. The asterisks *** represent significance at the 1% level. Coefficients with statistical significance are presented in bold type.

The final diagnostic test is the Variance Inflation Factor (VIF), which measures the degree of multicollinearity among the variables. The correlations suggest that GDP and GDP squared have a correlation of 0.84, which is significantly above the 0.7 threshold, indicating the presence of multicollinearity. The spatially lagged variable is excluded because it affects the residuals, not the linear dependencies among variables. Table 7 shows the results. All variables have a VIF below 5.0, indicating that they exhibit little multicollinearity. Therefore, the analysis proceeds to parameter estimation.

Table 7. The variance inflation factor (VIF).

Test	ENE	GDP	GDP2	RE	PAT	OPEN
VIF	4.514	4.090	1.186	1.350	2.533	1.291

Note: A VIF magnitude lower than 5.0 indicates that multicollinearity is not a problem. A VIF between 5.0 and 10.0 indicates moderate level multicollinearity, while a VIF exceeding 10.0 indicates serious multicollinearity.

4.2. Parameter Estimation

Table 8 presents the parameter estimates for all estimators. At the bottom of the table, Pesaran's CIPS Test indicates that all models have stationary residuals. Thus, spurious regression is unlikely to be an issue. Furthermore, Table 9 presents the spatial Hausman test statistic, indicating that the random effects estimator is inconsistent. Upon examining the parameter estimates, the random effects differ from those of the other models. Therefore, the spatial fixed effects are preferred because the intercept is correlated with the variables for the random effects.

Table 8. Parameter estimates.

Model	1	2	3
Dependent GHG	**Fixed Effects**	**Pooled**	**Random Effects**
Intercept	-	**0.120*** **	0.496
		(0.0)	(0.341)
Lambda	**-0.205*** **	**-0.127***	**0.139***
	(0.002)	**(0.068)**	**(0.057)**
ENE	**1.046*** **	**1.054*** **	**0.722*** **
	(0.0)	**(0.0)**	**(0.0)**
GDP	**-0.028**	**-0.040** **	**0.385*** **
	(0.158)	**(0.046)**	**(0.0)**
GDP^2	**-0.071*** **	**-0.068*** **	**0.021***
	(0.0)	**(0.0)**	**(0.065)**
RE	**-0.030*** **	**-0.038*** **	**-0.071*** **
	(0.008)	**(0.0)**	**(0.0)**
PAT	**-0.123*** **	**-0.117*** **	0.016
	(0.0)	**(0.0)**	(0.274)
OPEN	**-0.172*** **	**-0.174*** **	-0.011
	(0.0)	**(0.0)**	(0.401)
Rho	**0.524*** **	**0.674*** **	**0.881*** **
Rho p-value	**(0.0)**	**(0.0)**	**(0.0)**
Phi	-	-	**8.284*** **
Phi p-value			**(0.0)**
Pesaran's CIPS Test	**-3.638*** **	**-3.765*** **	**-143.13*** **
CIPS p-value	**(0.01)**	**(0.01)**	**(0.01)**
N (Countries)	68	68	68
T	34	34	34
Obs	2312	2312	2312

Note: Maximum likelihood estimates the fixed effects, pooled, and random effects. Robust standard errors are adjusted for autocorrelation, cross-sectional dependence, and heteroscedasticity using Driscoll and Kraay (1998). The table shows parameter estimates with reported p-values in parentheses. The asterisks ***, **, and * represent significance at the 1%, 5%, and 10%, respectively. Coefficients with statistical significance are presented in bold type. Models 1, 2, and 3 are estimated with spatial autocorrelation using the Kapoor, Kelejian, and Prucha (2007) method. Lastly, phi represents the parameter estimate for the variance component of the random effects.

Table 9. Spatial Hausman Test.

Test	Chi-square Statistic
Spatial Hausman Test	**27.445*** **
p-value	**(0.0)**
Degrees of freedom	**6**

Note: The null hypothesis indicates that both the fixed and random effects are consistent, but the random effects is more efficient. The asterisks *** represent significance at the 1%. Coefficients with statistical significance are presented in bold type.

The parameter estimates for the fixed effects (Model 1) and the pooled model (Model 2) are similar, and all are statistically significant except GDP, indicating that countries exhibit little heterogeneity. Furthermore, the lagged spatial GHGs (lambda) for Models 1 and 2 are negative and indicate that a domestic country's emissions are lower than neighboring countries with higher GHG emissions. Since the variables are normalized, the magnitude of the parameter estimate reflects the strength of each variable's influence on GHG emissions. Thus, the lagged spatial GHG mitigates emissions the second most in Model 1 and the third in Model 2. In addition, in Models 1 and 2, the spatial autocorrelation (rho) is positive and significant, indicating that spatial interdependence is present in the residuals. Overall, the results from Models 1 and 2 provide strong evidence that supports the hypothesis that a country mitigates GHG emissions more than its neighbors.

Energy (ENE) consumption is statistically significant in all regressions, with the largest magnitude in all models. The reason is that countries consume fossil fuels, which in turn increase CO_2 emissions. CO_2 is one of the primary GHGs. Prior research by Khoshnevis and Dariani (2019) and Saboori et al. (2012b) also found a positive and statistically significant relationship between energy consumption and CO_2 emissions.

Renewable energy is statistically significant and negative in all estimations. The marginal effect indicates that GHG emissions decrease when a country uses more renewable energy. In support of this, Radmehr et al. (2021) found that renewable energy reduced CO_2 emissions in seven European countries, though it surprisingly increased them in two others. Nonetheless, Ben Jebli, Ben Youssef, and Ozturk (2015) and Hasnisah et al. (2019) found that renewable energy had no significant effect on CO_2 emissions in 24 African and 13 Asian countries.

Patents (PAT) are statistically significant and negative in both the pooled and fixed effects models. Patents serve as a proxy for innovation, as some innovations develop new technologies to mitigate GHG emissions. This finding aligns with Zeraibi et al. (2021), although they used ecological footprints as their measure of environmental degradation. Lastly, patents (PAT) and renewable energy (RE) have key roles in driving technological progress and the substitution of fossil fuel energy (Liobikienė & Butkus, 2017).

Trade openness (OPEN) is negative and statistically significant in both the pooled and fixed effects models, suggesting that increased trade openness reduces GHG emissions. This finding does not support the Pollution Haven Hypothesis, which posits that trade liberalization should increase emissions as developed countries specialize in 'clean' technologies while developing countries utilize 'dirty' technologies. By using a panel of 68 countries with varied economic development, the results suggest that trade openness reduces GHG emissions. Although the literature offers mixed conclusions regarding CO_2 emissions, Khoshnevis and Dariani (2019) found trade openness to be statistically significant, whereas Radmehr et al. (2021) and Saboori et al. (2012b) reported significant results.

The findings in Table 8 do not support the EKC hypothesis. A positive coefficient on GDP and a negative coefficient on GDP squared indicate an inverted U-shape relationship. However, the results in this analysis do not conform to the expected signs, and thus, the results do not provide empirical support for the EKC.

The EKC literature on GHG emissions is extensive and contains many conflicting findings. One reason is that these studies omitted the spatial interdependence between countries. For example, Freire et al. (2023) found evidence of the EKC in Brazil for CO_2 and nitrous oxide emissions but not for methane. Meanwhile, Olale et al. (2018) and Yang et al. (2017) found evidence of the EKC for GHG emissions in Canada and Russia. Lastly, Adeel-Farooq et al. (2021) identified evidence of the EKC for GHG emissions in six Asian countries.

The EKC literature has not reached a consensus even after incorporating the spatial effects. For instance, Shabani et al. (2025) and You and Lv (2018) found EKC for CO_2 emissions in a panel of countries. Both Shahzad and Aruga (2024) and Wang et al. (2013) found empirical support for the EKC using the ecological footprint as a measure of environmental degradation.

However, Wang and He (2019) suggested that developing countries do not need to reach full industrial maturity to begin mitigating their environmental damage; they can leverage technology from developed countries.

The current study's findings, therefore, contribute to the growing literature in spatial economics by highlighting that the EKC and PHH may not hold in the context of GHG emissions when spatial interdependencies are considered.

5. CONCLUSION, POLICY RECOMMENDATIONS AND LIMITATIONS

This study shows that not only do a country's domestic conditions affect greenhouse gas emissions (GHG), but also the actions of neighboring countries.

To test this hypothesis, a spatial econometric model includes a spatial lagged variable for GHG emissions, capturing geographical interdependencies among 68 countries between 1990 and 2023. This finding supports the hypothesis that countries respond to and compete with their neighbors in lowering GHG emissions through positive spillover effects and regional interdependence.

The study's results do not empirically support the Environmental Kuznets Curve (EKC) or the Pollution Haven Hypothesis (PHH). Economic growth does not necessarily lead to lower GHG emissions, nor do developed countries export their pollution to developing countries. GHG mitigation originates from renewable energy, innovation, and coordinated, competitive actions between a country and its neighbors.

The policy implications are clear and align with the United Nations' Sustainable Development Goal 13 on Climate Action. Although the Kyoto Protocol and the Paris Agreement are essential, regional GHG emission mitigation and regional partnerships can strengthen the positive spillover effects among neighboring countries. Neighboring countries can share and transfer innovations and technologies, especially to developing countries, which further encourages emission reductions.

Ultimately, establishing regional alliances and shared environmental benchmarks can promote collective action in mitigating GHG emissions.

This study has three limitations.

First, the analysis utilizes available country-level data, which may exclude local area dynamics of emissions. For example, most of the population in the United States resides on the East or West Coast, while most people in China live on the eastern side. Heavily populated areas are more likely to have greater GHG emissions than sparsely populated areas.

Second, the spatial weight matrix relies on geographical distances and is not based on economic relationship dynamics such as GDP and trade flows. Economic distances remain unexplored.

Finally, spatial econometrics uses spatial correlations, which do not untangle the causal mechanisms of the competitive or cooperative relationships between countries. Consequently, future research could address these limitations.

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