SOCIAL SCIENCE REVIEW ARCHIVES

ISSN Online: 3006-4708

ISSN Print: 3006-4694

https://policyjournalofms.com

Toward Carbon Neutrality: An Empirical Analysis of CO_2 Drivers on South Korea's Carbon Emissions

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DOI: https://doi.org/10.70670/sra.v4i1.1842

Abstract

This study investigates the determinants of CO_2 emissions in South Korea, studying the potential impact of renewable energy, green technology innovations, population, energy usage and per capita income from 1990 to 2023. We analyzed annual time-series data using unit root test with breaks, a bootstrap ARDL cointegration, and Granger causation test under a STIRPAT framework to reach valid conclusion. The empirical results suggest the presence of long-run equilibrium relationship between the variables. Additionally, the findings demonstrate that green technology innovations and renewable technology reduced CO_2 emissions, whereas energy usage, population growth and per capita income, contributed positively to the environmental degradation. The findings indicate the presence of bidirectional causality between CO_2 emissions and all the key determinants. This implies that it is crucial to introduce and synchronize policies stimulating and continuing innovations in renewable energy and green technology, as well as mitigating the escalating energy demands and consumptions caused by an increase in population and per capita income. The findings of the current study contribute pertinent policy implementations for South Korea's planned policies in reaching carbon neutrality by the year 2050.

Keywords: CO_2 Emissions, Green Technology, Consumption, Carbon Neutrality, South Korea

Introduction

South Korea's CO_2 emissions per capita reached 12.27 tons in the year of 2024, ranking 9th globally and making it one of the highest emitters among developed nations.[1] Such alarming statistics represent a critical environmental challenge for a country that has committed to achieving carbon neutrality by 2050 through its ambitious Green New Deal program.[2] The urgency of the environmental crisis is further emphasized by the Constitutional Court of South Korea's ruling in August 2024, which declared the country's current climate measures "inadequate and unconstitutional" for failing to protect the basic rights of current and future generations.[3] The pressing environmental circumstances, in combination with South Korea's heavy dependency on oil and gas, with these energies contributing to more than 80% of primary energy supply, form a

[1] https://www.worldometers.info/co2-emissions/south-korea-co2-emissions/
[2] https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2021)690693
[3] https://ccpi.org/country/kor/

unique backdrop for considering the intricate linkages among economic development, technological advancement, and environmental deterioration.[4] The research investigates the determinants of CO_2 emissions, specifically examining the potential impact of green technology innovations (GTI), renewable energy (RE), energy consumption (EN), population (POP), and per capita income (PCI) from 1990 to 2023 in South Korea. Previous investigations have clearly established positive correlations between economic activities and CO_2 emissions in South Korea (Jin & Kim, 2020). However, what remains unknown are the precise quantitative relationships and causal mechanisms through which these variables interact within South Korea's unique policy environment, particularly following the implementation of the Korean Green New Deal in 2020. The key variables examined include green technology innovations measured through environment-related patents, hydro, solar, wind, and comprehensive energy consumption patterns. The analysis contextualizes these relationships within South Korea's specific regional and sectoral framework, focusing on the country's transition from a fossil fuel-dependent economy toward sustainable energy systems under the framework act on carbon neutrality and green growth.

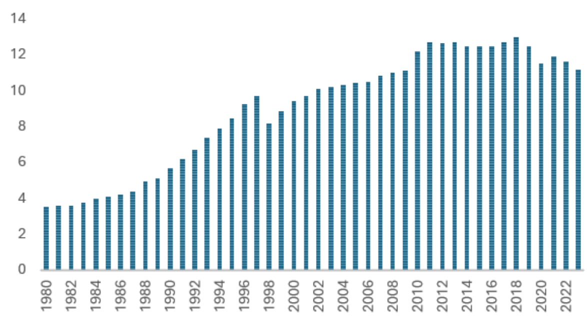

Fig 1. CO_2 emissions per capita from 1980 to 2023 (Source: OECD)

The investigation addresses significant theoretical, methodological, and policy gaps in existing literature. Theoretically, while the Environmental Kuznets Curve (EKC) hypothesis has been extensively tested globally, limited research specifically examines South Korea's unique development trajectory where rapid industrialization coincided with ambitious climate commitments (Kim et al., 2023). Methodologically, most current studies have focused on firm-level analyses or aggregated studies without distinguishing innovation characteristics (Amin et al., 2022; Shan & Shao, 2024), creating a gap in understanding how specific types of green technology affect national carbon emissions at the macroeconomic level. Furthermore, existing literature often employs traditional econometric methods that may not adequately address endogeneity, and structural breaks present in South Korea's data, particularly given major policy shifts like the 1997-1998 Asian financial crisis and post-2005 renewable energy transition policies. The practical urgency stems from South Korea's commitment to reduce greenhouse emissions by more than 40% by 2030 and achieve net-zero by 2050, requiring evidence-based policy frameworks that can guide effective implementation of the ₩73.4 trillion green new deal investment program. The analysis addresses critical unexplored and underexplored aspects of South Korea's environmental-economic nexus. First, there exists a significant knowledge gap regarding the interaction effects between economic policy uncertainty, green technology innovation, and environmental outcomes in South Korea's context, particularly how these relationships differ from global patterns identified in recent literature. Second, inconsistencies and unresolved issues persist in the literature regarding the effectiveness of South Korea's green technology investments, with some studies suggesting positive environmental impacts while others question their measurable effects given the country's continued

[4] https://climateactiontracker.org/countries/south-korea/

fossil fuel dependence (Zhao et al., 2024). Third, the investigation identifies controversies in the methodological approaches used to analyze environmental degradation in rapidly developing economies, particularly the appropriateness of traditional EKC frameworks versus more complex N-shaped relationships. The research poses clear research questions: How do green technology innovations, renewable energy adoption, and traditional energy consumption interact to influence CO_2 emissions in South Korea's unique policy environment? What are the short-run and long-run causal relationships between these variables? How do population dynamics and income growth affect these environmental outcomes within the context of South Korea's carbon neutrality objectives? The research makes substantial theoretical contributions by extending the STIRPAT framework to incorporate South Korea's specific green technology innovations and renewable energy variables. The analysis outlines innovative theoretical frameworks by combining EKC hypothesis testing with advanced econometric techniques, specifically employing the bootstrap ARDL cointegration approach that provides more robust inference than traditional methods, especially for small samples and mixed integration orders. Practically, the investigation aims to deliver actionable policy recommendations for South Korea's transition toward carbon neutrality by 2050. The anticipated practical outcomes include: (1) quantified effectiveness measures of green technology investments in reducing carbon emissions, (2) evidence-based guidelines for optimizing renewable energy adoption strategies, and (3) policy frameworks for balancing economic growth with environmental sustainability. The research articulates specific aims: to establish empirical evidence for the EKC hypothesis in South Korea's context, to quantify the short and long run impacts of green innovations on carbon emissions reduction, and to provide econometric validation of South Korea's Green New Deal policy effectiveness. These contributions will directly inform policymakers' decisions regarding the ₩73.4 trillion investment allocation and help South Korea achieve its ambitious 40% emission reduction target by 2030 while maintaining economic competitiveness in the global market. The rest of the paper is structured as follows. Section 2 provides literature review. Data, methodology, and empirical modelling included in section 3. Section 4 presents the result and discussion. Section 5 concludes paper with findings and policy implications.

Literature Review

Environmental Degradation and Green Technological Innovation

A rising body of literature has observed the relationship between technological innovation and environmental degradation, with increasing attention to the role of green technologies. Technology innovation is generally regarded as a double-edged sword in its environmental implications, varying across regions, stages of development, and the type of innovation applied. Feng et al. (2009) found that technological advancement, urbanization, and income levels significantly influenced carbon emissions, with technology having a mitigating effect. Similarly, Ali et al. (2016) concluded that technical progress and economic development contribute positively to environmental quality by reducing CO_2 emissions. Weber and Neuhoff (2010) recognized a negative association among innovation and environmental degradation, with energy-efficient technologies leading the way.

However, not all empirical evidence reinforces the idea that an innovation will always yield environmental benefits. For example, Ganda (2019) in their study indicated that in developing countries, technological development is possible to surge emissions because of the reliance on older energy systems. In low-income economies like Uganda. Bai et al. (2020) found that scientific change led to increased pollution rather than reducing it. These opposing conclusions have led to an emphasis shift from techno-innovation and innovation for the sake of innovation to one of green technological innovation—one that is explicitly focused on contributing to environmental sustainability. Houssam et al. (2024) undertook a typical innovation assessment and studied the

effects of 'green innovation' in N-11 countries. Their findings indicated that green innovation significantly improved environmental quality in the presence of renewable energy consumption. With the Environmental Kuznets Curve method, their findings supported the warming transition towards clean technology policy choice. Töbelmann & Wendler (2020) investigated data of EU-27 member states utilizing system GMM, and found only green innovation decreased CO2 emissions, not technological advancement. Lee and Min (2015) and Zhao et al. (2024) indicated that green R&D provides enhanced environmental quality, and earmarking tawny feet into green technology has a better impact than looking at the term innovation. Gao et al. (2018) also mentioned that green innovation aids in providing environmental sustainability. Godil et al (2021) discovered a statistically significant relationship in renewable energy, green innovation, and economic growth when looking specifically at China's economy. Wang et al. (2020) provided similar support, where financial development and green technology were referenced in relation to better environmental performance. Given South Korea now is allocating significant amounts of spending toward a green innovation stimulus and is seeking to establish a 30% smart city development target, minimum sustainable practices and carbon neutrality by 2050 would seem a good time to clear up the role of green technological innovation, with respect to environmentally degrading activities.
H1: Green technology innovation significantly influences CO_2 emissions in South Korea.

Environmental Degradation and Energy
Environmental Degradation and Non-Renewable Energy
The relationship between non-renewable energy usage and environmental degradation has been commonly examined in literature. Several studies emphasize that conventional energy sources, such as fossil fuel, significantly contribute to increased carbon emissions and environmental pollution. Empirical analysis by Saboori and Sulaiman (2013) as well as Rehman and Rashid (2017) found that higher levels of non-renewable energy consumption led to elevated CO_2 emissions in Malaysia. In the context of Pakistan, Abbas et al. (2021) observed that the use of conventional energy sources reduced environmental quality. Ashraf et al. (2020) also identified the adverse environmental impacts of fossil fuel-based energy, particularly in developing economies where energy demand is met largely through non-renewable resources. Given that, if use imported fossil fuels to meet the challenges of meeting energy needs, then these findings have serious implications. Khan et al. (2023) examined the fossil fuel consumption, CO_2 emissions, and environmental quality across 41 Sub-Saharan African countries, and concluded that fossil fuels substantially increase CO_2 emissions, thereby degrading environmental quality. Khurshid et al. (2024) examined the energy profile of Pakistan and found that coal, gas, and oil consumption contributed to pollution, habitat destruction and biodiversity loss. Şahin (2024), emphasized that non-renewable energy resources, once extracted and used, cannot be reused, and their extraction and utilization cause irreversible damage to the environment, highlighting the urgent need for substitutes. Murshed (2024) investigated 119 developing countries and urged transitioning towards renewable energy could reduce the non-linear effects of non-renewable energy on environmental degradation, provided that the countries receive adequate policy support and technological capacity. Together these studies underscore the importance of coordinated policy framework that reduce the dependence on non-renewable energy while developing renewable energy sources, in order to protect environmental quality and public health. Despite being on a path away from the reliance on non-renewable energy, the country continues to consume significant levels of energy through fossil fuels, making it difficult to reach carbon-neutral initiatives. Hence, there will continue to be valuable potential of research regarding the adverse effects of non-renewable energy on the environment.
H2: Non-renewable energy significantly influences CO_2 emissions in South Korea.

Environmental Degradation and Renewable Energy

Unlike fossil fuels, renewable energy sources are considered environmentally friendly alternatives capable of reducing greenhouse gas emissions while supporting economic growth (Demirbas, 2000). These energy sources, such as solar, hydropower and wind are naturally replenished and are thus central to strategies for sustainable development and environmental protection. Apergis and Payne (2009) using data from six Central American countries, concluded that consumption and renewable energy significantly reduce greenhouse gas emissions. Sarkodie and Adams (2018) demonstrated that non-renewable energy significantly increases carbon emissions and renewable energy sources contribute less to overall emissions in South Africa. For Hu et al. (2014) established that renewable energy fosters economic development in China, but its effect on air and water pollution were insignificant. Tsoutsos et al. (2005) clearly demonstrated the direct effect of solar energy to mitigate pollution, while Wang and Wang (2015) stressed the long-term benefits of wind energy. Sharif et al. (2020a) applied a QARDL model to investigate the ecological footprint of renewable and non-renewable energy usage over a five-decade span. Their findings indicated that renewable energy exerts favorable effect reducing on environmental degradation, lending support to the Environmental Kuznets Curve hypothesis. Sharif et al. (2020) identified a bi-directional causal relationship between renewable energy, fossil fuel and environmental degradation. Furthermore, (Kalmaz and Kirikkaleli (2019) recognized a long-run equilibrium between CO_2 emissions, energy use and macroeconomic variables in emerging economies. Bulut (2024) provided evidence from Türkiye showing that growing use of renewable energy consistently improves environmental quality, with technological development partly driving these benefits. Abdi et al. (2025) suggests that renewable energy consumption reduces carbon emissions and ecological damage substantially in both the short-run and long-run, strongly encouraging its adoption as a sustainable energy source in Somalia. Kartal (2025) demonstrated that renewable energy use is statistically negatively associated with pollution from air, water and natural resources thereby supporting human health and environmental sustainability. Obadiah Ibrahim Damak et al. (2025) revealed the statistically significant and negative relationship between renewable energy and CO_2 emissions, suggesting that greater reliance on renewable energy effectively mitigates environmental degradation in Japan. Furthermore, Dogan and Seker (2016) found that renewable energy and trade openness reduce carbon emissions among members of the OECD climate group, while non-renewable energy negatively affects environmental quality. Despite developments with renewable energy contributing to less than 10% of the total energy supply to the country, it is now particularly important to evaluate what the actual environmental impacts will be. As the country fully pursues a transition to clean energy, understanding how effective renewable energy sources can reduce CO_2 emissions has never been more crucial.

H3: Renewable energy significantly influences CO_2 emissions in South Korea.

Other Determinants

Not only energy sources, but also macroeconomic variables like per capita income and population, influence the degradation of the environment. Alola and Kirikkaleli (2019) explored the macroeconomic variables within the United States and found the evidence of causal linkages involving renewable energy usage, population dynamics, carbon emissions and per capita income. The results demonstrate how shift use, and socioeconomic factors are interconnected with environmental sustainability. Weber (2018) found that regional population growth in Europe strongly correlates with increased CO_2 emissions and land use for urban purposes, with population serving as a scale factor for environmental degradation, compared to Western context. Abidin et al.

(2023) reported that population growth and new housing development amplify ecological risks, affecting rivers environments and spatial dimensions of environmental assessment. Pham et al. (2020) demonstrated that population growth and urbanization harm environmental quality, although affluence can either mitigate or exacerbate these effects depending on consumption pattern and technological adoption. Maier (2015) observed that while population growth alone does not directly cause deterioration, it significantly corresponds with environmental stress, poverty, and high, per capita consumption, which in turn influence environmental outcome. Duraiappah (1996) argued that poverty drives population growth, which then contributes to environmental degradation through deforestation, land conversion and other mechanism.

H4: Per capita income significantly influences CO_2 emissions in South Korea.

H5: Population significantly influences CO_2 emissions in South Korea.

Based on the above discussion, significant work has been done on green technological innovation, energy consumption, and environmental degradation. Much of the literature is scattered across countries and lacks consensus, especially in applying robust empirical methodologies. Furthermore, there remains a gap in studies focusing specifically on South Korea, using a comprehensive framework like the STIRPAT model and advanced estimation methods such as the BARDL or QARDL approaches. Addressing these gaps can enhance both theoretical understanding and policy effectiveness and pursuit of carbon neutrality. Several authors have utilized the IPAT model to analyze the factors of carbon dioxide emissions. IPAT model is originally formulated by Ehrlich and Holdren, and then further developed into a more formal identity by (Raskin, 1995; York et al. 2002; Paramati et al. 2020) for the purposes of empirical analysis of the IPAT. While there is empirical evidence of the utility of the IPAT model as a theoretical model, as empirical tool, the deterministic form of the IPAT model is not useful. In recognizing the deterministically based limitations of the IPAT model, Dietz and Rosa (1997) developed the STIRPAT a statistical framework that reformulated the IPAT identity to a statistical form, that would allow for empirical testing for hypotheses, regarding social, economic, and technological driving factors contributing to environmental degradation. A STIRPAT-based empirical framework is applied in this study on the basis of theoretical foundation, and the framework is further extended to include energy consumption variables. The model is specified as:

$$CO_2EM_{it} = f(POP_{it}, EN_{it}, PCI_{it}, RE_{it}, v_{it}) \qquad \text{(i)}$$

In equation i, CO_2 emission as a determined by population (POP), energy consumption (EN), per capita income (PCI), and renewable energy (RE). We adapt the formulation from the empirical model of Paramati et al. (2017). Figure 2 displays the conceptual framework and hypothesized relationships for the study regarding the population, income, energy consumption, innovation, and CO_2 emissions.

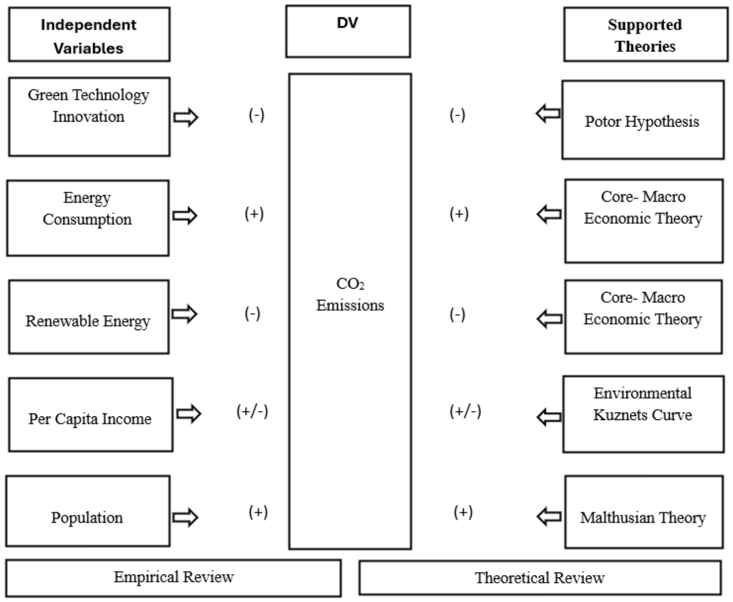

Fig 2. Conceptual and Theoretical Framework

Methodology

This study examines the impact of GTI, RE, EN, POP, and PCI on CO_2 emissions in South Korea, covering the time from 1990 to 2023. Table 1 reviews the variables used in our analysis and their sources.

Table 1: Source of Data

Variables	Definition	Data Sources
CO_2	Measured in term of per capita	OECD statistics database
GTI	Proxied by the number of environment-related patents	OECD statistics database
RE	Includes hydro, solar, wind, geothermal, wave, and tidal energy	Energy information administration (EIA)
EN	Measured in tons and consist of coal, petroleum, natural gas, and other fossil fuels	Korea energy economics institute (KEEI)
PCI	Measured by Total income/Total population	World Bank
POP	All residents regardless of citizenship or legal status	World bank

Following McNown et al. (2017), the bootstrapped (ARDL) cointegration approach is applied. This method extends the conventional ARDL bound testing procedure of Pesaran et al. (1999, 2001) by generating critical values for three separate cointegration tests, F1-test F2-test and T-test, allowing more robust inference, especially in small samples and mixed integration orders.

The general BARDL specification for three variables can be expressed as:

$$y_t = \sum_{i=1}^{p} a_i y_{t-i} + \sum_{j=0}^{q} \beta_j x_{t-j} + \sum_{k=0}^{r} \gamma_k z_{t-k} + \sum_{l=1}^{s} \tau_l D_{t,l} + \mu_t \quad \text{(ii)}$$

In the above equation, l, j, k denotes lag terms, where l = 1,2,3,4 …... P, j= 0,1,2, 3,4……q, k= 0,1,2,3,4 …… s and t represent time period. y_t is dependent variable. While x_t, y_t is independent variables of the study. The term $D_{t,l}$ are structural break dummy variables as tested by (Carrion-i-Silvestre et al. 2009). Parameters β, y correspond to the coefficient of the lagged independent variables and μ_t is error term. Equation (iii) presents the corresponding error correction form of the above model, as given below:

$\Delta y_t = \varphi y_{t-1} + \tilde{\gamma} x_{t-1} + \tilde{\psi} z_{t-1} + \sum_{i=1}^{p-1} \tilde{\lambda_i}\, \Delta y_{t-i} + \sum_{j=1}^{q-1} \tilde{\delta_j}\, \Delta x_{t-j} + \sum_{k=1}^{r-1} \tilde{\pi_k}\, \Delta z_{t-k} + \sum_{l=1}^{s} \tilde{\omega_l}\, D_{t,l} + \tilde{\mu_t}$
(iii)
In equation ii, $\varphi = \sum_{i=1}^{p} a_i, \quad \gamma = \sum_{i=1}^{q} \beta_i, \quad \psi = \sum_{i=0}^{r} \gamma_i$ estimated while using constant term that is denoted through ς given in the model iv.
$\Delta y_t = \tilde{c} + \phi y_{t-1} + \tilde{\gamma} x_{t-1} + \tilde{\psi} z_{t-1} + \sum_{i=1}^{p-1} \tilde{\lambda_i}\, y_{t-i} + \sum_{j=1}^{q-1} \tilde{\delta_j}\, x_{t-j} + \sum_{k=1}^{r-1} \tilde{\pi_k}\, z_{t-k} +$
$\sum_{i=1}^{s} \tilde{\omega_i}\, D_{t,i} + \tilde{\mu_t} t$ (iv)
To validate the cointegration, y_t, x_t and z_t in equation 3 is to be rejected and can be discussed as follows:

1. **F₁-test:** $H_0: \varphi = \psi = 0$ vs $H_1: \varphi \neq 0$ and/or $\psi \neq 0$ (joint insignificance of lagged-level variables in ECM).
2. **F₂-test:** $H_0: \psi = 0$ vs $H_1: \psi \neq 0$ (joint insignificance of explanatory variables' coefficients).
3. **t-test:** $H_0: \varphi = 0$ vs $H_1: \varphi \neq 0$ (no error correction).

Cointegration is confirmed if any of the null hypotheses are rejected. Stationarity is examined using both the ADF and ZA unit root tests. The ZA test allows for an endogenous structural break in the intercept or trend, making it suitable for South Korea's data, which may be influenced by major policy changes such as the 1997–1998 Asian financial crisis and post-2005 renewable energy transition policies. By combining break-adjusted unit root tests with the BARDL methodology, the empirical framework ensures robust detection of long-run equilibrium relationships among the studied variables in the context of South Korea's environmental and energy policy dynamics.

Results and Discussion

Table 2 provides the descriptive statistics of the variables included in the analysis. The mean indicate that per capita income (PCI) is the highest average followed by renewable energy (RE), green technology innovation (GTI), and CO_2 emissions. This pattern suggests that, within sampled economy, income levels are relatively high while technological innovation in the green sector is slightly more visible during this time period, when compared to CO_2 emissions. While standard deviation of green technology innovation shows a greater variability compared to other indicators, suggesting variability in terms of technological innovation initiatives.
Jarque-Bera test is applied to confirm the normality of the variables. In which all the probability values of all variables above 0.05 indicate that the distribution of the dataset is not significantly deviant from normality, allowing the dataset to be suitable for econometric analysis.

Table 2: Descriptive Statistic.

Variables	Mean	Min	Max	Std. Dev	JB	Prob
CO_2	2.984	2.183	3.042	0.011	1.934	0.291
GTI	2.873	2.324	2.948	0.059	2.871	0.275
RE	1.943	1.932	2.013	0.043	1.945	0.374
EN	3.104	2.943	3.243	0.083	2.146	0.316
POP	7.632	7.424	7.734	0.045	3.953	0.235
PCI	4.514	4.142	4.704	0.094	1.850	0.291

Source: Author Own Calculation

Table 3 reports the findings of the correlation analysis, including the VIF and tolerance levels (1/VIF). The correlation matrix indicates that CO_2 emission is negatively associated with renewable energy (RE) and green technology innovation (GTI). Whereas robust positive association with energy usage (EN) and a moderate positive association with population (POP) and per capita income (PCI). In addition, GTI and RE have a moderate positive association, suggesting some complementarity between them, although the other correlations are within acceptable limit, either statistically significant or insignificant at varying levels of significance. To further assess multicollinearity, we calculated the VIF for all explanatory variables. Individual VIF value ranged between 1.216 and 1.532, with a mean VIF of 1.365, well below the commonly used cut-off value of 5. Additionally, Tolerance value (1/VIF) exceeded 0.10, confirming that the independent variables are not highly correlated and can be reliable in subsequent regression models. After examining the correlation and multicollinearity between the variables. We established the order of integration to determine the correct cointegration technique for examining the long-run association between CO_2 emissions and its determining factor. Incorrectly identifying the integration order could lead to biased statistical inference. Therefore, we applied the ADF test, a widely used technique for testing stationarity that accounts for structural breaks in panel data (Carrion-i-Silvestre et al., 2009; Chen et al., 2022). The ADF test is applied to access the stationary of the variables and to identify whether the variables are stationary at order zero, order one or mixed integration.

Table 3: Correlation analysis outcomes.

	CO_2	**GTI**	**RE**	**EN**	**POP**	**PCI**
CO_2	1					
GTI	-0.681**	1				
RE	-0.581***	0.291	1			
EN	0.832**	0.278	0.198	1		
POP	0.398**	0.251	0.368*	0.573**	1	
PCI	0.381**	0.298**	0.361**	0.312**	0.218	1

	VIF	**1/VIF**
GTI	1.381	0.724
EN	1.398	0.715
RE	1.297	0.771
POP	1.532	0.653
PCI	1.216	0.822
Mean	1.365	

*.** and ***denote the significance at the 10%, 5% and 1% levels significantly
Source: Author Own Calculation

The ADF test also performs well for datasets with relatively small sample sizes. However, traditional unit root tests, such as ADF and PP tests, often suffer from low power and may not find adequate evidence to reject the null hypothesis (Dickey & Fuller, 1981; Phillips & Perron, 1988). The ADF test increases statistical power and provides more reliable suggestions of the existence of unit root, even in panel data that contain structural breaks. To address potential biases associated with ignoring structural breaks, we employed Zivot-Andrews (ZA, 2002), which accounts for a single endogenous structural break in the time series. The identified break years are presented in Table 4. The results show that both ADF and ZA tests indicate non-stationarity of the variables at their levels. However, after first difference D(ADF) and D(ZA), all variables become stationary, even when considering structural breaks. These results confirm that the variables are integrated of order one, I(1), and are suitable for cointegration analysis.

Table 4: Unit Root Test.

Variables	ADF (Level)	D(ADF)	ZA (level)	Break year	D(ZA)	Break Year
CO_2	0.498	-5.324**	-1.291	2013	-5.445**	2008
GTI	-0.382	-4.957**	-0.298	2010	-6.948**	2014
REN	-2.742	-3.753***	0.372	2006	-0.732***	2011
ENG	-0.468	-5.048***	0.035	2017	-0.583***	2009
POP	-0.183	-6.342***	0.093	2020	4.968***	2012
PCI	-0.978	-3.984***	0.482	2015	-6.831***	2021

*.** and ***denote the significance at the 10%, 5% and 1% levels significantly
Source: Author Own Calculation

Table 5 presents the results from the BARDL cointegration analysis. The combined F-test and t-tests provide strong evidence reject the null hypothesis of no cointegration, thereby confirming the long-run relationship among the variables. Using CO_2 emission as the dependent variable, the result demonstrates that GTI, RE, EN, POP, and PCI are cointegrated with CO_2 emission. The estimated model indicates that the optimal lag structure is (1,1,2,2,0,1) with structural break detected in 2012. The F-statistics of 18.572, along with the significance of t-statistics for all lagged independent variables, confirms the validity of the cointegrating vector. The coefficient of determination (R^2) is 0.847, implying that all independent variables together explain approximately 85 percent of the variation in CO_2 emissions. Additional diagnostics tests affirm the robustness of the model: Q-stat (3.737) and LM test (1.094) indicate no issues regarding serial correlation, while Jarque Bera statistics (0.538) supports the normality of the residuals, satisfying the assumption of classical linear regression. Overall, these diagnostics attest to a stable long-run relationship between carbon emissions and their key determinants.

Table 5: Estimation of Co-integration based on ARDL Bootstrapping.

						Diagnostic Test			
(Estimated model)	(Lag lengths)	(Break Year)	(F_{pss})	(T_{pv})	(T_{iv})	(R^2)	(Q-stat)	LM(2)	(JB)
Model	1,1,2,2,0,1	2012	18.572**	-6.934**	-3.183**	0.847	3.737	1.094	0.538

$CO_2EM_{it} = f(POP_{it}, PI_{it}, EN_{it}, RE_{it}, v_{it})$
*.** and ***denote the significance at the 10%, 5% and 1% levels significantly
Source: Author Own Calculation

Table 6 presents the finding of long-run estimation. The findings reveal that GTI exerts a statistically significant negative effect on CO_2 emissions. Specifically, a 1% increase in GTI leads to a 0.291% reduction on CO_2 emission, demonstrating the role of technological progress in mitigating environmental degradation. These outcomes align with previous studies demonstrating that GTI significantly lowers emissions among OECD countries (Paramati et al., 2020; Wang et al., 2023). Moreover, earlies research has underscored the importance of innovative systems for emission reduction (Jordaan et al., 2017) and the crucial role of low-carbon technologies for mitigation emissions in East Asian countries (Wang et al., 2025). Renewable energy also exhibits a negative impact on CO_2 emissions, with a 1% increase associated with a 0.321% reduction in emission, underscoring the importance of renewable energy in South Korea's decarbonization plan. Similar conclusions were drawn by Adams and Acheampong (2019), who identified renewables adoption as a contributing factor in a global emission mitigation. Wang et al. (2023) also provided empirical evidence of the ecological benefits of renewables within the Asia-Pacific region. In contrast, energy consumption exerts a positive and significant effect on CO_2 emissions at the 1% level. Specifically, a 1% increase in energy usage raises CO_2 emissions by 0.381%, reflecting the South Korea's reliance on traditional energy sources pushes carbon intensity. Similarly, Khan et al. (2020) found that energy consumption leads to emissions-enhancing behavior in Asian economies. Population growth also positively influences carbon emissions, with a coefficient of 0.273, indicating that demographic expansion leads to growth in energy demand and emissions level. This finding aligns with Yeh and Liao (2017), who noted that population growth continues to exacerbate environmental challenges in Taiwan. Per capita income shows a positive relationship with CO_2 emissions with a coefficient of 0.193, indicating the rising per capita income level historically contributes to increased environmental stress. A key insight from the Environmental Kuznets Curve hypothesis literature is that emissions rise in the early stages of income growth until other economic factors may improve the environment. Supporting this theory, Acheampong et al. (2021) found that rising income levels in East Asia led to higher carbon emissions until reached a higher development stage, where environment improvement became evident.

The overall model fit is high, with an R^2 of 0.972 and an adjusted R^2 of 0.924. The Durbin-Watson statistics of 2.392 indicate no evidence of autocorrelation. Stability tests, including CUSUM and CUSUMsq confirm that the long-run parameters remain stable over time. Additionally, the diagnostic test for normality, heteroskedasticity, serial-correlation and model specification suggests that the estimated model adequately represents the data. These results imply that South Korea, can reduce CO_2 emissions by combining GTI and RE, whereas POP, EN, and increased PCI continue to exert upward pressures on environmental degradation.

Table 6: Estimation BARDL, Co-integration (long run) analysis.

DV	Coeff	t-stat	p. value
C	0.092***	3.184	0.001
GTI_t	-0.291**	-2.931	0.000
RE_t	-0.321**	-3.837	0.000
EN_t	0.381***	4.978	0.000
POP_t	0.273***	4.193	0.000
PCI_t	0.193***	2.192	0.000
R^2	0.972		
Adjusted R^2	0.924		
Durban Watson	2.392		

Stability Analysis Test	F stat	P value
X^2 Normal	0.292	0.174
X^2 serial	0.378	0.341
X^2 ARCH	0.378	0.281
X^2 Hetro	0.413	0.382
X^2 Reset	0.681	0.183
CUSUM	Stable	
CUSUM sq	Stable	

*.** and ***denote the significance at the 10%, 5% and 1% levels significantly

Source: Author Own Calculation

Table 7 presents the results of empirical analysis from the short-run analysis. The results show that green technological innovation significantly reduces CO_2 emissions, supporting the idea that technology provides a pathway to reducing environmental degradation in the short term. Similarly, renewable energy exhibits a significant negative effect on CO_2 emissions, suggesting that continued investment in the adoption of renewable energy helps to reconfigure the domestic energy mix away from traditional energy resources, thereby lowering carbon intensity. In contrast, energy usage, population growth, and per capita income all positively influence CO_2 emissions at the 1% significance level, indicating that these factors continue to drive short-run decreases in carbon emissions in South Korea. While the structural break dummy variable shows a positive effect on emissions, its impact is minimal, implying that structural shocks do not substantially influence short-run emission trends. The error correction term is negative and statistically significant (-0.326), highlighting its crucial role in adjusting short run disequilibrium toward long-run equilibrium. Also, as mentioned in the above literature review, a few diagnostic tests indicated that the model was relatively well specified with no evidence of normality, serial correlation, conditional heteroskedasticity or ARCH effects. CUSUM and CUSUMsq diagnostics suggested that short run parameter estimates are stable over the whole sample period. The model also has a high degree of explanatory power with R^2 of 0.909 and adjusted R^2 of 0.831. The Durbin-Watson of 2.948 suggested no autoregressive residual errors. These diagnostics provide compelling justification, that the short run model specification is sound and reliable.

Table 7: Estimation of BARDL Co-Integration (Short-run) analysis.

Dependent Variables	**Coefficient**	**t-statistic**	**P. value**
C	0.049***	0.531	0.000
GTI_t	0.192***	-3.85	0.000
RE_t	0.294**	-3.93	0.001
EN_t	0.201**	2.942	0.000
POP_t	0.194***	3.928	0.000
PCI_t	0.291***	1.923	0.001
R^2	0.909		
Adjusted R^2	0.831		
Durban Watson	2.948		

Stability analysis Test	F stat	p. value
X^2 Normal	0.382	0.284
X^2 serial	0.294	0.382
X^2 ARCH	0.391	0.281
X^2 Hetro	0.193	0.694
X^2 Reset	0.219	0.713
CUSUM	Stable	
CUSUM sq	Stable	

*.** and ***denote the significance at the 10%, 5% and 1% levels significantly
Source: Author Own Calculation

The final part of the analysis focuses on a Vector Error Correction Model (VECM)-based Granger causality framework to examine the causal relationship among variables. The results are reported in Table 8, which show there a strong bidirectional causality between CO_2 emissions and green technology innovation. Green technology innovation granger-cause CO_2 emissions in a strong way, also CO_2 emissions granger-cause green technology innovation at the 1% significance level. These results suggest a feedback relationship among environmental performance and innovation technology, emphasizing their reciprocal relationship. Similarly, renewable energy and CO_2 emissions demonstrate strong bidirectional causation, in which significantly affect each other. An increase in renewable energy decreases emissions, while a change in CO_2 emissions affects the expansion of renewable energy generation facilities. The energy consumption and emissions nexus also indicate strong bidirectional causation. Energy consumption granger-cause CO_2 emissions, and in turn, CO_2 emissions granger-cause energy consumption, also with strong F-statistics. We further find that population growth and population granger-cause CO_2 emissions, whereas CO_2 emissions causes granger-cause pressures of demographic, indicating a two-way causation. In addition, it also appears that per capita income granger-causes CO_2 emissions, and CO_2 emissions also granger-causes per capita income as well, though at different levels of significance (1% and 10%). In summary, our analyses provide support for feedback causation between CO_2 emissions and each of the environmental explanatory variables, indicating that economic, demographic, and technological drivers together shape environmental performance in South Korea.

Table 8: Estimation of Granger Causality Test.

Causal Pair	Direction	F-statistic	P. Value
GTI & CO_2	GTI → CO_2	21.493**	0.000
	CO_2 → GTI	15.938**	0.000
RE & CO_2	RE→ CO_2	21.499*	0.000
	CO_2 → RE	35.292**	0.000
EN & CO_2	EN → CO_2	49.849***	0.000
	CO_2 → EN	39.872***	0.000
POP & CO_2	POP → CO_2	7.092***	0.000
	CO_2 → POP	9.937***	0.000
PCI & CO_2	PCI → CO_2	9.292***	0.000
	CO_2 → PCI	5.139***	0.000

*.** and ***denote the significance at the 10%, 5% and 1% levels significantly

Source: Author Own Calculation

Conclusion

After the Paris Climate Conference, South Korea intensified efforts in meeting the carbon neutral aim. The paper identifies the effects of emissions of CO2 and green technology innovation (GTI), energy consumption (EN), population (POP), renewable energy (RE) and per capita income (PCI) in South Korea from 1990 to 2023. The results present evidence of long run cointegration in all variables. Green technology innovation and renewable energy reduce emissions in the short run as well as in the long run, illustrating their important role in curbing environmental harm. On the other side, energy consumption, population and per capita income create long run positive effects on emissions in the long run, creating more pressure on the environment. Additionally, there is evidence of granger causality, and panel causality test also supports bidirectionality of the variables. The empirical findings of this study carry several important policy implications. First, the results confirm that technological innovation and renewable energy reduce CO_2 emissions. Therefore, South Korea should significantly increase investments in renewable energy infrastructure and strengthen green technology innovation. By implementing these policies, the government can establish clear path toward a sustainable and low-carbon economy. Furthermore, the evidence of a bidirectional relationships among CO_2 emissions, green technology innovation and renewable energy suggests that policymakers should adopt a complementary approach by developing an integrated environmental policy framework that simultaneously promotes innovation and sustainability. Second, the statistically significant effects of per capita income, population, and energy consumption pose challenges for policymakers. Local governments need to design innovative incentive programs that guide residents away from high carbon and energy sources while addressing the increased environmental pressures associated with higher energy consumption. Moreover, population related factors require policies aimed at alleviating demographic pressure, thereby indirectly reducing emissions. Finally, the evidence suggests that South Korea can achieve its carbon neutrality target only through systemic transformation of with systemic macroeconomic processes. Policymakers must therefore implement coordinated strategies that explicitly link energy consumption, population change and income growth to emissions reduction as part of broader sustainable development agenda.

Despite its contributions, this study has several limitations that should be acknowledged for a balanced understanding. First, the analysis focuses exclusively on the South Korean economy, examining carbon neutrality through the lenses of green technology innovation and renewable energy adoption. While this country-specific focus provides valuable insights, it limits the generalizability of the findings, as other East Aisa Summit (EAS) countries, with distinct institutional, economic, and environmental contexts are excluded from consideration. Second, although prior research has extensively linked economic growth to environmental degradation, particularly within the framework of the Environmental Kuznets Curve (EKC) hypothesis, this study does not explicitly examine CO_2 emissions in relation to the EKC. The omission restricts the ability to compare the results with the broader EKC-related literature. Given these constraints, future research should expand the analysis to include cross-country comparisons among East Asian Summit countries members and incorporate the EKC framework to assess the non-linear dynamics between growth and environmental outcomes. Such extensions would enrich empirical evidence and provide more robust implications for both academic research and policy formulation.

Acknowledgement

The authors declare that this research received no external funding and that there are no conflicts of interest regarding the publication of this paper. The authors also express their gratitude to anyone who provided support or guidance during the preparation of this study.

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