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# Short- and Long-Run Drivers of $CO_2$ Emissions in the Top Ten $CO_2$-Emitting Economies: Evidence from Decoupling and Nonlinear Dynamics

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## Abstract

This study employs a multi-stage STIRPAT-based framework by combining decoupling analysis, cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model and panel threshold model to examine economic growth (GDP), population (POP), energy efficiency (EE), decarbonization (DEC) and renewable energy (REN) as drivers of CO2 emissions in the top ten $CO_2$-emitting economies from 1990 to 2024 using World Bank data. The decoupling analysis reveals heterogeneous performance, either strong decoupling or weak decoupling during the sampled period. No country falls within the expansive coupling or negative decoupling categories. The CS-ARDL estimates show that GDP consistently raises emissions both in the short and long run, while POP exerts significant environmental pressure in the long run. In contrast, EE, DEC and REN reduce emissions, with their effects becoming stronger over time. In the panel threshold regression, EE (output per unit of energy used) and DEC (reciprocal of the CO2 produced per unit of energy used) are used as threshold variables. The threshold analysis confirms significant nonlinear effects of EE and DEC on carbon emissions, with threshold values estimated at 2.904 and 0.219, respectively. The findings reveal that economic growth increases $CO_2$ emissions across all regimes; however, the magnitude of this effect declines after the threshold levels are exceeded, indicating that higher EE and stronger decarbonization efforts help mitigate environmental degradation. Additionally, POP effects vary across regimes, suggesting the presence of heterogeneous environmental impacts under different efficiency and decarbonization conditions. Overall, the findings demonstrate that combining decoupling analysis with short- and long-run elasticity estimation and nonlinear threshold modelling provides a coherent and policy-relevant understanding of emissions dynamics in major polluting economies.

**Keywords:** $CO_2$ emissions, energy efficiency, decarbonization, renewable energy, economic growth.

## 1. Introduction

Rising $CO_2$ emissions remain one of the most critical environmental challenges of the 21st century because of their contribution to global warming. Even newly industrialized countries have given top priority to industrial output to achieve economic growth at the cost of the environment. Consequently, achieving sustained economic growth with lower environmental degradation remains a central policy challenge. Under the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol was adopted in 1997 to establish emission-reduction commitments for industrialized countries and economies in transition. The Paris Agreement, adopted in 2015 and entering into force in 2016, further strengthened global climate cooperation through broad international participation. However, several major economies that signed the agreement, including the United States, China, Russia, and other large economies, remain among the world's leading $CO_2$ emitters. This contradiction highlights the need to reassess the drivers of $CO_2$ emissions in the top ten $CO_2$-emitting economies.

According to the Emissions Database for Global Atmospheric Research (EDGAR), China accounts for 33.12% of global $CO_2$ emissions, followed by the United States (11.69%), India (7.96%), Russia (5.07%), Japan (2.45%), Iran (2.09%), Indonesia (2.05%), Saudi Arabia (1.65%), South Korea (1.48%), and Germany (1.46%) (European Commission, 2025). Furthermore, these economies represent 51% of the total world population, 80% of fossil fuel consumption globally and 65% of GDP worldwide (World Bank, 2026). Focusing on these major emitters allows for a more policy-relevant analysis, as emission reductions within these economies can generate disproportionately large effects on global environmental quality. Moreover, these countries represent diverse stages of economic development, energy structures, and environmental policy frameworks, which is important for a comparative setting for examining heterogeneity in the growth–emissions nexus.

A crucial question is whether major emitting economies can achieve sustained economic growth without a corresponding increase in $CO_2$ emissions, a phenomenon referred to as decoupling. Wang et al. (2025) suggest that economies have experienced varying degrees of decoupling. Similarly, according to Bianco et al. (2024), 27 European Union countries have achieved decoupling from 1995 to 2019. However, several countries have also experienced negative decoupling, particularly among Organization for Economic Cooperation and Development (OECD) countries during 1990-2004 and 2015-2019 (Magazzino et al., 2024). These findings suggest that the decoupling process between CO2 emissions and GDP growth is complex and dynamic.

Building on the decoupling literature, researchers have employed various models to identify key factors influencing carbon emissions. Among the commonly identified determinants of $CO_2$ emissions, four important factors are economic activity (GDP per capita), population (POP), energy efficiency (EE), and decarbonization (DEC). Among these, GDP reflects the level of economic activity and production, which is generally associated with greater $CO_2$ emissions. Yang et al. (2018) in China, Roy et al. (2017) in India, Salim et al. (2019) in developing countries and Pata (2018) in Turkey have confirmed GDP as the dominant and largest contributor of CO2 emissions. Similarly, population size represents a key scale effect, thereby contributing to higher carbon emissions (Sadorsky, 2014; Cramer, 2002; Zhu et al., 2012; Ma et al., 2017).

In contrast, reductions in emissions are expected to arise from improvements in energy efficiency and decarbonization. Energy efficiency captures the amount of energy required per unit of economic output, with gains reflecting a transition toward cleaner and more efficient production, distribution, and consumption technologies (Li et al., 2023; Cansino et al., 2019; Waheed et al., 2018). Decarbonization, on the other hand, measures the carbon intensity of energy use, which can be reduced through a structural shift from fossil fuels toward low-carbon and renewable energy sources (Ito, 2017; Zoundi, 2017; Freire-González et al., 2024; Wang et al., 2025). Together, these two factors represent the main channels through which economies can achieve sustained reductions in $CO_2$ emissions.

Although extensive literature is available on decoupling of carbon emissions from economic growth, several important research gaps persist. First, existing studies generally adopt a single analytical framework. For example, studies like Freire-González et al. (2024) and Wang et al. (2025) employed decoupling analysis to assess whether GDP growth and $CO_2$ emissions are separating over time. Environmental Kuznets Curve (EKC) based studies including Işık et al. (2019), Danish et al. (2018), Pata (2018), and Leal & Marques (2020) mainly focused on growth-emissions relationship but have excluded population, energy efficiency, and decarbonization as main drivers. Similarly, Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT)-based studies such as Lin et al. (2017), Yang et al. (2018), and Salim et al. (2019) estimate multivariate elasticities but do not distinguish between short and long-run dynamics. Research on energy efficiency (Meng et al., 2024; Li et al., 2023; Wei et al., 2023) and decarbonization (Kongkuah & Alessa, 2025; Ito, 2017; Zoundi, 2017) has also largely relied on single-framework approaches. There is no study that integrates decoupling analysis, short and long-run estimation, and nonlinear threshold dynamics within a single framework.

Second, all STIRPAT and EKC studies such as Lin et al. (2017), Roy et al. (2017), Ma et al. (2017), Salim et al. (2019), and Sadorsky (2014) demonstrate that the effects of GDP and population on $CO_2$ emissions are constant across countries and over time. Meng et al. (2024) and Li et al. (2023) also use linear analysis. Similarly, studies on energy efficiency and decarbonization such as Kongkuah & Alessa (2025) and Ito (2017), employ linear estimation techniques. However, the impact of economic growth and population on emissions may change once economies reach certain levels of energy efficiency or decarbonization, implying the presence of nonlinear and regime-dependent dynamics that remain largely unexplored.

Finally, in these studies, there is a persistent methodological limit. Although studies like Lin et al. (2017), Salim et al. (2019), Sadorsky (2014), and Martínez-Zarzoso & Maruotti (2011) cover large panels, they apply pooled and standard fixed-effects models for analysis. These studies overlook the potential concern of cross-sectional dependence. The top ten carbon emitters of the world are known to be highly interconnected through trade, energy markets, technological diffusion and policy spillovers. Ignoring cross-sectional dependence in such scenarios may therefore produce biased and inconsistent estimates.

Based on the identified research gaps in the existing literature, the present study addresses the following questions: 1) Do the top ten $CO_2$-emitting economies demonstrate decoupling between economic growth and emissions? 2) To what extent does heterogeneity exist across economies in the decoupling process? 3) How do economic growth, population, energy efficiency, and decarbonization affect $CO_2$ emissions in the short and long run? and 4) Do these relationships vary across different levels of energy efficiency and decarbonization?

Our study contributes to the literature in the following ways: First, it develops a structured multi-stage empirical framework within the STIRPAT model to examine the drivers of $CO_2$ emissions in the top ten $CO_2$-emitting economies over the period 1990–2023. Initially, decoupling analysis is used to establish facts on the relationship between growth and emissions. The analysis is then extended using the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model, which accounts for cross-sectional dependence and heterogeneity.

Second, the study extends the analysis by applying the panel threshold model of Hansen (1999) to examine whether the effects of economic growth and population on $CO_2$ emissions vary across different technological and decarbonization regimes. In this framework, energy efficiency and decarbonization serve as regime-defining threshold variables, allowing the analysis to capture nonlinear and regime-dependent dynamics that are often overlooked in existing literature.

## 2. Literature Review

The literature on $CO_2$ emissions has evolved around three major strands. First, the EKC hypothesis examines the relationship between economic growth and environmental degradation. Second, using frameworks like STIRPAT studies have focused on demographic and structural factors such as population growth and urbanization. The third strand investigates technological transition, including EE and DEC. Since the Industrial Revolution, rapid industrial expansion and increasing dependence on fossil fuels have intensified environmental degradation and global warming (Stern et al., 1996; Bhattacharya et al., 2017). Consequently, a substantial body of empirical research has emerged to examine the economic, demographic, and technological drivers of $CO_2$ emissions using various analytical frameworks and econometric approaches.

### *2.1 Economic Growth and CO2 Emissions*

One of the most studied determinants of $CO_2$ emissions is economic growth. Existing literature examines the growth-emissions relationship through analytical frameworks such as the EKC hypothesis, STIRPAT model, and decoupling analysis.

#### 2.1.1 The EKC Hypothesis

The EKC hypothesis offers a broader theoretical relationship between economic growth and emissions and how it evolves during development. It shows that during the initial stages of economic development, carbon emissions increase with economic growth, degrading the environment. However, after a certain threshold, carbon emissions decrease when economic growth increases, improving the environmental quality. Many studies show that economic growth and carbon emissions have an inverted U-shaped curve (Farooq et al., 2022; Danish et al., 2018; Pata, 2018). Many studies have used CO2emissions in the EKC model as an indicator of environmental degradation. A study by Işık et al. (2019) employs a heterogeneous estimation method in ten U.S states to show that certain states such as Florida, Illinois, Michigan, Ohio and New York supported the EKC hypothesis because of the inverted U-shaped relationship.

Similarly, studies by Danish et al. (2018), Pata (2018) and Iwata et al. (2010) found similar results for the UK, confirming the EKC hypothesis. Leal & Marques (2020) explored the EKC hypothesis for 20 highest OECD carbon-emitting countries. Similarly, for developing countries, Hasanov et al. (2019) confirmed the EKC hypothesis and in Turkey it was confirmed by Koçak & Şarkgüneşi (2018). Leal & Marques (2020) employed the Driscoll–Kraay estimator and results for highly globalized groups showed an inverted U-shaped relationship. However, the result was opposite for low-globalized groups. Based on the above studies, the presence of EKC is convincing, which implies that emissions initially increase with increasing income.

However, above studies have limitations as they rely on first-generation panel estimators such as FMOLS, DOLS, and standard fixed effects models. These models do not account for cross-sectional dependence. Studies such as Işık et al. (2019) remain within linear frameworks and does not capture regime-dependent threshold dynamics. Based on this methodological gap, the use of CS-ARDL is justified as it addresses cross-sectional dependence and the Hansen (1999) panel threshold model captures nonlinear regime-switching behaviour that prior EKC studies overlooked.

#### 2.1.2 STIRPAT and Extended STIRPAT Model

Building on the STIRPAT framework, several studies have extended the model by adding socioeconomic and technological variables to explain $CO_2$ emissions across countries. Among the major analytical approaches, the IPAT framework introduced by Ehrlich and Holdren (1971) explains environmental impact as a function of population, affluence, and technology. To improve empirical applicability and analytical flexibility, Dietz and Rosa (1994) developed the STIRPAT model as an extension of the IPAT framework. Since then, STIRPAT has become one of the most widely used models in environmental economics because of its flexibility in incorporating additional socioeconomic and technological variables (Shi, 2003; Li and Lin, 2015).

Many other studies have extended STIRPAT model to analyse the impact of different factors on the environmental quality. Yang et al. (2018), apart from economic development, added temperature, urbanization and trade openness to check their impact on the environment in China. The results suggest that urbanization and economic development are the main contributors to CO2 emissions together with population growth, foreign trade and energy intensity. To extend the scope for India, Roy et al (2017) incorporated energy intensity and energy demand in the STIRPAT model. The study concludes that all the factors added in the model contribute to an increase in CO2 emissions.

However, the factor having the biggest share in the impact is economic growth. Similarly, to extend the model for 53 countries with different income levels, Lin et al. (2017) add urban employment, labor productivity and level of industrialization in STIRPAT. For low-income countries, the study found a small influence of economic development on the environment, whereas energy intensity, population and affluence have a major role in increasing CO2 emissions. Wang et al. (2017) investigate the impact of fixed asset investment on CO2 emissions in addition to energy consumption, trade openness and industrialization in developing countries. The results vary at different levels of development, but economic growth and fixed assets are leading contributors to CO2.

### 2.1.3 Decoupling Analysis

The relationship between economic growth and environment has mostly been explored through the lens of EKC and many studies have supported it. However, in many studies it has been rejected too (Churchill et al., 2018), while other studies showed a linear relationship (Roca et al., 2001) or even an N-shaped (Friedl and Getzner, 2003). Freire-González et al. (2024) did an extensive analysis on 164 countries from 1822 to 2018 and found that the relations between GDP growth and CO2 emissions is positive, however weakening over time. According to the study, globally, decoupling has not been achieved, especially in most of the Asian, American and African countries failing to decouple. A recent study by Wang et al. (2025) investigated the decoupling of CO2 emissions from economic growth in top 30 economies. The study found strong division in the decoupling such that Germany and Sweden, with the help of carbon pricing, renewable energy use and service sector expansion, achieved maximum decoupling. While developing countries failed to do so due to dependence on fossil fuels. Tranoulidis and Farmaki (2026) conducted analysis for Greece and confirmed that economic growth is the primary driver of $CO_2$ emissions.

### *2.2 Population and Urbanization*

Another important strand of literature examines the role of demographic factors such as population growth in $CO_2$ emissions. Cramer (2002), Zhu et al. (2012), and Sadorsky (2014) identify population growth as a major contributor to $CO_2$ emissions. Similarly, Ma et al. (2017) find that population has a positive impact on $CO_2$ emissions in China. For Arab economies, Abdelfattah et al. (2018) confirm that population, together with energy production and industrialization, contribute to carbon output. Salim et al. (2019) analyse 53 Asian developing countries and conclude that economic activities driven by population growth are the source of environmental degradation. While Sadorsky (2014) finds urbanization effects are insignificant in 16 emerging economies, Martínez-Zarzoso and Maruotti (2011) find that urbanization effects vary by income level.

### *2.3 Energy Efficiency, Decarbonization and Carbon Emissions*

Recent literature also emphasizes on the role of technological transition, particularly improvements in EE and DEC, in reducing $CO_2$ emissions. The differences in decoupling performance across different economies points to the importance of specific policies such as improving energy efficiency and is known to be critical in reducing carbon emissions as energy consumption is one of the main causes of carbon emissions. There are several studies examining the linkage between energy efficiency and environment. Li et al. (2023) analyzed the impact of energy intensity on CO2 emissions in Beijing. The study discovers that in industrial sectors, transportation and manufacturing had the best results when it comes to reduction in CO2 emissions due to lower energy intensity.

Meng et al. (2024) examine the long and short-run relationship between renewable energy, energy efficiency and carbon emissions in Belt and Road Initiative (BRI) countries. The results indicate long term positive relationship between energy efficiency and environmental sustainability. Similarly, Wei et al. (2023) did a study on Brazil and found that energy efficiency can enhance environmental sustainability. Through a comparative analysis in BRI countries, Cansino et al. (2019) highlight the positive role of policy support in energy transition and promoting sustainable development.

Beyond improving energy efficiency, decarbonization is also seen as an important pathway in reducing carbon emissions in the top-emitting countries. It is important to note that decarbonization and renewable energy are related but conceptually different. Decarbonization measures the carbon intensity of energy use and can be achieved through multiple pathways. Among those pathways, renewable energy adoption is the most prominent. The following studies examine renewable energy as an empirical channel through which decarbonization works. Chen et al. (2026) analyzed the top ten manufacturing economies from 1990 to 2022. The study found that fossil fuel consumption worsens the environmental quality whereas renewable energy deployment and innovation mitigate pollution. The results support the argument that decarbonization through clean energy transition is a viable pathway for reducing carbon intensity.

Kongkuah and Alessa (2025) investigate how different renewable energy technologies affect carbon intensity in 184 countries. Empirical findings show that carbon intensity is inversely related to renewable energy use. Among renewable energy technologies, hydropower had the most impact, followed by solar and geothermal technologies. Wind power demonstrates heterogeneous outcomes such that it had positive impacts in high- and middle- income groups. Similarly, Ito (2017) examined the relationship between renewable energy and CO2 emissions in 42 developing countries and found that renewable energy reduces CO2emissions in the long run. Zoundi (2017) suggests a negative correlation between renewable energy and emissions in 25 African countries. For Pakistan, Waheed et al. (2018) and Chen et al. (2019) for Chinese regions also found similar results.

Despite extensive literature, many of these studies employ linear estimation frameworks that assume constant relationships between emissions and their drivers across all countries and time periods. Only a few studies highlight the presence of nonlinear effects in emission dynamics. For example, Chen et al. (2022) use a dynamic panel threshold model across 97 countries to show that renewable energy reduces $CO_2$ emissions only after it surpasses a critical consumption threshold. Chovancová et al. (2024) find that once GDP per capita crosses a threshold, the effectiveness of renewable energy in reducing $CO_2$ emissions diminishes, which directly challenges the assumption of linear growth-environment relationships. These findings suggest that the relationship between economic growth, technological transition, and carbon emissions is fundamentally regime-dependent, which motivates the use of a panel threshold model in this study.

## 3. Methodology

This study utilizes the STIRPAT framework, originally developed as a stochastic reformulation of the IPAT identity (Impact = Population × Affluence × Technology) for the top ten emitters from 1990 to 2024. The top ten emitters include the United States, China, India, Germany, Indonesia, Iran, Japan, South Korea, Russia and Saudi Arabia. The STIRPAT model enables flexible empirical analysis by allowing non-proportional and non-linear relationships between environmental impact and its driving forces. In this study, environmental impact is proxied by carbon dioxide emissions ($CO_2$), while the explanatory variables include its drivers like economic growth, population size, energy efficiency (EE), and decarbonization (DEC). The functional form of the model is specified as:

$$\mathrm{CO}_{2_{it}} = f(\mathrm{GDP}_{i,t}, \mathrm{POP}_{i,t}, \mathrm{EE}_{i,t}, \mathrm{DEC}_{i,t})$$

To facilitate estimation and interpretation, the model is transformed into a log-linear specification, which allows the estimated coefficients to be interpreted as elasticities. The econometric form of the model is expressed as:

$$\ln\mathrm{CO}_{2_{it}} = \alpha_i + \beta_1 \ln\mathrm{GDP}_{it} + \beta_2 \ln \mathrm{POP}_{it} + \beta_3 \mathrm{EE}_{it} + \beta_4 \mathrm{DEC}_{it} + \mu_{it} \quad (1)$$

where: $\ln \mathrm{GDP}_{\mathrm{it}_\mathrm{t}}$denotes the natural logarithm of gross domestic product, capturing the affluence effect, $\ln \mathrm{POP}_{\mathrm{it}}$ is the natural logarithm of population, representing demographic pressure, EE refers to energy efficiency, reflecting technological improvements in energy use, and $\mathrm{DEC}_{\mathrm{it}}$ represents decarbonization, capturing the energy transition toward lower carbon intensity, $\alpha_{\mathrm{it}}$ the constant term, $\beta_1, \beta_2, \beta_3, \beta_4$ are the parameters to be estimated, $\mu_{\mathrm{it}}$ is the stochastic error term. The inclusion of energy efficiency and decarbonization extends the traditional STIRPAT model by providing a more detailed representation of the technology component. Energy efficiency reflects improvements in energy use per unit of output, while decarbonization captures reductions in carbon emissions per unit of energy consumption. The decarbonization effect on emissions is also proxied by renewable energy consumption (REN), as different energy sources have markedly different $CO_2$ outputs per unit, and a $CO_2$ reduction can be achieved by switching to less carbon-intensive sources, particularly REN.

$$\ln\mathrm{CO}_{2_{\mathrm{it}}} = \alpha_\mathrm{i} + \beta_1 \ln\mathrm{GDP}_{\mathrm{it}} + \beta_2 \ln \mathrm{POP}_{\mathrm{it}} + \beta_3 \mathrm{EE}_{\mathrm{it}} + \beta_4 \mathrm{REN}_{\mathrm{it}} + \mu_{\mathrm{it}} \quad (2)$$

The empirical strategy proceeds in the following sequence: decoupling analysis, testing for cross-sectional dependence and slope heterogeneity, second-generation panel unit root tests (CIPS and CADF) Westerlund cointegration test, and estimation of short-run and long-run elasticities using the CS-ARDL model. This structured approach ensures robustness by addressing key panel data issues such as cross-sectional dependence, heterogeneity, and non-stationarity.

### *3.1 Decoupling Analysis*

First, the study employs the Tapio decoupling elasticity approach to examine the relationship between environmental pressure and economic growth. This method analyses whether economic growth is occurring independently of environmental degradation. Two main variables are used to compute decoupling elasticity: total $CO_2$ emissions are taken as an environmental quality indicator and GDP is taken as an economic indicator. The percentage change in both variables is calculated as:

$$\%\Delta \mathrm{E} = \frac{\mathrm{E_t} - \mathrm{E_0}}{\mathrm{E_0}}$$

$$\%\Delta \mathrm{G} = \frac{\mathrm{G_t} - \mathrm{G_0}}{\mathrm{G_0}}$$

Where:

- $\mathrm{E_t}$, $\mathrm{G_t}$= Emissions and GDP values in year t
- $\mathrm{E_0}$, $\mathrm{G_0}$= Emissions and GDP values in the base year

Tapio Decoupling Elasticity Index (D) is computed after calculating per year emissions and GDP growth rates as:

$$D = \frac{\%\Delta E}{\%\Delta G}$$

This index measures the responsiveness of environmental pressure to economic growth. Decoupling States are classified based on D values, where $D < 0$ indicates strong decoupling, indicating that GDP is increasing along with emission reduction, $0 < D < 0.8$ indicates that emissions are increasing more slowly than GDP, $0.8 \leq D \leq 1.2$ indicates expansive coupling where emissions and GDP grow together and, $D > 1.2$ indicates negative decoupling where emissions grow faster than GDP. The decoupling index is calculated for the study period (1990–2024). To obtain an overall trend, the average decoupling index is computed for each country.

### *3.2 Short Run and Long Run Elasticities (Linear Dynamics)*

Next, to estimate short-run and long-run elasticities, the study proceeds with CS-ARDL estimates after running the required tests. Given the panel structure, cross-sectional dependence (CD) is tested using multiple approaches, including the Breusch–Pagan LM test, Pesaran scaled LM test, and Pesaran CD test. These tests account for potential interdependencies across countries due to globalization, trade linkages, and common shocks.

Slope homogeneity is examined using the Pesaran and Yamagata test to determine whether slope coefficients are homogeneous or heterogeneous across panel units. The presence of heterogeneity justifies the use of estimators that allow for country-specific dynamics. To determine the order of integration, second-generation panel unit root tests are employed to account for cross-sectional dependence. Specifically, the cross-sectionally augmented IM Pesaran and Shin (CIPS) test introduced by Pesaran (2007) and the cross-sectionally augmented ADF (CADF) unit root tests are applied. The advantage of these tests is that they control cross-sectional dependence while checking the order of integration. These tests provide robust inference in the presence of common factors affecting panel units.

The long-run relationship among variables is examined using the Westerlund error-correction-based cointegration test (Ehigiamusoe & Lean, 2019). This approach is suitable under cross-sectional dependence and heterogeneity. It tests for the existence of a stable long-run equilibrium relationship among $CO_2$ emissions and explanatory variables in both models. Next, to estimate both short-run and long-run elasticities, this study employs the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model, which effectively addresses cross-sectional dependence by incorporating cross-sectional averages of the variables. The CS-ARDL (p, q) specification for model 1is given as:

$$\ln CO_{2,it} = \alpha_i + \sum_{j=1}^{p} \phi_{ij} \ln CO_{2,i,t-j} + \sum_{j=0}^{q} \beta_{1ij} \ln GDP_{i,t-j} + \sum_{j=0}^{q} \beta_{2ij} \ln POP_{i,t-j}$$

$$+\sum_{j=0}^{q} \beta_{3ij}\ EE_{i,t-j} + \sum_{j=0}^{q} \beta_{4ij}\ DEC_{i,t-j} + \gamma_i \bar{Z}_t + \varepsilon_{it}$$

where, $\alpha_i$ is country specific fixed effect, $\bar{Z}_t$represents the cross-sectional averages of the dependent and independent variables, included to capture unobserved common factors, pand qdenote optimal lag lengths. The error-correction representation of the CS-ARDL model is expressed as:

$$\Delta \ln CO_{2,it} = \lambda_i\left(\ln CO_{2,i,t-1} - \theta_{1i} \ln GDP_{it} - \theta_{2i} \ln POP_{it} - \theta_{3i} EE_{it} - \theta_{4i} DEC_{it}\right)$$
$$+\sum_{j=1}^{p-1} \psi_{ij}\ \Delta \ln CO_{2,i,t-j} + \sum_{j=0}^{q-1} \delta_{1ij}\ \Delta \ln GDP_{i,t-j}$$
$$+\sum_{j=0}^{q-1} \delta_{2ij}\ \Delta \ln POP_{i,t-j} + \sum_{j=0}^{q-1} \delta_{3ij}\ \Delta EE_{i,t-j} + \sum_{j=0}^{q-1} \delta_{4ij}\ \Delta DEC_{i,t-j} + \gamma_i \bar{Z}_t + \varepsilon_{it}$$

Where, $\lambda_i$is the error-correction term indicating the speed of adjustment toward long-run equilibrium, $\theta_{ki}$representing long-run coefficients, differenced terms capture short-run dynamics.

The CS-ARDL specification for model 2 is given as:

$$\ln CO_{2,it} = \alpha_i + \sum_{j=1}^{p} \phi_{ij} \ln CO_{2,i,t-j} + \sum_{j=0}^{q} \beta_{1ij} \ln GDP_{i,t-j} + \sum_{j=0}^{q} \beta_{2ij} \ln POP_{i,t-j}$$
$$+\sum_{j=0}^{q} \beta_{3ij}\ EE_{i,t-j} + \sum_{j=0}^{q} \beta_{4ij}\ REN_{i,t-j} + \gamma_i \bar{Z}_t + \varepsilon_{it}$$

The error-correction representation of the CS-ARDL model 2 is expressed as:

$$\Delta \ln CO_{2,it} = \lambda_i\left(\ln CO_{2,i,t-1} - \theta_{1i} \ln GDP_{it} - \theta_{2i} \ln POP_{it} - \theta_{3i} EE_{it} - \theta_{4i} REN\right)$$
$$+\sum_{j=1}^{p-1} \psi_{ij}\ \Delta \ln CO_{2,i,t-j} + \sum_{j=0}^{q-1} \delta_{1ij}\ \Delta \ln GDP_{i,t-j}$$
$$+\sum_{j=0}^{q-1} \delta_{2ij}\ \Delta \ln POP_{i,t-j} + \sum_{j=0}^{q-1} \delta_{3ij}\ \Delta EE_{i,t-j} + \sum_{j=0}^{q-1} \delta_{4ij}\ \Delta REN_{i,t-j} + \gamma_i \bar{Z}_t + \varepsilon_{it}$$

### *3.3 Panel Threshold Model (Non-Linear Dynamics)*

To further explore potential nonlinearities in the relationship between drivers of $CO_2$ emissions, this study employs the panel threshold regression model developed by Hansen (1999). This approach allows the impact of explanatory variables to vary across regimes defined by threshold variables, thereby capturing asymmetric effects that cannot be identified through linear models such as CS-ARDL. In this study, EE and DEC are used as threshold (regime-defining) variables, while GDP and POP serve as regime-dependent regressors within the STIRPAT framework. The baseline panel threshold model is specified as follows:

$$\ln CO_{2,it} = \mu_i + \beta_1' X_{it} \cdot I(q_{it} \leq \gamma) + \beta_2' X_{it} \cdot I(q_{it} > \gamma) + \varepsilon_{it}$$

where: $\ln CO_{2,it}$is the dependent variable, $\mu_i$captures individual-specific fixed effects, $X_{it} = (\ln GDP_{it}, \ln POP_{it})$represents regime-dependent regressors, $q_{it}$denotes the threshold variable (either $EE_{it}$ or $DEC_{it}$), $\gamma$is the unknown threshold parameter to be estimated, $I(\cdot)$is an indicator function that takes the value 1 if the condition holds and 0 otherwise, $\beta_1$and $\beta_2$are slope coefficients corresponding to different regimes, $\varepsilon_{it}$is the error term. To account for multiple transition channels, the model is extended by estimating separate threshold regressions using each threshold variable:

Threshold based on Energy Efficiency (EE):

$$\ln CO_{2,it} = \mu_i + \beta_1^{EE} X_{it} \cdot I(EE_{it} \leq \gamma_{EE}) + \beta_2^{EE} X_{it} \cdot I(EE_{it} > \gamma_{EE}) + \varepsilon_{it}$$

Threshold based on Decarbonization (DEC):

$$\ln CO_{2,it} = \mu_i + \beta_1^{DEC} X_{it} \cdot I(DEC_{it} \leq \gamma_{DEC}) + \beta_2^{DEC} X_{it} \cdot I(DEC_{it} > \gamma_{DEC}) + \varepsilon_{it}$$

The panel threshold model enables the assessment of whether the effects of economic growth and population on $CO_2$ emissions differ across regimes defined by levels of energy efficiency and decarbonization. A significant threshold implies that improvements in EE or DEC alter the elasticity of emissions with respect to GDP and population, thereby providing evidence of nonlinear environmental dynamics within the STIRPAT framework.

## 4. Results and Discussion

The data sources and description of variables are reported in Table 1.

**Table 1: Description of Variables**

| Variable | Symbol | Definition | Measurement |
|---|---|---|---|
| $CO_2$ Emissions | $CO_2$ | Carbon dioxide emissions (total) excluding LULUCF | (Mt $CO_2$e) |
| Economic Growth | GDP | gross domestic product per capita | Constant (2015US$) |
| Population | POP | Population | Total |
| Energy Efficiency | EE | Output per unit of energy used | Own calculation: GDP per unit of energy (tons oil equivalent |
| Decarbonization | DEC | Reciprocal of the $CO_2$ produced per unit of energy used | Own Calculation: $1/CO_2$ per unit of Energy (tons $CO_2$) |
| Renewable Energy | REN | Renewable energy consumption % of final energy consumption | Percentage |

Data Source: World Bank (2026)

**Table 2: Descriptive Analysis of Variables**

| Variables | Mean | S. D | Minimum | Maximum |
|---|---|---|---|---|
| $CO_2$ Emissions | 2002.365 | 2588.607 | 161.7687 | 13124.73 |
| Economic Growth | 18997.03 | 17148.49 | 531.8984 | 66682.62 |
| Population | 38,500,000 | 142,000,000 | 66510 | 1,410,000,000 |
| Energy Efficiency | 4.721 | 3.047 | 1.1016 | 15.029 |
| Decarbonization | 4.7159 | 5.982 | 0.1986 | 34.471 |
| Renewable Energy | 12.876 | 15.701 | 0.01643 | 59.2 |

### *4.1 Decoupling Analysis*

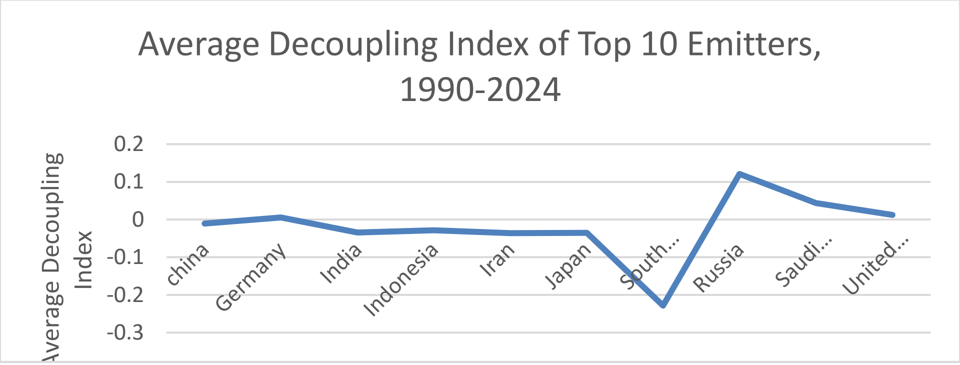


**Figure 1: Decoupling Analysis**

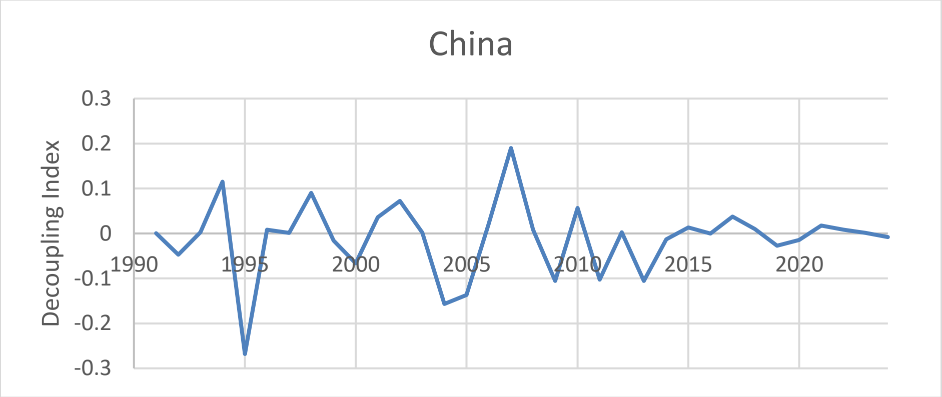
Fig.1 indicates that most of the top emitters achieved either strong decoupling or weak decoupling during 1990–2024. No country falls within the expansive coupling or negative decoupling categories, implying that none of them experienced emissions growth equal to or faster than GDP growth on average over the study period. China, India, Indonesia, Iran, Japan and South Korea have a negative decoupling index, indicating strong decoupling. Although China experienced rapid economic growth over the study period, emissions growth was controlled sufficiently to produce a negative average D value. This suggests improvements in energy efficiency, renewable energy expansion, and structural economic transition. India also falls under strong decoupling, though only marginally negative. Economic growth outpaced environmental pressure over the long term, indicating gradual improvements in carbon efficiency despite continued industrialization and energy demand growth.

Indonesia’s negative D value indicates strong decoupling, suggesting that economic growth was achieved with comparatively lower growth in emissions, possibly due to efficiency improvements and shifts in economic structure. Iran demonstrates strong decoupling, though the value remains close to zero. This implies limited but positive progress toward reducing the emissions intensity of economic growth. Japan shows strong decoupling with a modest negative index. This reflects technological efficiency, energy conservation measures, and long-term industrial modernization, despite periods of increased fossil fuel dependence.

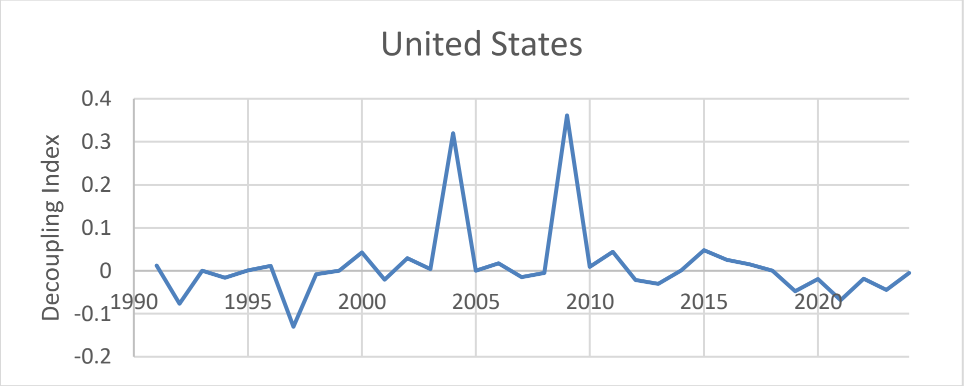
South Korea records the most negative value among all countries, indicating the strongest decoupling performance in the sample. This suggests that GDP growth occurred alongside substantial restraint or reduction in emissions growth relative to economic expansion. Some countries like Germany, Russia, Saudi Arabia and United States showing Weak

Decoupling (0 < D < 0.8) meaning that both economic growth and environmental pressure are increasing however, emissions are increasing more slowly than the economy.

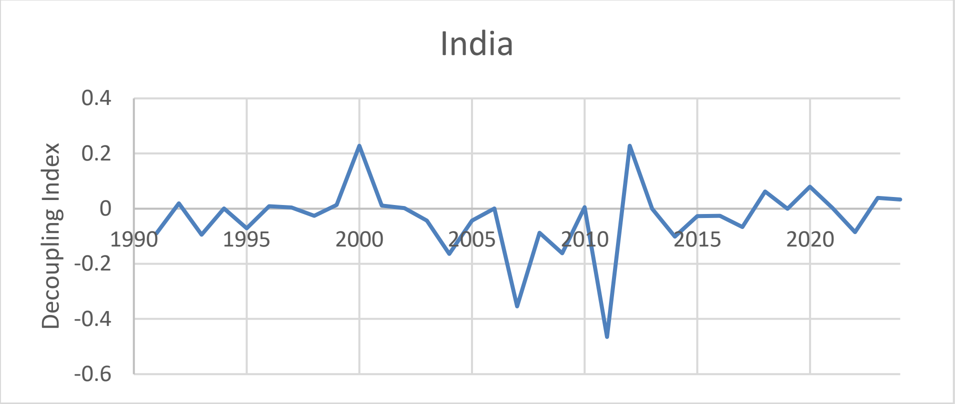
The individual country decoupling index is also analysed from 1990-2024 period.



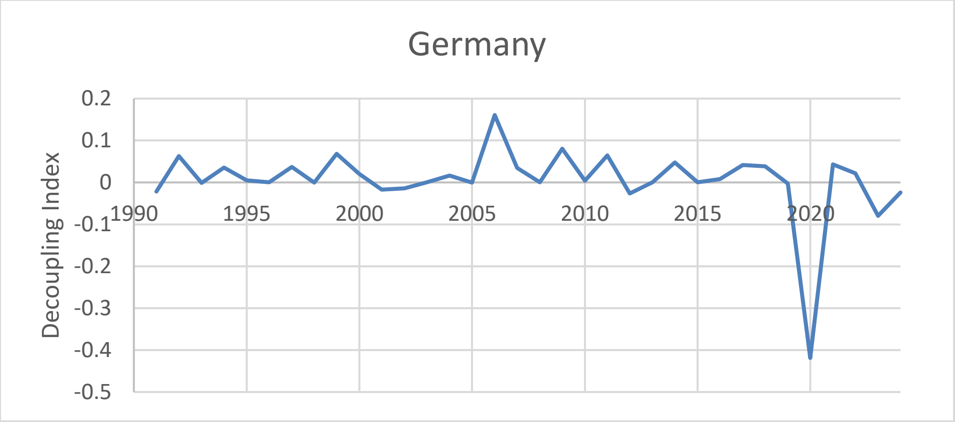
China’s Tapio Decoupling Index from 1991–2024 reveals a transition from unstable coupling during rapid industrialization toward more stable relative decoupling in the post-Paris Agreement era. The post-Kyoto period exhibited substantial volatility associated with energy-intensive economic expansion, while the post-Paris period demonstrates improved environmental efficiency and reduced carbon intensity, although absolute decoupling remains limited.



United States mainly demonstrate weak decoupling with several episodes of strong decoupling. Post 2015 Paris Agreement, the index remains closer to weak decoupling suggesting improved environmental efficiency.

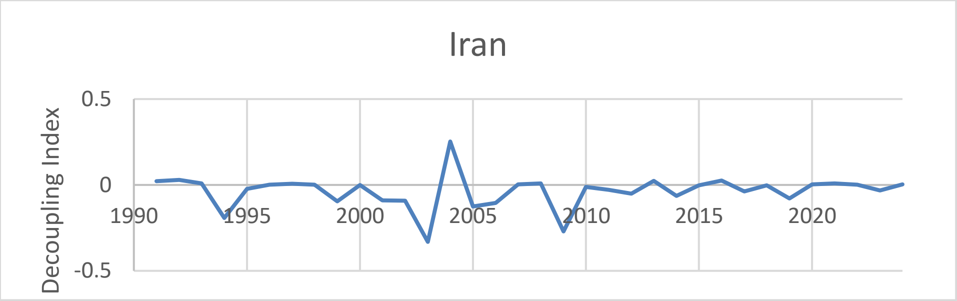


India’s rapid industrialization and energy demand limited sustained strong decoupling while renewable energy expansion after Paris agreement improved performance modestly.

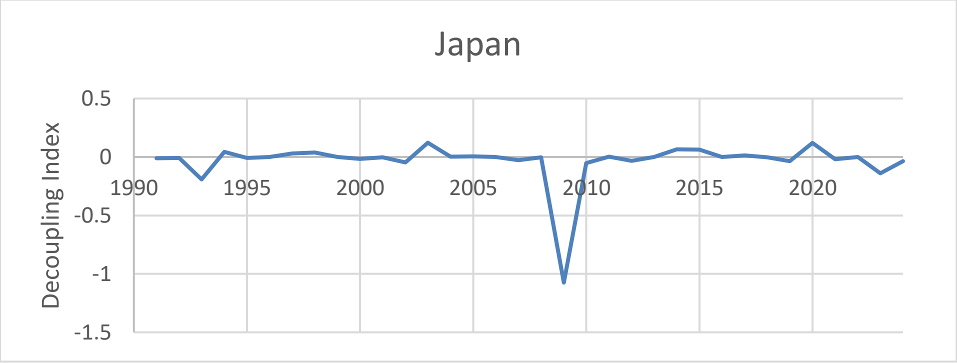


Germany’s Tapio Decoupling Index from 1991–2024 indicates a relatively stable decoupling trajectory characterized by sustained weak decoupling and intermittent periods of strong decoupling. The post-Kyoto and post-Paris periods demonstrate increasing environmental efficiency associated with renewable energy expansion, industrial modernization, and climate policy institutionalization.

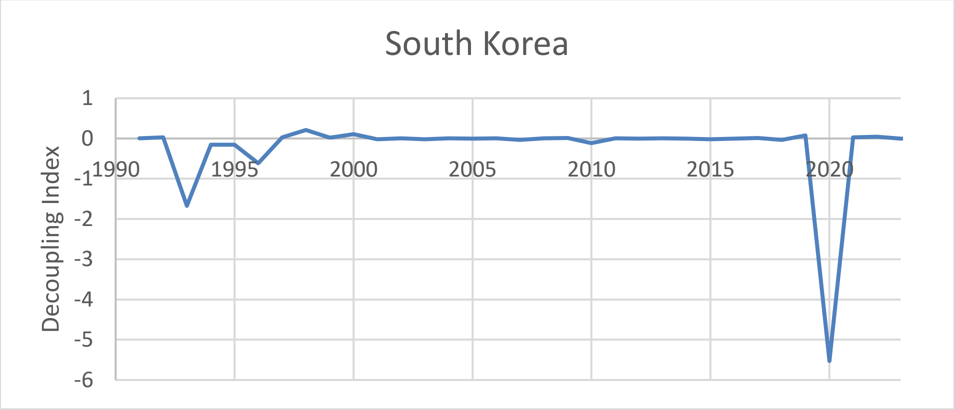
Indonesia demonstrates unstable decoupling behavior. The major negative value around 2010 indicates strong decoupling likely linked to reduced emission growth or economic disturbances. However, persistent volatility suggests dependence on land use emissions, deforestation pressure and limited structural decarbonization.



Iran as heavily fossil fuel dependence country having energy subsidy and slower renewable energy transition mainly exhibit coupling and weak coupling. International environmental agreements have limited impact on long-term decoupling.

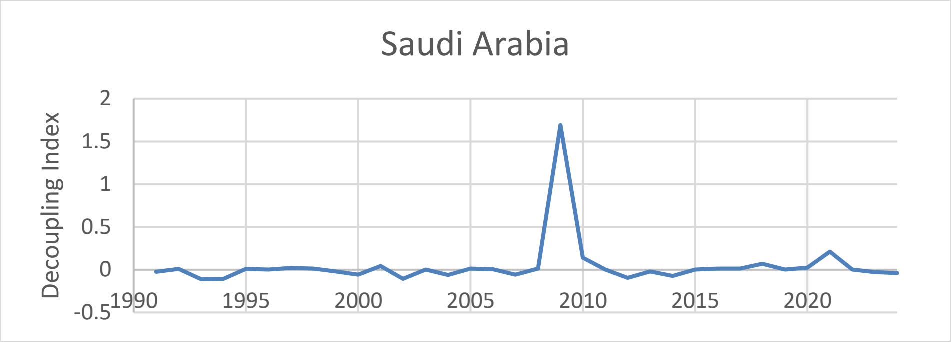


Japan largely exhibits weak decoupling with temporary episodes of strong decoupling having substantial negative drop around 2011.



South Korea mostly exhibits weak decoupling with occasional negative decoupling. The sharp decline around 2021 indicates temporary strong decoupling possibly associated with pandemic recovery distortions.

Russia exhibits highly volatile decoupling behavior extreme positive spikes indicating negative decoupling and negative values in some years suggest temporary strong decoupling. Kyoto and Paris commitments produced limited structural decarbonization.



Saudi Arabia mostly demonstrates coupling and weak decoupling. The large spike around 2009 represents expansive negative decoupling, which may be linked with oil market shocks.

Overall, the comparison of Tapio Decoupling Index trends from 1991 to 2024 shows clear differences between advanced industrial economies, emerging economies, and fossil-fuel-dependent countries. Germany, Japan, and to some extent the United States demonstrate relatively stable weak decoupling with occasional strong decoupling, reflecting stronger environmental governance, technological advancement, and renewable energy integration. China and India show transitional decoupling patterns, where rapid industrialization and rising energy demand initially limited decoupling, although post-Paris Agreement policies improved environmental efficiency and carbon intensity reduction. In contrast, Indonesia, Russia, Iran, and Saudi Arabia exhibit more unstable or coupling-dominated trajectories due to dependence on fossil fuels, land-use emissions, commodity market shocks, and slower structural decarbonization.

Overall, the Kyoto Protocol and Paris Agreement contributed to improvements in relative decoupling and environmental efficiency across many countries, but their impact on achieving sustained absolute decoupling and long-term structural decarbonization remains uneven and limited, particularly in energy-intensive and resource-dependent economies.

### *4.2 Short Run and Long Run Elasticities*

**Table 3: Cross-Sectional Dependence Results**

| **Breusch-Pagan LM** | **Pesaran Scaled LM** | **Pasaran CD** |
|---|---|---|
| Model 1 | | |
| $905.555^{***}$ | $90.713^{***}$ | $1.669^{*}$ |
| Model 2 | | |
| $876.323^{***}$ | $93.456^{***}$ | $4.245^{***}$ |

***represents statistical significance at 1%.

To check whether residuals across the top 10 emitters are correlated, the test statistic probabilities of cross-sectional dependence (CD) tests reported in Table 3 show that H0 of no cross-sectional dependence is rejected at 1% level of significance, indicating the presence of CD in sampled economies. These economies are most likely to be interconnected due to global energy markets, climate policies, trade linkages and technological diffusion.

**Table 4: Second- Generation Unit Root Results**

| Variables | CIPS | | CADF | |
|---|---|---|---|---|
| | Level | First Difference | Level | First Difference |
| $CO_2$ Emissions I(1) | -2.542 | $-4.752^{***}$ | -2.235 | $-4.935^{***}$ |
| Economic Growth I(1) | -2.442 | $-4.588^{***}$ | -2.099 | $-4.059^{***}$ |
| Population I(0) | $-5.457^{***}$ | | $-5.483^{***}$ | |
| Energy Efficiency I(1) | -2.732 | $-5.082^{***}$ | -2.480 | $-5.082^{***}$ |
| Decarbonization I(0) | $-3.086^{***}$ | | $-3.996^{***}$ | |
| Renewable Energy I(1) | -3.567 | $-4.983^{***}$ | -3.093 | $-4.568^{***}$ |
| Critical values -2.72, -2.84, and -3.06 at 10%, 5%, and 1% in CIPS. | | | | |

Probabilities, * p<0.1; ** p<0.05; *** p<0.01

Due to the presence of CD, the best choice is to apply second-generation unit root tests. The second-generation panel unit root results based on the CIPS and CADF tests in table 4 reveal a mixed order of integration. $CO_2$ emissions, GDP, REN and EE are non-stationary at levels but become stationary at first differences, indicating I(1) behavior. In contrast, POP and DEC are stationary at levels, implying I(0). These findings justify the use of panel ARDL-type models that can accommodate variables with different integration orders.

**Table 5: Westerlund Cointegration Results**

| Westerlund error correction based cointegration results | | | | |
|---|---|---|---|---|
| Lags=1, lead=0, Kernel window (3), bootstrap (200) | | | | |
| Model 1 | | | | |
| | value | Z-value | Asymptotic p value | Bootstrap p value |
| Group-tau | -1.481 | 4.821 | 0.908 | 0.000 |
| Group-alpha | -2.991 | 5.258 | 1.000 | 0.000 |
| Panel-tau | -3.563 | 4.749 | 1.000 | 0.000 |
| Panel-alpha | -1.633 | 4.501 | 0.911 | 0.000 |
| Model 2 | | | | |
| Group-tau | -1.863 | 5.432 | 1.000 | 0.000 |
| Group-alpha | -3.457 | 5.874 | 0.992 | 0.000 |
| Panel-tau | -3.873 | 5.764 | 0.932 | 0.000 |
| Panel-alpha | -1.653 | 4.876 | 1.000 | 0.000 |

The Westerlund cointegration results in Table 5 indicate that a long-run equilibrium relationship exists between $CO_2$ emissions and explanatory variables in models 1 and 2 across the top 10 emitting countries (1990–2024). Group statistics significance (group tau and group alpha) shows that cointegration exists in at least some countries and panel statistics significance (panel tau and panel alpha) shows that cointegration exists for the overall panel. The asymptotic p-values fail to reject the null hypothesis of no cointegration. However, the bootstrap p-values are statistically significant at the 1% level. This divergence is attributable to the presence of cross-sectional dependence among the panel units, as confirmed by the cross-sectional dependence tests reported earlier. Westerlund (2007) notes that asymptotic p-values may become unreliable under cross-sectional dependence because the theoretical distributions are derived under cross-sectional independence assumptions. The bootstrap procedure corrects for this problem by generating empirical critical values that account for the observed dependence structure. Therefore, following Westerlund (2007), the bootstrap p-values are considered more reliable, and the results provide evidence of a long-run cointegrating relationship among the variables.

Before proceeding to long-run elasticities, slope homogeneity is also checked to see whether slope coefficients are the same across countries in the selected panel.

**Table 6: Slope Homogeneity Results**

| Statistics | | | |
|---|---|---|---|
| $\widetilde{\Delta}$ | $\widetilde{\Delta}_{\mathrm{adj}}$ | $\Delta\mathrm{HAC}$ | $(\Delta\mathrm{HAC})_{\mathrm{adj}}$ |
| $\sqrt{N}\left(\frac{N^{-1}\bar{S}-k}{\sqrt{2k}}\right)\sim X_k^2$ | $\sqrt{N}\left(\frac{N^{-1}\bar{S}-k}{v(T,k)}\right)\sim N(0,1)$ | $\sqrt{N}\left(\frac{N^{-1}S_{HAC}-k}{\sqrt{2k}}\right)\sim X_k^2$ | $\sqrt{N}\left(\frac{N^{-1}S_{HAC}-k}{v(T,k)}\right)\sim N(0,1)$ |
| Model 1 | | | |
| $28.916^{***}$ | $31.767^{***}$ | $17.517^{***}$ | $18.921^{***}$ |
| Model 2 | | | |
| $21.873^{***}$ | $23.625^{***}$ | $10.183^{***}$ | $10.999^{***}$ |

***represents statistical significance at 1%

The Pesaran–Yamagata slope homogeneity test results in Table 6 indicate that there is strong slope heterogeneity. The impact of explanatory variables on $CO_2$ emissions is different for each country. The most appropriate technique for a long panel confirming the presence of CD and mixed order of cointegration is CS-ARDL. The CS-ARDL estimates are reported in the table below.

**Table 7: CS-ARDL Estimates of Drivers of CO2 Emissions in Top 10 Emitters**

| Variables | Short Run | Long Run | Short Run | Long Run |
|---|---|---|---|---|
| | Model 1 | | Model 2 | |
| Lag ($CO_2$) | $0.0595^{***}$<br>(0.0562) | | 0.2089<br>(0.0781) | |
| Economic Growth | $0.9392^{***}$<br>(0.0820) | $1.0387^{***}$<br>(0.1387) | 0.7095<br>(0.0826) | 0.9601<br>(0.0987) |
| Population | 0.00037<br>(0.00029) | $0.00054^{**}$<br>(0.00039) | 0.00083<br>(0.0013) | $0.00029^{*}$<br>(0.0039) |
| Energy efficiency | $-0.2698^{***}$<br>(0.4686) | $-0.3065^{***}$<br>(0.2494) | -0.2028<br>(0.0534) | -0.2904<br>(0.7436) |
| Decarbonization | $-1.0020^{*}$<br>(0.6079) | $-1.3803^{*}$<br>(0.9948) | | |
| Renewable energy | | | $-0.0210^{***}$<br>(0.0185) | $-0.0632^{***}$<br>(0.02267) |
| ECT (-1) | $-0.1904^{***}$<br>(0.0327) | | -0.293<br>(0.730) | |
| RMSE | 0.01 | 0.01 | 0.03 | 0.03 |
| Observations | 340 | 340 | 340 | 340 |

Standard errors in parentheses. * ** ***represents statistical significance at 10%, 5%, 1% respectively

The CS-ARDL model separates short-run dynamics from long-run equilibrium relationships. In Table 7, the short-run positive and significant lagged $CO_2$ (0.0595) indicates that $CO_2$ emissions are persistent, that is, past emissions slightly increase current emissions, and environmental damage tends to carry over time. Economic Growth (0.9392, 0.7095) has a strong positive effect on pollution-intensive and a 1% increase in growth increases $CO_2$ emissions in the short-run by 0.93% and 0.71% in both models, respectively. The insignificant short-run coefficient of POP in both models may indicate that changes in POP do not immediately affect emissions. Population pressure accumulates over time as an increase in POP demands more energy that led to higher emissions. The negative and significant short-run coefficients of EE and DEC indicate that energy efficiency and transition improve the environment in the short-run.

In the long run, GDP and POP increase emissions and the magnitude of effect is high in the long run as compared to the short run in both models. The significant positive relationship between emissions and POP in both models shows that POP pressures accumulate over time, increase in energy demand increases emissions. EE, DEC and REN impact are negative as seen in short-run but strong as compared to the short run. The results indicate that long-term efficiency policies are more powerful than short-term actions and a large negative value of DEC indicates that DEC is the most powerful long-run tool and transitioning energy systems significantly reduces emissions. Negative and significant ECT shows the existence of a long-run equilibrium, about 19% and 29% of disequilibrium is corrected each period in both models. Both short-run and long-run elasticities indicate that economic growth consistently raises emissions, population has no immediate, but significant pressure on the environment in the long run, EE, DEC and REN both reduce emissions and the effects are stronger over time.

The results aligned with the literature, like Roy et al (2017), by incorporating energy intensity and energy demand in the STIRPAT model, conclude that all factors contribute to an increase in CO2 emissions in India, the factor having the biggest share in the impact is economic growth. Similarly, Lin et al. (2017) found a small influence of economic development on the environment, whereas energy intensity, population and affluence have a major role in increasing CO2 emissions in 53 low-income countries. Wang et al. (2017) also found economic growth as leading contributor of CO2 emissions in developing countries in addition to energy consumption, trade openness and industrialization. The results vary at different levels of development, but economic growth and fixed assets are leading contributors of CO2.

The positive impact of POP on $CO_2$ emissions can be explained through several interconnected channels. Rapid population growth increases the overall demand for energy, food, housing, transportation, and public services, leading to higher fossil fuel consumption and greater carbon emissions. As populations expand, governments and private sectors need to develop additional infrastructure, including residential buildings, roads, industrial zones, electricity networks, and transportation systems, all of which are energy-intensive and contribute substantially to $CO_2$ emissions through construction activities and increased material use. Cramer (2002), Zhu et al. (2012), Sadorsky (2014) identify population growth as a major contributor to rising $CO_2$ emissions. Similarly, York et al (2003) and Knight et al. (2013) show that urbanization exerts significant environmental pressure through increased energy use, transportation demand, and economic activity. Ma et al. (2017) add urbanization and GDP index to investigate the driving forces of CO2 emissions in China. Martínez-Zarzoso and Maruotti (2011) found that urbanization has varying results according to the income levels such that least developed countries had higher environmental impact due to urbanization than developed regions.

Recent literature has also identified EE, DEC and REN as technological transitions to clean energy. A long-run positive relationship exists between EE in BRI countries (Meng et al., 2024) and in Brazil (Wei et al., 2023). Kongkuah and Alessa (2025) found that carbon intensity reduces when higher amounts of renewable energy are generated. Among renewable energy technologies, hydropower had the most impact, followed by solar and geothermal technologies. Similarly, Ito (2017) found that renewable energy reduces CO2 emissions in the long run in 42 developing countries and Zoundi (2017) also has similar findings for 25 African countries. Waheed et al. (2018) for Pakistan and Chen et al (2019) for Chinese regions also found similar results.

Chen et al. (2026) also analyzed that while fossil fuel consumption worsens environmental quality, REN deployment mitigates pollution, highlighting the importance of clean energy technology in achieving sustainable development goals across the world's top 10 manufacturing economies from 1990 to 2022. Tranoulidis & Farmaki (2026) has found the importance of GDP, urbanization, and the share of REN as key determinants of CO2 emissions in Greece where economic growth has emerged as a primary driver of CO2 emissions, which highlights constant challenge of decoupling GDP expansion from CO2 output. Also, an increase in the share of REN in the national energy mix is associated with a substantial reduction in CO2 emissions in absolute terms, confirming the mitigating role of REN adoption, underscoring the effectiveness of the transition to cleaner energy sources.

### *4.3 Panel Threshold Analysis*

**Table 8: Threshold Effect Results**

| | **Single Threshold Estimator** | | | **Threshold Test** | |
|---|---|---|---|---|---|
| **Threshold Variables** | **Value** | **Lower** | **Upper** | **F-Stat** | **Probability** |
| Energy Efficiency | 2.9038 | 2.8825 | 2.9219 | 164.49 | 0.000 |
| Decarbonization | 0.2191 | 0.2189 | 0.2197 | 872.36 | 0.000 |

**Table 9: Threshold Regression Results**

| **Dependent Variable: $LCO_2$** | | | | | | |
|---|---|---|---|---|---|---|
| **Variables** | **Energy Efficiency** | | | **Decarbonization** | | |
| | Coefficient | $EE_{it} \leq 2.904$ | $EE_{it} > 2.904$ | Coefficient | $DCO_{2it} \leq 0.219$ | $DCO_{2it} > 0.219$ |
| GDP | $0.0857^{***}$<br>(0.0289) | $0.2687^{***}$<br>(0.1381) | $0.2355^{***}$<br>(0.1353) | $0.0564^{***}$<br>(0.0060) | $0.2672^{***}$<br>(0.0105) | $0.1620^{***}$<br>(0.0892) |
| POP | 0.0280<br>(0.0253) | 0.0457<br>(0.047 | $-0.0386^{*}$<br>(0.0308) | 0.0024<br>(0.0156) | 0.00283<br>(0.0468) | $-0.00173^{***}$<br>(0.0129) |
| Constant | $-1.9486^{***}$<br>(0.0158) | | | | | |
| F stat | $201.46^{***}$ | | | $640.81^{***}$ | | |
| $R^2$ within | 0.7908 | | | 0.9201 | | |
| Between | 0.0070 | | | 0.1546 | | |
| Overall | 0.0073 | | | 0.3139 | | |
| Rho | 0.9791 | | | 0.9759 | | |
| Observations | 350 | | | 350 | | |

Panel threshold estimates are reported in Tables 8 and 9. EE is the reciprocal of energy intensity, and it measures how we can reduce the amount of energy used per unit of output. Threshold estimate of EE level (2.9038) indicating a clear cutoff in energy intensity of energy use ≤ 2.9038, indicating low EE and > 2.9038 indicating high EE or cleaner energy. Threshold effect test value of EE is statistically significant, showing that the relationship between GDP, POP, and $CO_2$ changes across regimes and a nonlinear (regime-dependent) model is justified over a linear one. Model fit and structure show that within $R^2 = 0.7908$, indicating strong explanatory power within countries and rho = 0.9791 shows that most variation comes from country-specific effects. Highly significant fixed effects indicate that the model explains 79% of within-country variation in $CO_2$ emissions and country heterogeneity is very important. The baseline effect coefficient of GDP and POP shows a positive and significant linear impact on CO2 emissions.

The regime-specific effects of GDP show highly significant and positive coefficients (0.2687 and 0.2355) in low efficiency and high efficiency regime respectively. This indicates that GDP increases $CO_2$ emissions in both regimes but, the effect is slightly smaller in high EE regime. So, economic growth is still pollution-intensive, but EE dampens the impact slightly. The regime- specific effect results of POP show a positive but insignificant coefficient (0.0457) in low efficiency regime and a negative and significant coefficient (-0.0386) in high efficiency regime. This finding implies that a higher EE regime may enable economies to accommodate population growth with lower environmental pressure through efficient resource utilization and cleaner technologies. This is an interesting result indicating that EE changes the role of POP in emissions and slightly moderates GDP's effect. When efficiency is low, more people demand more energy, which leads to higher emissions. But, as efficiency increases, more people may use energy more efficiently, benefit from cleaner technology, and generate scale efficiencies that lead to lower emissions.

Decarbonization is to minimize the effect of CO2 produced per unit of energy use. It reflects how clean the energy mix is. Threshold estimate of DEC level (0.2191) indicating a clear cutoff in carbon intensity of energy use ≤ 0.219 indicating -low decarbonization or high carbon intensity and > 0.219 indicating high decarbonization or cleaner energy. This threshold separates dirty energy systems with cleaner energy systems. Threshold significance test shows that the threshold effect is statistically significant at 1% and a nonlinear regime-switching relationship exists. Model performance indicators show that within $R^2 = 0.9201$, indicating that this model explains 92% of within variation and rho = 0.9759 shows very strong fixed effects. Baseline effects show that economic growth (0.0564) strongly increases CO2 emissions and POP (0.0024) has no overall linear effect.

Regime-specific effects show that GDP growth increases emissions in both regimes, but positive effect slightly reduces in high decarbonization or cleaner systems. POP has a significant and negative impact on emissions in high DEC regime, indicating that once the threshold is crossed, the effect becomes negative and statistically significant, indicating that demographic expansion may manage emissions with high decarbonization. The findings demonstrate that both energy efficiency and decarbonization exert significant threshold effects on carbon emissions. Economic growth consistently increases emissions across regimes; however, higher levels of decarbonization appear to mitigate this effect. The results imply that achieving critical levels of energy efficiency and decarbonization is essential for reducing the environmental consequences of economic growth.

## 5. Conclusion

This study examines the drivers of $CO_2$ emissions in the top ten global emitters over the period 1990-2024. It employs a multi-stage empirical framework built on the STIRPAT model, followed by Tapio decoupling analysis, CS-ARDL estimation, and Hansen's (1999) panel threshold regression. By doing so, it provides a comprehensive analysis of dynamics of CO2 emissions. First, the decoupling analysis reveals that progress of separating economic growth from $CO_2$ emissions is slow.

### *5.1 Summary of Findings*

Major global CO2 emitters show an uneven relationship such that Germany, Japan, and to some extent the United States demonstrate relatively stable weak decoupling with occasional strong decoupling, reflecting stronger environmental governance, technological advancement, and renewable energy integration. China and India show transitional decoupling patterns, where rapid industrialization and rising energy demand initially limited decoupling, although post-Paris Agreement policies improved environmental efficiency and carbon intensity reduction. In contrast, Indonesia, Russia, Iran, and Saudi Arabia exhibit more unstable or coupling-dominated trajectories due to dependence on fossil fuels, land-use emissions, commodity market shocks, and slower structural decarbonization. Our findings are consistent with Wang et al. (2025) and Freire-González et al. (2024), which suggest a divide in decoupling performance across major economies.

The CS-ARDL estimates confirm that economic growth is the most consistent driver of $CO_2$ emissions across the top ten emitters. The findings align with Roy et al. (2017), who identified economic growth as the single largest contributor of emissions in India. Furthermore, Yang et al. (2018), also suggested that urbanization and economic development are the dominant drivers in China. Results also suggest that population has an insignificant impact on emissions in the short run but in the long run it becomes significant. This finding is consistent with the broader literature of STIRPAT. For example, Cramer (2002), Zhu et al. (2012), and Sadorsky (2014) argue that POP is a long-run contributor to environmental degradation. Whereas EE reduces emissions in both the short and long run, having a larger effect in the long run, aligning with Meng et al. (2024) and Li et al. (2023). Most notably, DEC is found to be the most significant long-run variable for emission reduction. It is consistent with Ito (2017) and Zoundi (2017), who suggest that in the long run, developing countries should move towards renewable energy consumption to reduce emissions.

The panel threshold results reveal that the relationship between economic growth, POP, and $CO_2$ emissions is heterogeneous and varies depending on varying energy efficiency levels of the countries. Under the energy efficiency threshold, GDP increases emissions in both below and above high threshold economies. However, the impact is slightly smaller than the threshold. Surprisingly, POP has a reverse sign with emissions. In low-efficiency countries it raises emissions, whereas it reduces emissions in the high-efficiency ones. This finding suggests that a larger population, in high-efficiency countries, allows more people to adopt efficient technologies and creates scale economies. This is a novel contribution since previous studies have not analyzed the nonlinear effect of POP. More striking results come from under the decarbonization threshold. GDP growth reduces emissions where energy systems are clean which means the relationship is reversed. This finding strongly aligns with the arguments given by Wang et al. (2025) and Cansino et al. (2019). These studies suggest that transition towards renewable energy can restructure the relationship between GDP growth and environmental outcomes.

### *5.2 Theoretical Implications*

These findings suggest the following theoretical implications. The consistent positive relationship between GDP and emissions across all regimes aligns with the scale effect in the STIRPAT framework. It is also consistent with the early-stage pollution hypothesis of the EKC. However, the prediction of pollution decline according to EKC is partially supported. This is because rather than growth, decarbonization weakens the GDP-emissions link, which suggests that the technique effect comes from energy transition rather than income thresholds alone. Secondly, reversal of the population-emissions relationship in high-efficiency regimes is in contrast with the uniform scale effect as predicted by the IPAT and STIRPAT frameworks. This indicates that demographics is mediated by the technological capacity of the economy. The decoupling analysis further reveals that the EKC is inverted U-shape, but fails to establish the heterogeneous trajectories of top emitters. This points to the importance of institutional quality in determining the phase where emission-growth relationship prevails.

### *5.3 Policy Implications*

These comprehensive findings also suggest the following policy implications. First, economic growth will continue to raise emissions across all top emitters regardless of their development stage. This confirms that governments can not simply rely on GDP expansion alone for environmental solutions. Governments must decouple growth from emissions through a combination of carbon pricing, industrial energy efficiency, and clean energy transition targets. Secondly, while energy efficiency may reduce emissions in both the short and long run, the threshold results confirm they are insufficient to break the link between growth and emissions as suggested by Lin et al. (2017) and Salim et al. (2019). Policymakers need to treat energy efficiency as a necessary but not a sufficient variable and pair efficiency with decarbonization targets to push economies past the estimated DEC threshold.

In this study, the estimated DEC threshold value of 0.2191 corresponds to a carbon intensity of approximately 4.56 tonnes of $CO_2$ per unit of energy. This means that economies must reduce their carbon output per unit of energy used below this level before economic growth begins to lose its positive association with emissions. For high-carbon economies like China and the United States, to reach this threshold, a shift in the energy mix toward low-carbon sources is required. This implies the rise of the share of renewables in total primary energy supply, implementation of carbon pricing mechanisms and phasing out coal-based electricity generation.

It is important to note that energy efficiency and decarbonization are interconnected, although they are analysed as separate variables. Energy efficiency ratios are altered when transitioning to renewable energy. Policymakers should therefore design an integrated energy transition strategies that pursue both dimensions simultaneously.

### *5.4 Limitations and Future Research*

Despite the mentioned contributions and policy implications, the study has some limitations. First, our analysis is restricted to top ten global emitters which limits generalization. The threshold values for energy efficiency and decarbonization are due to specific structural characteristics of these top-emitting economies and therefore similar results may not hold for smaller economies. Secondly, while STIRPAT model captures the impact of important factors like GDP growth, population, energy efficiency and decarbonization, several other factors can be included for nuanced analysis. Variables such as urbanization, trade openness and institutional quality may be considered for future study. Finally, the study uses CS-ARDL and the Hansen (1999) threshold approach separately as complementary methods to address dynamics and nonlinearity. However, the use of the conventional panel threshold model rather than the augmented panel threshold model is acknowledged as a limitation of this study. Future research can address nonlinearity and cross-sectional dependence simultaneously within a single framework.

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**Declaration of AI Use**

No generative AI was used in conducting the research or writing this manuscript.

**Data Availability**

The datasets are available from the corresponding author upon reasonable request.

**Declaration of Conflict of Interest**

The authors declare no conflict of interest / no competing interests.

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