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Trend Changes and the Driving Forces of Environmental Indicators in Countries Worldwide: A Structural Change Analysis of Variations in CO₂ Emissions and Eco-Efficiency

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Abstract: Many authors state that climate change is driven by increasing CO₂ emissions worldwide. An understanding of the major driving forces affecting emissions over time in both developed and developing countries is important. Thus, in this study, structural break analysis is used to identify when the trends of environmental indicators—CO₂ emissions and environmental efficiency (EE)—across countries worldwide change. Our findings revealed notable structural breaks occurring in countries in 1994, coinciding with ballooning fossil energy prices. Regarding CO₂, 55 of 143 countries experienced a structural break. Furthermore, another wave of structural breaks emerged in 2014, corresponding to the implementation of CO₂ emission reduction plans by certain nations. For CO₂, 64 of 143 countries experienced a structural break. Upon detecting breakpoints and their trends, we utilized LMDI factor decomposition analysis to discern their driving factors, thereby elucidating the underlying dynamics. In Latin America and the Caribbean, most breakpoints were undesirable shifts, but recently, desirable shifts have increased in North America, Oceania, and Europe, which include many countries with high economic levels, improving energy-related factors. Sub-Saharan Africa can also be said to have undergone an undesirable shift regarding energy-related factors. This study clarifies the precise influences on the trend of CO₂ emissions at the global level by identifying the point in time when there is a significant statistical, rather than a subjective, breakpoint.

Keywords: decomposition analysis; structural break; eco-efficiency; trend shift; CO₂ emissions



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1. Introduction

Discerning the factors influencing long-term and global fluctuations in emissions is necessary for devising effective policies and international frameworks aimed at reducing carbon dioxide (CO₂) emissions [1]. Concurrently, prioritizing the advancement of development in developing nations is crucial for addressing poverty and hunger, as underscored by Ref. [2]. In the realm of green growth, environmental efficiency (EE), delineated as CO₂ emissions per unit of gross domestic product (GDP), has emerged as a pivotal metric, as highlighted by Ref. [3]. Additionally, the relationship between economic development and CO₂ emissions differs according to the characteristics of each country [4], and analysis needs to be carried out on a country-by-country basis. The objective of this study is to identify the point in time at which there is a statistical break in environmental indicators and to ascertain the factors that contribute to such a change. Thus, in this study, we ascertain the shifts in trends pertaining to CO₂ emissions and EE and the underlying contributors to these alterations. To elucidate trend variations, we employ structural break tests to pinpoint pivotal moments of transformation. Furthermore, to discern the factors precipitating these breaks at the point of trend alteration, we employ the logarithmic mean Divisia index (LMDI) factor decomposition analysis. This approach facilitates an in-depth understanding

of how time series trends across various countries evolve over a 30-year span, thus shedding light on the influence of breaks in the measured periods. Notably, estimated values often change in response to shifts in measurement periods, potentially leading to divergent conclusions. Hence, discerning the presence or absence of structural breaks and identifying their precise occurrence is imperative for robust analysis and informed decision making. The contributions of this paper are two-fold. First, the statistical analysis of environmental indicator trends revealed that improving the energy mix may help these trends become desirable. Second, for methodology, to find breakpoints, we used the Chow test, which can identify trend shifts and which has been utilized in financial studies.

2. Literature Review and Objective

2.1. Literature Review

Recently, global carbon neutrality research has rapidly developed because of its growing necessity. Researchers have subsequently studied the United Nations Framework Convention of Climate Change (UNFCCC) of 1992, the Kyoto Protocol of 1997, and the Paris Agreement of 2015 [5].

Measures to reduce emissions of CO₂, a key greenhouse gas (GHG), are pivotal for combating climate change and depend on transitioning from fossil fuel-based energy sources, which are major emitters of CO₂, to renewable alternatives [6]. The increased use of renewable energy positively impacts environmental indicators such as the carbon footprint [7,8]. Additionally, the implementation of carbon pricing mechanisms can strongly incentivize efforts to curb CO₂ emissions. Furthermore, economic stagnation pulls down CO₂ emissions [9]. Globally, various drivers, such as economic expansion, population growth, geopolitical shifts, trade dynamics, and lifestyle changes, are fostering high levels of energy consumption and subsequent CO₂ emissions, since economic growth is intertwined with emissions, as noted by Refs. [10,11]. Then, factor decomposition analysis is used to analyze how much those factors specifically affect CO₂ emissions.

Factor analysis studies on global CO₂ emissions rely heavily on methodologies such as LMDI factor decomposition analysis, as elucidated by Refs. [12,13], and index decomposition analysis (IDA), as exemplified by Ref. [14]. LMDI factor decomposition analysis is favored for its simplicity and its intuitive understanding of the factors influencing CO₂ emissions. Ref. [15] provides a detailed analysis of the factors affecting CO₂ emissions and CI in 56 sectors in rapidly developing India. However, although Ref. [7] allows for any factor decomposition analysis, if perfect decomposition is achieved, it does not sufficiently target eco-efficiency, which is particularly important for a country with ongoing industrialization.

This LMDI decomposition analysis is often used in addition to a decoupling analysis, which uses the ratio of the rate of change in CO₂ emissions to the rate of economic growth to weaken the correlation between CO₂ emissions and the economy and to decouple them from each other. LMDI decomposition analysis is used to determine which factors affect changes in the relationship between the economy and CO₂ emissions. In an analysis of the power industry in the Yellow River basin of China [16], the decoupling of carbon emissions and electricity production was analyzed. The study revealed that the energy structure and energy consumption contribute to CO₂ emissions, while the carbon intensity decreases them. In a study of CO₂ emission trends in the European Union [17], the carbon intensity of fossil fuels, the energy consumption structure, and energy intensity were found to lower CO emissions, while per capita GDP was found to have a positive effect. However, in the analysis of various countries over a long period, evaluating more than 100 countries, the starting point of decoupling is subjective, depending on which point in time is used, and as a more objective method, structural break analysis is used in this study.

Subsequently, econometric methods have been used to dissect trend shifts in environmental indicators. For instance, when a shock of CO₂ emission occurred, only few developed countries showed a temporary effect [18]. On the other hand, in analyzing the time series data of CO₂ emissions in the EU, fractional integration methods, as demonstrated by Ref. [19], reveal notable trends: countries such as Spain, Italy, Greece, and

Bulgaria exhibit positive trends in CO₂ emissions, whereas the UK demonstrates a significant negative trend.

Furthermore, studies such as that provided in Ref. [20], which examined structural breaks in CO₂ emission patterns since 1965 among the top 20 emitting countries, underscore the significance of policy effectiveness. While numerous upward structural breaks in CO₂ emission patterns are observed, indicating increasing emissions, fewer downward breaks are noted. The downward trend is attributed to the efficacy of national policies, as posited by the authors.

2.2. Objective and Research Framework

The objective of this study is to examine data from 1990 to the present from 143 countries worldwide with the aim of understanding the downward trend in CO₂ emissions, which is crucial for achieving carbon neutrality. What sets this study apart is its statistical approach, as opposed to subjective determinations, to identifying structural breakpoints. Unlike studies that select specific timeframes based on subjective criteria, such as analyzing the impact of events such as recessions on CO₂ emissions, our study aims to objectively identify structural breakpoints and to analyze certain factors based on those points in time. This statistical methodology enhances the robustness and reliability of our findings, providing a clearer understanding of the dynamics driving CO₂ emissions trends globally. Figure 1 presents the framework of this study.

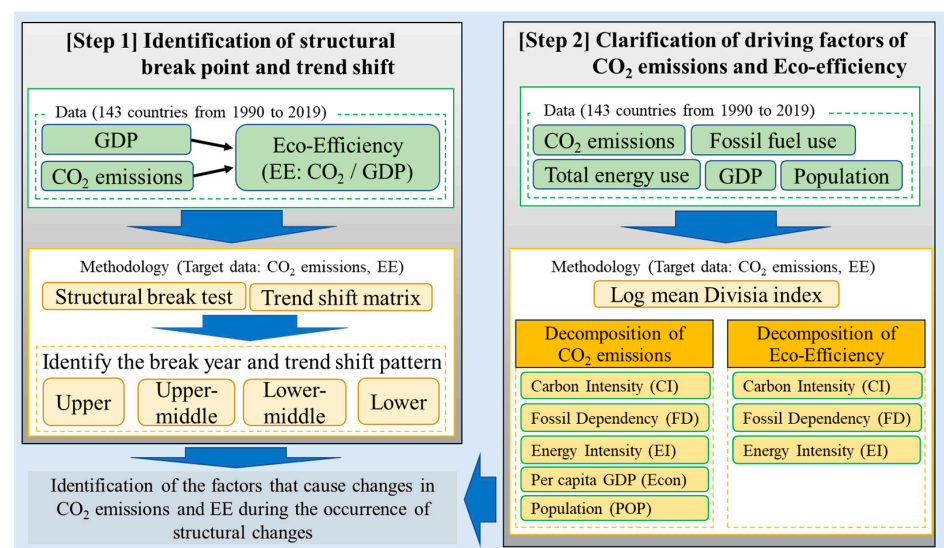


Figure 1. Research framework of this study.

3. Materials and Methods

In this study, we employed three-year moving averages of CO₂ emissions and EE across a 30-year period for 143 countries. Structural break tests were conducted to categorize these changes and elucidate the factors underlying these shifts by utilizing LMDI factor decomposition analysis.

3.1. Data

The data utilized in this study comprise various indicators obtained from reputable sources. The population data are sourced from the World Development Indicators and are presented in total population figures. The GDP data are also sourced from the World Development Indicators and are expressed in International PPP million, based on 2017 data. Total energy use data are obtained from the IEA World Energy Balance 2021 and are presented in terajoules (TJ). Fossil fuel use is derived by subtracting renewable energy consumption from total energy use and is also sourced from the IEA World Energy Balance 2021, expressed in TJ. Additionally, CO₂ emission data are sourced from IEA CO₂ emissions from fuel combustion 2021 and are expressed in kilotons (kt) of CO₂. When combining the

data, the number of countries for which data were available for years prior to 1990 was significantly reduced, so as many countries as possible with available data from 1990 to 2019, which was the latest period for which data were available, were included, resulting in 143 countries.

3.2. Structural Break

Typically, the Chow test [21] is used for structural break tests. This test assesses whether a linear regression relationship remains stable throughout the estimated period, determines whether it conforms to more than one regression model, and ascertains whether a subset of multiple regression coefficients are statistically equivalent. Since this method provides information on breakpoints and their trends, many studies have adopted this technique [22]. In this study, the analysis targets CO₂ emissions and eco-efficiency, and the Chow test is used with the aim of determining when the break occurred and what kind of break it was. According to the regression analysis and the results of Equation (1), if a structural break is identified at time T_b , Equation (1) is decomposed into Equations (2) and (3). This approach enhances the depth and accuracy of our analysis, enabling us to effectively pinpoint significant shifts and their implications.

$$y_{it} = \beta t + \varepsilon, \quad t = 1 \dots T \quad (1)$$

where y_i denotes the CO₂ emission or EE of a country i at period t , and β is a coefficient of independent variables t , which is actually also period t .

$$y_{it} = \beta_1 t + \varepsilon_1, \quad t = 1 \dots T_b \quad (2)$$

$$y_{it} = \beta_2 t + \varepsilon_2, \quad t = T_{b+1} \dots T \quad (3)$$

The null hypothesis can then be expressed as follows:

$$H_0 : \beta_1 = \beta_2 \quad (4)$$

This study used 30 years of data from 1990 to 2019, but the Structural break test used in this study requires a confidence interval over a period of time when a breakpoint occurs. Note that in this study, all data prior to 1993 and after 2016 are included in the confidence intervals for the first and the last breakpoints.

The classification of structural breaks comprises four distinct categories. First, the upper shift denotes a scenario in which the regression coefficient post-structural break surpasses the value of its pre-structural break. Second, the upper-middle classification applies when the regression coefficient of the pre-structural break is positive and that of the post-structural break diminishes but remains positive. Additionally, this classification encompasses instances where the regression coefficient transitions from positive to negative, yet the coefficient post-change remains greater than zero. Third, the lower-middle classification applies when the regression coefficient of the pre-structural change is negative and that of the post-structural break increases, but remains negative. Finally, a lower classification is assigned when the regression coefficient post-structural break diminishes compared to its pre-break value.

In this classification scheme, the coefficients of the regression lines for CO₂ and EE are categorized based on their slopes as desirable, weakly desirable, weakly undesirable, and undesirable, analogous to the decoupling indicator introduced by Ref [23]. Below is a concise summary of the study's findings.

This classification framework offers a comprehensive approach that not only accommodates positive and negative shifts, but also states that are progressing, albeit not at an optimal pace (upper-middle), and states that exhibit a desirable downward trend, albeit at a slower rate post-break (lower-middle). Such nuanced categorization enables a thorough examination of the dynamics surrounding structural shifts, facilitating a more nuanced understanding of the data. Table 1 shows the classification criteria.

Table 1. Range of the trend shifts.

		$\beta_1 > 0^*$	$\beta_1 < 0^*$
$\beta_2 > 0^*$	$\beta_2 > \beta_1^*$	upper	upper
	$\beta_1 > \beta_2^*$	upper-middle	Not classified
$\beta_2 < 0^*$	$\beta_2 > \beta_1^*$	Not classified	lower-middle
	$\beta_1 > \beta_2^*$	lower	lower

* β is a coefficient of CO₂ emission and EE. β_1 denotes the trend before the structural break, and β_2 denotes the trend after the structural break.

3.3. LMDI Decomposition Analysis

For each of these categories, we conducted LMDI factor decomposition analysis, as outlined by Ang [24], to explore the impact of each factor on CO₂ emissions and changes in EE at the point of the structural break. LMDI factor decomposition analysis is flexible and allows us to dissect emissions without residuals, providing a straightforward method to obtain analysis results in an accessible manner [25].

The factors scrutinized for their influence on change included carbon intensity (CI), fossil fuel dependency (FD), and energy intensity (EI), which are derived from the extended Kaya identity. By employing this analytical framework, we aim to elucidate the intricate interplay between these factors and the observed shifts in CO₂ emissions and EE, thereby facilitating a deeper understanding of the underlying dynamics driving environmental trends.

$$\text{CO}_2 = \frac{\text{CO}_2}{\text{Fossil fuel use}} \times \frac{\text{Fossil fuel use}}{\text{Total energy use}} \times \frac{\text{Total energy use}}{\text{GDP}} \times \frac{\text{GDP}}{\text{Population}} \times \text{Population} \quad (5)$$

$$= \text{CI} \times \text{FD} \times \text{EI} \times \text{ECON} \times \text{POP}$$

The change in CO₂ emissions from time $t - 1$ to t can be represented as follows:

$$\frac{\text{CO}_2^t}{\text{CO}_2^{t-1}} = \frac{\text{CI}^t}{\text{CI}^{t-1}} \times \frac{\text{FD}^t}{\text{FD}^{t-1}} \times \frac{\text{EI}^t}{\text{EI}^{t-1}} \times \frac{\text{ECON}^t}{\text{ECON}^{t-1}} \times \frac{\text{POP}^t}{\text{POP}^{t-1}} \quad (6)$$

This is log-transformed to obtain Equation (7).

$$\ln\left(\frac{\text{CO}_2^t}{\text{CO}_2^{t-1}}\right) = \ln \text{CO}_2^t - \ln \text{CO}_2^{t-1} \quad (7)$$

$$= \ln\left(\frac{\text{CI}^t}{\text{CI}^{t-1}}\right) \times \ln\left(\frac{\text{FD}^t}{\text{FD}^{t-1}}\right) \times \ln\left(\frac{\text{EI}^t}{\text{EI}^{t-1}}\right) \times \ln\left(\frac{\text{ECON}^t}{\text{ECON}^{t-1}}\right) \times \ln\left(\frac{\text{POP}^t}{\text{POP}^{t-1}}\right)$$

By multiplying both sides of Equation (7) by the weight, denoted as $\omega^t = (\text{CO}_2^t - \text{CO}_2^{t-1}) / (\ln \text{CO}_2^t - \ln \text{CO}_2^{t-1})$, we obtain Equation (8).

$$\text{CO}_2^t - \text{CO}_2^{t-1} = \Delta \text{CO}_2^{t,t-1} \quad (8)$$

$$= \omega^t \ln\left(\frac{\text{CI}^t}{\text{CI}^{t-1}}\right) \times \omega^t \ln\left(\frac{\text{FD}^t}{\text{FD}^{t-1}}\right) \times \omega^t \ln\left(\frac{\text{EI}^t}{\text{EI}^{t-1}}\right) \times \omega^t \ln\left(\frac{\text{ECON}^t}{\text{ECON}^{t-1}}\right) \times \omega^t \ln\left(\frac{\text{POP}^t}{\text{POP}^{t-1}}\right)$$

Hence, the change in CO₂ emissions can be decomposed into five factors: CI, FD, EI, economic activity (ECON), and population (POP). This allows us to elucidate the influence of each factor on the observed changes. In this study, LMDI factor decomposition analysis was used to clarify the impact of each factor on CO₂ emissions, and each calculated factor was divided by CO₂ emissions and presented as a percentage to provide an intuitive understanding.

We then present a model for LMDI factor decomposition analysis of EE. EE is an index of development sustainability. It has been used in many studies because of its ease of calculation and the clarity of the indicator [26]. It can be calculated by dividing CO₂ emissions by GDP, and thus, as in the case of CO₂ emissions, LMDI decomposition analysis can be applied. Similar to the approach for CO₂ emissions, this model is grounded in Kaya's identity equation. However, compared to Equation (5) for CO₂, in this equation, the

factors ECON and POP are excluded from the analysis. This streamlined model enables us to focus specifically on the factors affecting EE, facilitating a more targeted examination of environmental efficiency dynamics.

$$EE = \frac{CO_2}{GDP} = \frac{CO_2}{Fossil\ fuel\ use} \times \frac{Fossil\ fuel\ use}{Total\ energy\ use} \times \frac{Total\ energy\ use}{GDP} = CI \times FD \times EI \quad (9)$$

The change in EE emissions from time $t - 1$ to t can be represented as follows:

$$\frac{EE^t}{EE^{t-1}} = \frac{CI^t}{CI^{t-1}} \times \frac{FD^t}{FD^{t-1}} \times \frac{EI^t}{EI^{t-1}} \quad (10)$$

This is log-transformed to obtain Equation (11).

$$\ln\left(\frac{EE^t}{EE^{t-1}}\right) = \ln EE^t - \ln EE^{t-1} = \ln\left(\frac{CI^t}{CI^{t-1}}\right) \times \ln\left(\frac{FD^t}{FD^{t-1}}\right) \times \ln\left(\frac{EI^t}{EI^{t-1}}\right) \quad (11)$$

By multiplying both sides of Equation (11) by the weight, denoted as $\omega^t = (CO_2^t - CO_2^{t-1}) / (\ln CO_2^t - \ln CO_2^{t-1})$, we obtain Equation (12).

$$EE^t - EE^{t-1} = \Delta EE^{t,t-1} = \omega^t \ln\left(\frac{CI^t}{CI^{t-1}}\right) \times \omega^t \ln\left(\frac{FD^t}{FD^{t-1}}\right) \times \omega^t \ln\left(\frac{EI^t}{EI^{t-1}}\right) \quad (12)$$

Therefore, the change in EE can be decomposed into three components: CI , FD , and EI . This decomposition allows us to understand the individual contributions of these factors to the observed changes in EE. As in the LMDI factorization analysis for CO_2 , each calculated factor is divided by EE and presented as a percentage to provide an intuitive understanding.

4. Results

4.1. Structural Break Results

4.1.1. Structural Breakpoint of CO_2 Emission

The structural break results for CO_2 emissions are shown in Figure 2. The horizontal axis represents the year in which the structural break was observed, and the vertical axis represents the number of times the structural break occurred for each type of trend shift.

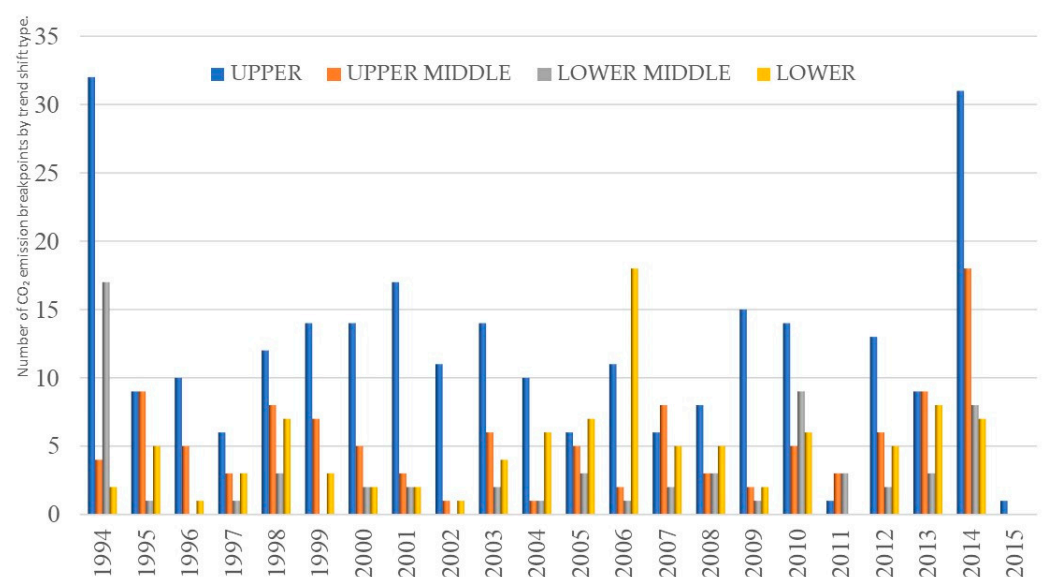


Figure 2. Number of CO_2 emission breakpoints by trend shift type. Although the period analyzed was 1990–2019, the method used in this study could not detect structural breaks in 1990–1993 and 2016–2019.

Structural break analysis revealed that in 141 countries, structural breaks in CO₂ emissions were observed at 540 time points. In two countries, no structural break occurred, while in three other countries, there was no discernible structural break in CO₂ emissions. Across the categorized types, the remaining countries demonstrated 264 instances of upper shifts, 113 upper-middle shifts, 64 lower-middle shifts, and 99 lower shifts. Notably, 2014 had the highest number of breaks.

4.1.2. Structural Breakpoint of EE

Similarly, structural breaks in EE were noted in 142 countries at 537 time points. Among the classifications, one country showed no structural break, while there were 153 upper shifts, 44 upper-middle shifts, 114 lower-middle shifts, and 153 lower shifts in the other countries. In particular, the greatest number of structural breaks in EE occurred in 1994. Unlike for CO₂, the EE results show the largest number of lower-shift countries. Upper shift is the second most common, by a slight margin. This detailed analysis provides valuable insights into the patterns and trends surrounding both CO₂ emissions and EE across countries and timeframes. The results of EE structural breaks are shown in Figure 3.

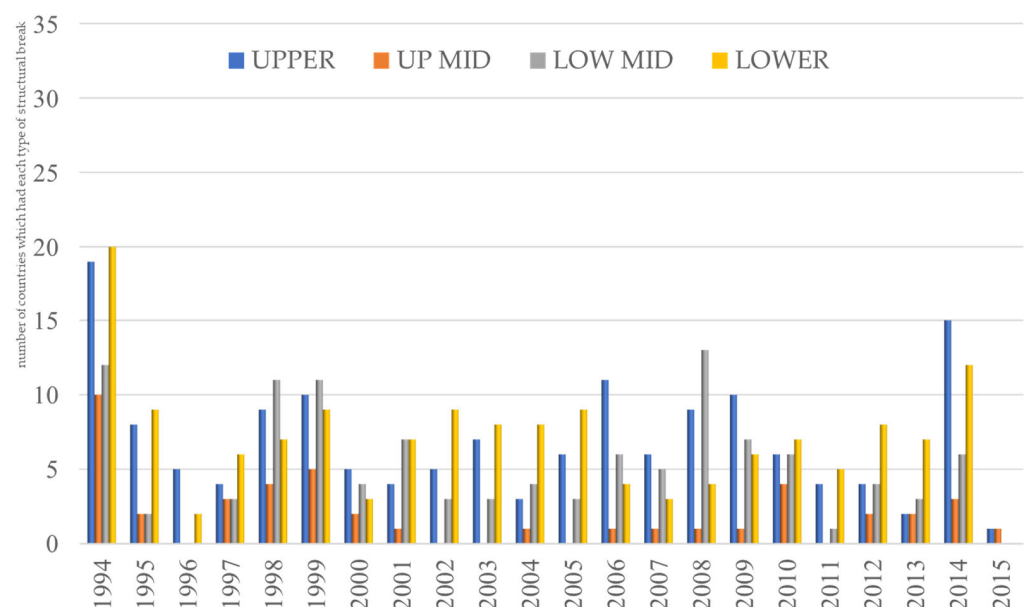


Figure 3. Number of EE breakpoints by trend shift type. Although the period analyzed was 1990–2019, the method used in this study could not detect structural breaks in 1990–1993 and 2016–2019.

A previous study [19] noted a concentration of breakpoints in the early 1990s; similarly, 1994 emerged as the most common time point in this study. Additionally, 2014 had a particularly high number of breakpoints.

In 1994, a significant number of structural breakpoints for both CO₂ emissions and EE were observed; these were characterized primarily by upper trend shifts in CO₂ emissions. Notably, this period preceded the Kyoto Protocol, during which international incentives for emission reduction were not yet established. Moreover, the Gulf War, a period marked by escalating energy prices, occurred only three years earlier; thus, the prevalence of upper shifts in 1994 may be attributed to economic and geopolitical factors related to the war.

Compared to those in 1994, the shifts that predominated in 2014, a year of notable structural breaks, were more diverse. These shifts occurred following COP15 (the Copenhagen Accord), during which developed countries were tasked with setting their own greenhouse gas reduction targets, while developing countries were also required to establish targets for greenhouse gas emission mitigation. COP15 plays a pivotal role in shaping global climate action strategies.

4.2. LMDI Decomposition Analysis Results

To better understand the patterns of structural breakpoints for both CO₂ emissions and EE, a scatter plot of the breakpoints by geographic region was created. Figures 4–7 illustrate the breakpoints as of 1994 and 2014 for each type of shift, along with regional subregion information.

The vertical axes of the scatter plots in Figures 4 and 5 represent the sum of the 3-year moving average changes in carbon intensity (ΔCI) and fossil fuel dependency (ΔFD) divided by the 3-year moving average CO₂ emissions. The horizontal axis depicts the sum of the 3-year moving average changes in energy intensity (ΔEI), economic activity ($\Delta ECON$), and population (ΔPOP), which are also divided by the 3-year moving average CO₂ emissions. These plots are structured so that energy-related factors are plotted on the horizontal axis and economic-related factors on the vertical axis, facilitating a comprehensive visual representation of the relationships between these variables.

4.2.1. Results of CO₂ Emissions in 1994

The scatter plots of CO₂ emissions in 1994, depicted in Figure 4, reveal a decreasing trend in variability. On the vertical axis, there is a noticeable shift toward a downward trend, indicating a transition toward utilizing energy sources with lower CO₂ emissions per unit of energy, or increasing renewable energy use. Conversely, on the horizontal axis, a left shift suggests energy conservation efforts, possibly driven by incentives, or decreases in economic activity or population.

Countries falling within the first quadrant exhibited states that were undesirable or improving, but not sufficiently. These nations may have prioritized economic efficiency at the expense of environmental impacts. Conversely, countries in the fourth quadrant demonstrated improvements in their energy mix, yet CO₂ emissions continued to rise, possibly due to economic factors and other influences.

In the third quadrant, where both the horizontal and vertical axes are negative, there is a notable decrease in CO₂ emissions. However, for some countries, CO₂ emission trends exhibited an upper shift, despite their existence in the third quadrant, indicating that a level shift had occurred due to one or more incidents. In contrast, countries in the second quadrant showed worsening trends in regards to their energy mix and other factors; furthermore, they may have been impacted by negative economic factors and other influences.

In 1994, predominant upper shifts were observed in most countries; these shifts coincided with increases in variability. In particular, large variations were evident in the first and third quadrants, suggesting a correlation between the vertical and horizontal axes. Such situations indicate that despite rising energy prices, economic development remains a priority, even if it involves utilizing energy sources with higher CO₂ emissions per unit of energy. In several studies [27,28], higher oil prices have been found to increase CO₂ emissions in the short term, and in this study, this is manifested as a large number of structural breaks in 1994.

Notably, in the third quadrant of Figure 4, Bosnia and Herzegovina, which belong to the North America, Oceania, and Europe group, displayed negative level shifts before and after the structural break, despite yielding overall negative impacts on CO₂ emissions.

Overall, 55 countries are included in this scatter plot. We focused on four groups of countries that had a particularly large number of CO₂ breakpoints in 1994. The percentage of breakpoints in these four groups was 74.55%, with 13 countries in the lower-middle group of North America and Europe, 12 countries in the upper group of North America and Europe, 10 countries in the upper group of Latin America and the Caribbean, and 10 countries in the upper group of Sub-Saharan Africa. The mean CI + FD for the lower-middle group was −2.55%, and the EI + EA + P was 1.51%; for the upper group of North America and Europe, the mean CI + FD was −3.01%, and the EI + EA + P was 1.08%. The upper group of Latin America and the Caribbean averaged 12.09% CI + FD and 7.39% EI + EA + P. The upper group of Sub-Saharan Africa had an average of 6.75% CI + FD and 3.53% EI + EA + P.

The upper trend shift implies an increasing trend after the breakpoints compared with before them. Therefore, the upper shift in Latin America and the Caribbean and the upper shift in Sub-Saharan Africa, which are mostly included in the first quadrant and are positive on both the vertical and horizontal axes, are the most undesirable conditions. The upper-shift countries and lower-middle shift countries in North America and Europe are mostly in the second quadrant. In the second quadrant, $CI + FD$ is negative, and $EI + EA + P$ is positive, which is desirable in terms of energy-derived factors, but undesirable in terms of economic-related factors. Eastern Asia and Southeast Asia had only one country with a $CI + FD$ of -4.79% and an $EI + EA + P$ of 6.90% .



Figure 4. Scatter plot of trend shifts in CO₂ emissions in 1994.

4.2.2. Results for CO₂ Emissions in 2014

In 2014, countries in the first and fourth quadrants included Central and South Asia, Southeast Asia, and Sub-Saharan Africa, while North America and Europe were represented in quadrants 2 and 3. These observations underscore the complex interplay among economic, energy, and environmental factors shaping CO₂ emissions trends globally. Result of CO₂ in 2014 was shown in Figure 5.

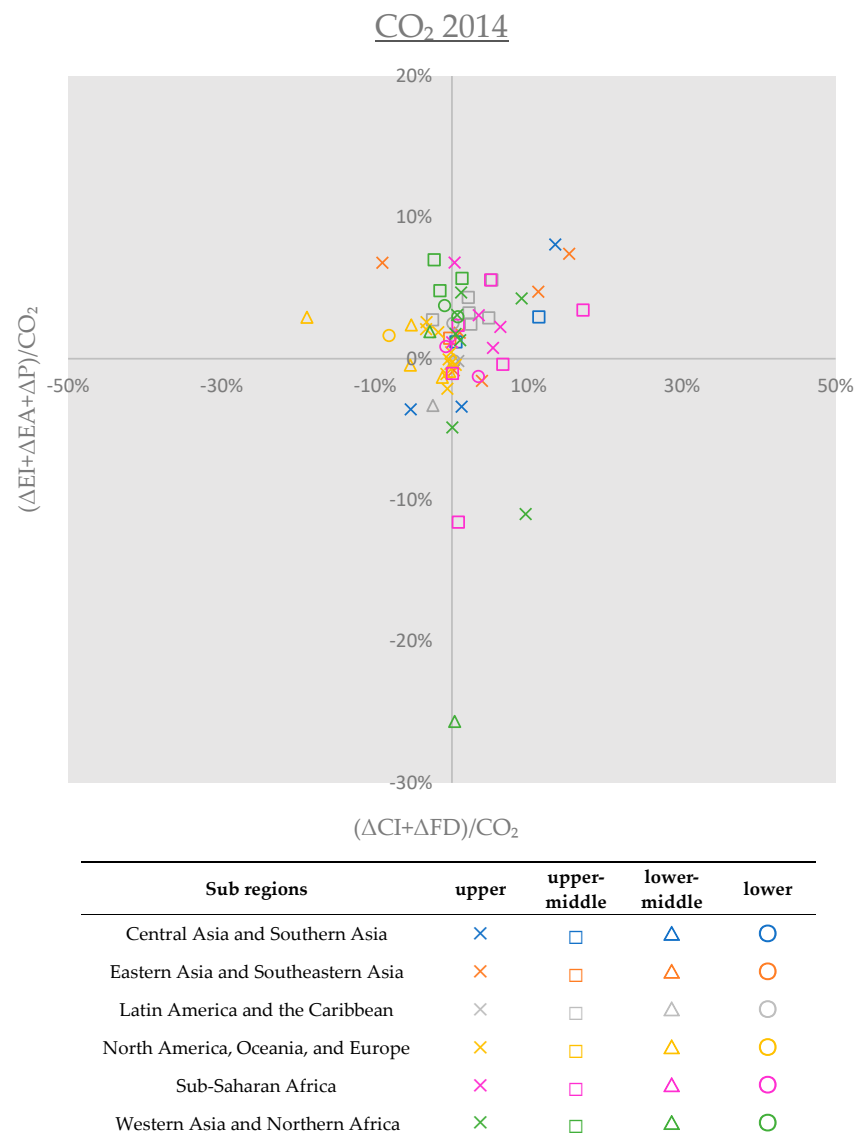


Figure 5. Scatter plot of trend shifts in CO₂ emissions in 2014.

Overall, 64 countries are included in this scatter plot. Among these 64 countries, there are six groups of subregional and trend-shifting combinations with more than half of the breakpoints in 2014: six countries in the upper group in Eastern Asia and Southeast Asia; six countries in Latin America and the Caribbean in the upper-middle group of six countries; North America and Europe in the upper group of nine countries; Sub-Saharan Africa in the upper group of six countries; and Western Asia and Northern Africa in the upper group of Eastern Asia and Southeast Asia, with an average CI + FD of 3.79% and an average EI + EA + P of 3.06%; the upper-middle group of Latin America and the Caribbean had an average CI + FD of 2.41% and an EI + EA + P of 3.53%; and North America and Europe's upper group had a CI + FD average of −1.37% and an EI + EA + P average of 0.32%. Sub-Saharan Africa had an average upper group, with a CI + FD of 5.11% and an EI + EA + P of −0.28%, while Western Asia and North Africa had an average upper group, with a CI + FD of 3.18% and an average EI + EA + P of −0.11%.

Sub-Saharan Africa was mostly included in quadrant 1 in 1994, but in 2014, it also included 4 of 13 countries in the fourth quadrant, showing improving trend shifts, including upper shifts as well as upper-middle shifts and lower shifts. In 2014, there were 14 countries with more breakpoints in western Asia and northern Africa than in 1994, when 6 countries

had breakpoints. Of these, five of the seven countries in the upper shift are included in the first quadrant.

4.2.3. Results for EE in 1994

In the scatter plots in Figures 6 and 7, the horizontal axis illustrates the sum of the ΔCI and ΔFD divided by the 3-year moving average EE, while the vertical axis displays the 3-year moving average ΔEI divided by the 3-year moving average EE.

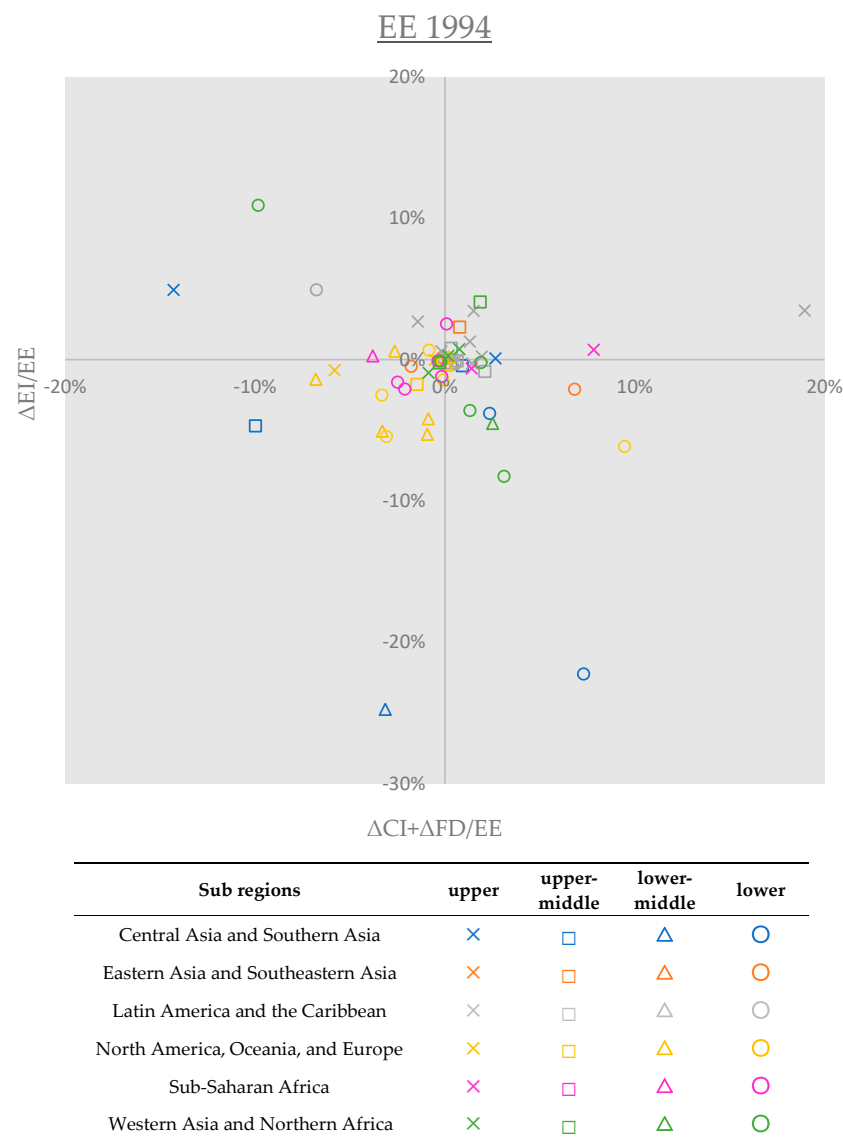


Figure 6. Scatter plot of trend shifts in EE in 1994.

Overall, 66 countries are included in this scatter plot. Of these 66 countries, there are three groups of countries which are conspicuously large, totaling 35% of the 1994 EE breakpoints. nine countries in the upper group of Latin America and the Caribbean, nine countries in Latin America and the Caribbean upper group have an average CI + FD of 2.65% and an EI of 0.14%. The average CI + FD and EI values for the lower-middle group of North America and Europe were −1.81% and −0.24%, respectively; the average CI + FD and EI values for the lower group of Western Asia and Northern Africa were −1.31% and −1.65%, respectively, in the lower group.

Six of the eight countries in the lower-middle of North America and Europe are in the third quadrant, and the two countries that are not in this quadrant are distributed very

close to the third quadrant. Similarly, most North American and European countries are in the third quadrant.

4.2.4. Results of EE in 2014

Compared to that in 1994, a smaller variation was observed in 2014, as seen in Figure 7. This scatter plot includes 40 countries. Of these 40 countries, there are four groups that are conspicuously large, totaling 45% of the 2014 breakpoints for the combination of subregion and trend shift: four countries in the upper-middle group in Eastern Asia and Southeast Asia, four countries in the lower group of Latin America and the Caribbean, countries in Sub-Saharan Africa's upper group, and countries in Sub-Saharan Africa's lower group. The upper-middle group in the Eastern Asia and Southeast Asia group had an average CI + FD of 0.56% and EI of 0.31%, the lower group in Latin America and the Caribbean had an average CI + FD of 0.23% and EI of −0.15%, the Sub-Saharan Africa upper group had an average CI + FD of 0.69% and EI of −1.07%, and the Sub-Saharan Africa lower group had an average CI + FD of 1.12% and EI of −0.34%.

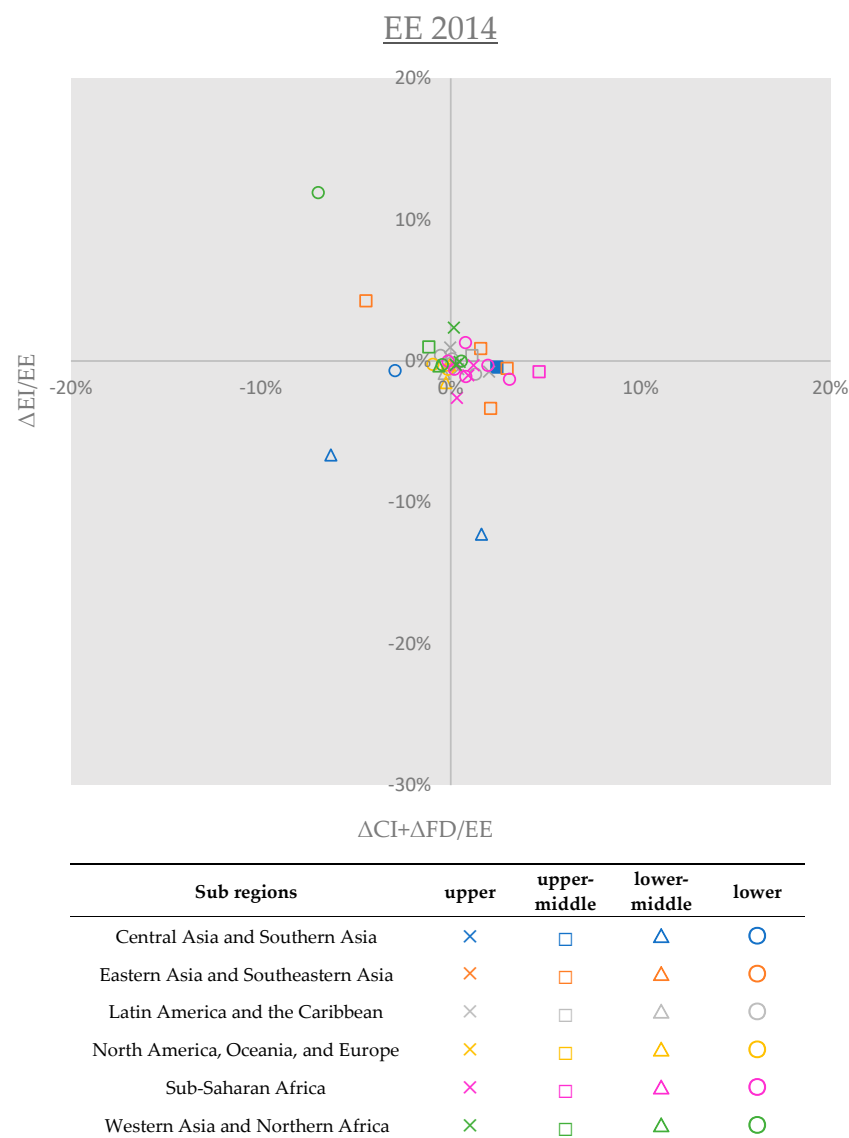


Figure 7. Scatter plot of trend shifts in EE in 2014.

Sub-Saharan African countries shifted to the right when compared to the results in 1994, which indicates that energy-related factors are moving toward increasing the EE index,

increasing the undesirable trend shift. In addition, four North American and European countries, all in the third quadrant, with a lower or lower middle shift, are included in Figure 7. In addition, compared to CO₂, EE excludes indicators such as EA and population, which may lead to more desirable trend shifts for regions with many developing countries.

Some countries exhibited different outcomes for CO₂ emissions and EE. For example, Bosnia and Herzegovina experienced a CO₂ emission break in 1994, as depicted in Figure 4 by an upper shift in the third quadrant. However, EE did not undergo a similar break, as subsequent GDP growth aligned with the change in CO₂ emissions levels. In the aftermath of conflicts, countries sometimes prioritize economic growth to restore people's standard of living to normal. This was also observed in several developing countries, i.e., in some countries in Central Asia and Southern Asia. In such scenarios, it becomes crucial to shift the focus away from solely monitoring CO₂ emissions or CO₂ emissions per capita and instead concentrate on monitoring trend changes in EE. Controlling EE trends to prevent an upward shift becomes imperative to ensure sustainable development and mitigate adverse environmental impacts.

5. Conclusions

5.1. Discussion

In this paper, to identify large changes in environmental index trends in both developed and developing countries, we adopted a statistical approach to identify points of structural breaks, as opposed to using subjective determinations. We utilized LMDI factor decomposition analysis to discern the underlying dynamics surrounding these changes. We focused on the difference between the trends, before and after the structural breaks in the two environmental indicators, and analyzed them from the viewpoint that a decreasing trend would be more desirable. Our analysis revealed that the years with the most significant changes were 1994 and 2014, of which 1994 coincided with the aftermath of the Gulf War, during which energy prices experienced dramatic fluctuations [29].

Furthermore, major shifts in IMF energy prices, including a transition from oil to more environmentally harmful energy sources such as coal, contributed to these structural breaks. Previous studies, such as that in Ref. [19], have also highlighted similar findings, emphasizing the association between significant energy price changes and policy shifts in the early 1990s. However, our study revealed that a notable number of structural breaks occurred in 2014 as well.

During this period, there was a growing awareness in the Western world regarding the imperative to utilize environmental resources more efficiently. While some countries succeeded in reducing CO₂ emissions by improving their energy mix, others continued to prioritize economic growth, resulting in sustained high CO₂ emission trends. Notably, certain regions, although contributing to high emissions, might not consume the products they produce within their own borders, leading to a situation where CO₂ emissions are essentially exported.

Moreover, it is crucial to acknowledge that trends in EE may not align directly with trends in CO₂ emissions. Therefore, it becomes imperative to manage CO₂ emission levels in tandem with GDP growth, particularly when promoting economic activity is deemed necessary. This method ensures a balanced approach to economic development, while mitigating environmental impacts.

Furthermore, trend changes often coincide with significant fluctuations in energy prices or shifts in environmental policies. For policy makers striving for carbon neutrality, it is crucial to recognize that sharp increases in energy prices typically lead to an increase in CO₂ emissions. Therefore, it becomes imperative to transition to an energy mix that imposes a lower environmental burden.

Summarizing the results by subregion, in the Central Asia and Southern Asia regions, various trend shifts were observed in 1994, but many of these countries gained independence after the collapse of the Soviet Union. Economic factors affecting CO₂ change in Central and Southern Asia increased from −8.61% to 1.04%, while energy factors increased

from -0.53% to 4.25% . In Eastern Asia and Southeastern Asia, there were almost no significant changes in 1994, and undesirable trend shifts occurred in 2014. The change in the percentage structure of fossil energy use is thought to have affected the 2014 results. Economic factors affecting CO₂ change in Eastern Asia and Southeastern Asia decreased from 6.90% to 2.83% ; on the other hand, energy factors increased from -4.79% to 3.21% . In Latin America and the Caribbean, according to Figures 4 and 6, most of the breakpoints exhibited undesirable changes, but according to Figures 5 and 7, desirable changes increased. Economic factors affecting CO₂ change in Latin America and the Caribbean decreased from 6.64% to 2.00% , while energy factors decreased from 10.13% to 1.33% . Comparing Figures 4 and 5, it can be noted that North America, Oceania, and Europe, which have many countries with high economic levels, continue to remain in quadrants 2 or 3 and continue to improve regarding energy-related factors. Economic factors affecting CO₂ change in North America, Oceania, and Europe increased from -0.21% to 0.48% , meanwhile, energy factors decreased from -2.64% to -3.45% . Sub-Saharan Africa can also be said to have undergone an undesirable shift regarding energy-related factors, as it was located in quadrant 1 or quadrant 4 in 2014, whereas in 1994, there was a variation in these results. Economic factors affecting CO₂ change in Sub-Saharan Africa increased from -7.53% to -0.03% , while energy factors decreased from 6.75% to 3.76% . Lastly, economic factors affecting CO₂ change in Sub-Saharan Africa decreased from 3.53% to 0.92% , as the other energy factors increased from 0.72% to 1.22% . Compared to other regions, western Asia and northern Africa have greater variations on the vertical axis, as seen when comparing Figures 6 and 7, which show the results of the analysis of EE, without accounting for EA and POP, with Figures 4 and 5. Therefore, a more appropriate classification may be needed for this area, e.g., by economic level.

5.2. Limitations

In this study, the structural break points of the environment index were identified, and we focused on the trend shift, which is the type of change that occurred; however, it is also possible that a level shift occurred. If this is the case, then some kind of shock may have occurred at that time. Identifying the cause of the level shift is an issue for future study. Additionally, in a few subregions, we found few of the required characteristics. There might be more proper categorical features for analysis. Additionally, in this paper, trends were obtained by performing the analysis over a long period of time, but this approach has limitations in short characteristic periods. For example, in the 2019–2021 COVID-19 disaster, some economies grew negatively.

5.3. Policy Implications

Overall, the trends in environmental indicators in countries with developing industries and developing countries are more desirable for the former and less desirable for the latter, but the important result is to continuously achieve a lower shift over a long period. Policy makers are tasked with proactively adjusting their energy strategies to mitigate environmental impacts. This process entails transitioning toward cleaner and more sustainable energy sources, reducing reliance on fossil fuels, and promoting energy efficiency measures. By adopting these proactive measures, policy makers can effectively navigate the challenges posed by rising energy prices, while advancing toward carbon neutrality goals.

In countries and regions where CO₂ emissions are expected to increase in the future due to population growth, economic growth, and domestic production of fossil energy, the hurdles to achieving carbon neutrality will be higher. However, for each of the breakpoints identified by the structural break analysis at the country level in this study, it will be important for countries to cooperate with each other on the path to decarbonization and with other countries with the same level of CO₂ emission trends. Cases in which trade is facilitated, e.g., through economic partnerships, have occurred, and improvements in environmental performance can be seen [30]. Environmental performance can be further

improved if environmental perspectives are incorporated here and if both parties are aware of what is needed to move closer to achieving carbon neutrality in each country.

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