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Analysis of the Effect of Sector Value added to GDP on Carbon Emissions in Kenya

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Abstract

This study examines the asymmetric effect of sectoral value added to GDP on carbon dioxide (CO_2) emissions in Kenya over the period 1990–2021, grounded in the Environmental Kuznets Curve (EKC) theoretical framework. Despite existence of enormous literature examining the linkage between economic growth and carbon emissions, only a few have focused on how growth in different sectors contribute to the establishment of this nexus. Using annual time series data from World Banks' World Development Indicators database, the study applies the Augmented Dickey-Fuller and Phillips-Perron unit root tests, the Nonlinear Autoregressive Distributed Lag (NARDL) model and Wald tests for asymmetry. The variables considered include carbon emissions as the dependent variable and renewable energy, agriculture value added to GDP, service value added to GDP and industry value added to GDP as the independent variables. The unit root test results under Augmented Dickey Fuller and Philips-Perron indicate that the variables were first difference stationary. The bounds test results confirm the existence of a long-run cointegrating relationship at the 5% significance level, with an error correction term of −0.904. The NARDL results indicate that in the long-run, agriculture value added growth significantly increases CO_2 emissions (+2.734) whereas it's decline leads to a reduction in emissions (coef. -1.800 p=0.077) in. The service sector growth reduces emissions (−0.213) while it's decline increases emissions (0.594). Industrial growth on the other hand is associated with lower emissions (−0.727), whereas its decline substantially raises emissions (+5.486). Renewable energy consumption consistently reduces emissions both in the short and long run (-3.755 and -5.036 respectively). Wald tests confirm a strong and significant long-run asymmetry in the service and industrial sectors with agriculture presenting a weak long-run asymmetry (p=0.092). The findings suggest that sectoral composition critically shapes Kenya's emissions trajectory and that policy interventions must distinguish between growth and decline phases. Short-term agricultural policies should prioritize climate-smart farming and sustainable land-use

practices, while service sector strategies should emphasize green public transport and digital economy expansion. The anomalous industrial result warrants further investigation with additional controls for fossil fuel energy consumption and structural breaks.

Keywords: Carbon emissions, GDP, sector value-added, NARDL, ADF, PP, Kenya

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Introduction

Background Information

Economic growth has transformed economies through higher incomes, industrial expansion and technological progress. However, these gains have often been accompanied by rising carbon dioxide (CO_2) emissions, particularly where growth has relied on fossil fuels and energy-intensive production. This has intensified concerns over climate change and raised questions about how countries can sustain economic development while reducing their carbon footprint (IPCC, 2021; Climate Watch, 2024).

Some of the urgent environmental challenges that have become a subject of discussion since the 1992 Rio de Janeiro Earth Summit, include global warming, deforestation and biodiversity loss have been placed at the forefront of international and national policy agendas (Zmami and Ben-Salha, 2020). Recognizing these challenges, the international community adopted the Paris Agreement in 2015, committing countries to limit the increase in global average temperature to well below 2°C above pre-industrial levels while pursuing efforts to limit warming to 1.5°C. Achieving these goals requires decoupling economic growth from carbon emissions through cleaner technologies, renewable energy adoption and structural transformation toward less carbon-intensive economic activities(Balogh and Jámbor, 2017).

In 2023, global GHG emissions reached approximately 53.0 $GtCO_2e$ representing a 1.9% increase from 2022. These emissions were largely driven by fossil fuel combustion and industrial processes, which together contributed about 73.7% of total carbon emissions, 18.9% of Methane, 4.7% of Nitrous oxide and 2.7% fluorinated gases (F-gases) (Crippa *et. al.,* 2024). The energy sector was responsible for 76% of the global GHG emissions followed by agriculture sector at 12% with industrial processes, waste and Land Use Change and Forestry (LUCF) contributing 6.4%, 3.4% and 2.6% respectively. A similar trend is seen when considering carbon emissions with energy sector at 83%, agriculture sector at 6.8% and Industrial processes, waste and LUCF at 5.4%, 2.8% and 2.0% respectively (Climate Watch, 2024).

Africa's contribution to global carbon emissions remains relatively modest but steadily rising. Although it accounts for less than 4% of global energy-related carbon dioxide (CO_2) emissions, it is among the regions most vulnerable to the adverse effects of climate change (IEA, 2024). Rising temperatures, prolonged droughts, erratic rainfall, floods and land degradation continue to undermine agricultural productivity, food security, water resources and livelihoods, thereby constraining economic growth and sustainable development. Despite its relatively small contribution to global emissions, the continent faces disproportionately high climate-related risks, highlighting the need to pursue economic development through pathways that are both climate-resilient and environmentally sustainable (IPCC, 2022; AfDB, 2024).

Carbon emissions across Africa are also highly uneven, reflecting differences in industrialization levels, energy systems and economic structures. South Africa remains the continent's largest CO_2 emitter, followed by Egypt, Algeria, and Nigeria, largely because their economies depend more heavily on fossil fuels and energy-intensive industries (Climate Watch, 2024; IEA, 2024). Many Sub-Saharan African countries, including Kenya, contribute relatively little to continental emissions owing to lower levels of industrialization and a greater reliance on renewable energy (AfDB, 2024). However, ongoing structural transformation, urbanization, industrial expansion and rising energy demand are expected to increase emissions unless economic growth is accompanied by investments in cleaner technologies and low-carbon production systems (UNECA, 2023). The paradox of low emissions but high vulnerability underscores the urgent need for climate-resilient development pathways and clean energy investment across the continent (AfDB, 2020).

According to AfDB (2025), East Africa region maintained its dominance of being the fastest growing region in Sub-Saharan Africa in 2024. Its real GDP growth rate was estimated at 4.4 percent in 2024 and is projected to rise to 5.3 percent in 2025. At these growth rates, half of East Africa's economies which include South Sudan, Rwanda, Uganda, Ethiopia, Tanzania and Kenya are expected to grow by 5 percent or higher in 2025. Kenya, in particular, has experienced sustained economic expansion while pursuing an ambitious development agenda under Vision 2030 and simultaneously committing to reduce greenhouse gas emissions by 32% by 2030 through its Nationally Determined Contributions (Government of Kenya, 2020).

Although Kenya's economic growth moderated from 5.7% in 2023 to 4.7% in 2024, the economy remained resilient, with a nominal gross domestic product (GDP) of approximately KSh 16.2 trillion in 2024 (KNBS, 2025). This continued expansion has been

accompanied by rising energy demand, rapid urbanization, expanding transport infrastructure and increased industrial activity, all of which have implications for carbon dioxide (CO_2) emissions. While Kenya's electricity system is among the cleanest in Africa, owing to its substantial reliance on geothermal, hydroelectric, wind and solar energy, emissions from transport, manufacturing, construction and other fossil fuel-dependent activities continue to rise as the economy expands (IEA, 2024; KNBS, 2025).

Despite contributing only a small share of global carbon emissions, Kenya remains highly vulnerable to the impacts of climate change. Recurrent droughts, floods, changing rainfall patterns, and increasing temperatures continue to undermine agricultural productivity, water resources, food security, and rural livelihoods, posing significant challenges to economic development and poverty reduction (IPCC, 2022; Government of Kenya, 2023). In response, the government has strengthened its climate policy framework through the Climate Change Act (2016), the National Climate Change Action Plan (2023-2027), and its updated Nationally Determined Contributions (NDCs) under the Paris Agreement, committing to reduce greenhouse gas emissions by 32% by 2030 relative to the business-as-usual scenario, conditional on international support (Government of Kenya, 2020). Achieving these commitments requires evidence-based policies that identify the sectors contributing most to emissions while safeguarding economic growth.

Kenya's economic structure further underscores the importance of adopting a sectoral perspective. The service sector remains the largest contributor to GDP, reflecting the growing importance of finance, trade, transport, information and communication, tourism and other service-related activities. Agriculture, forestry, and fishing continue to contribute more than one-fifth of GDP while remaining the backbone of rural livelihoods and employment. In 2024, agriculture expanded by 4.6%, while stronger growth was recorded in financial and insurance activities (7.6%), real estate (5.3%) and transport and storage (4.4%). By contrast, construction and mining contracted by 0.7% and 9.2%, respectively, highlighting the uneven performance of Kenya's productive sectors (KNBS, 2025). These differences indicate that economic growth is driven by sectors with distinct production technologies, energy requirements, and environmental footprints, suggesting that their contributions to carbon emissions are unlikely to be uniform.

The environmental implications of sectoral growth are equally heterogeneous. Agriculture is essential for food production and economic livelihoods, yet its direct contribution to carbon dioxide emissions is relatively limited compared with industry because a substantial proportion of its emissions arise from methane and nitrous oxide. Industrial activities, particularly manufacturing and construction, are generally more carbon intensive owing to their dependence on fossil fuels and energy-intensive production processes. Although the service sector is often considered less carbon intensive, its rapid expansion increases demand for transport, commercial buildings, digital infrastructure, and electricity, which indirectly contributes to CO_2 emissions. These sector-specific differences suggest that aggregate GDP may obscure the channels through which economic growth influences environmental outcomes.

The relationship between economic development and environmental quality has long been a central concern in environmental economics with Environmental Kuznets

Curve (EKC) hypothesis and Structural Transition Theory providing the framework for understanding how economic transformation may influence carbon dioxide (CO_2) emissions. The EKC hypothesis posits that environmental degradation tends to increase during the early stages of economic development as production, industrialization, and energy consumption expand. However, beyond a certain level of income, further economic growth may contribute to improved environmental quality through technological innovation, stronger environmental regulations, greater public awareness, and a shift towards cleaner production and consumption patterns (Grossman & Krueger, 1991; Panayotou, 1993; Stern, 2004).

While the EKC focuses primarily on the relationship between income and environmental quality, Structural Transition Theory argues that the environmental effects of economic growth are shaped by changes in the composition of economic activity. As economies evolve from agriculture to industry and subsequently towards service-oriented production, sectors differ considerably in their production technologies, energy requirements, and carbon intensities (Chenery, 1960; Syrquin, 1988). Consequently, economic growth does not affect carbon emissions uniformly; rather, its environmental impact depends on which sectors drive growth and the extent to which structural transformation is accompanied by cleaner technologies, energy efficiency, and sustainable production systems.

These theoretical perspectives are particularly relevant for Kenya, where economic transformation is occurring alongside ambitious climate commitments and increasing pressure to achieve sustainable development. Although aggregate measures of economic growth provide useful insights into the growth-environment relationship, they may conceal important sector-specific dynamics that are critical for effective climate policy. Disaggregating economic growth into agricultural, industrial and service sector value added offers a more comprehensive understanding of how structural change influences carbon emissions and provides evidence to support targeted mitigation strategies aligned with Kenya's Vision 2030, the National Climate Change Action Plan (2023-2027) and the country's Nationally Determined Contributions (NDCs). It is within this theoretical and policy context that the present study examines how value added in the agricultural, industrial and service sectors influences carbon dioxide (CO_2) emissions in Kenya.

Several studies have linked economic growth as measured by Gross Domestic Product (GDP) or per capita GDP to the deterioration in the environment. Examples of studies that found a positive link between economic growth and the environment include those of Aboagye (2017), Aboagye *et. al.,* (2020), Kwakwa *et. al.,* (2018), Gamage *et. al.,* (2017) and Haq *et. al.,* (2016) among others. Agriculture, industry and service are the main sectors that drive economic growth in any country. Agriculture, being the primary sector of many economies, plays a crucial role in boosting the economy, structural transformation and poverty reduction (Cervantes-Godoy and Dewbre, 2010).

Despite its important contribution to growth, poverty reduction and food security, Agriculture, Forestry and Land Use Change (AFOLU) is responsible for about 25% of global greenhouse gas emissions. The major causes of these emissions being deforestation, livestock rearing, rice cultivation, use of manure and chemical fertilizers, waste and landfills from municipal (Appiah *et. al.,* 2018). Expansion of agricultural value added is expected to exert a positive effect on

carbon dioxide emissions since expansion of agricultural production is associated with mechanization, land-use changes and increased energy use within the sector (Kwakwa, 2023).

Industrialization, a key driver of economic growth, is usually accompanied by environmental degradation (Loganathan*, et. al.,* 2014). Major challenges in the bid to reduce emissions lie in the major hard-to-abate sectors such as cement, steel, chemicals, plastics and heavy-goods transport. The key subsectors in Kenya's industrial sector comprise of manufacturing, construction, mining and quarrying (KNBS, 2020). Growth in the industrial sector generally increases carbon emissions, reflecting the sector's reliance on fossil fuels, energy-intensive production processes, and manufacturing activities.

The structural transformation in an economy leads to a change in the composition of economic activity which shifts production from high polluting industry to low polluting services (Marsiglio, *et. al.,* 2016). Service sector growth is expected to have a negative effect on carbon emissions since it is less polluting compared to agriculture and industry (Aboagye *et. al.,* 2020). However, contrary to the common perception that the service sector is relatively clean, some studies found that service sector expansion can raise carbon dioxide emissions if growth of transport, tourism, commercial activities, communication and other service-related activities increases energy demand and fossil fuel consumption (Kwakwa, 2023).

Energy consumption has a positive association with economic growth since its intake enhances output growth especially in developing economies (Chunyu *et. al.,* 2021). This positive association also enhances carbon emissions hence decline in environmental quality especially if energy comes from non-renewable sources such as fossil fuel (Shafiei and Salim 2014). As indicated by El-Montasser and Ben-Salha, (2019), the impact of energy use on the environment is negative when considering renewable energy sources such as hydropower, geothermal, wind and solar energy. According to Enerdata, (2023), energy consumption in Kenya increased at an average yearly rate of 2.2% between 2010 and 2022. As of the year 2022, per capita energy consumption was approximately 0.54 tons of oil equivalent (toe) and per capita electricity consumption at 190 kWh. In Sub-Saharan Africa, Kenya is a pioneer in the development of renewable energy with geothermal, hydroelectric and wind power accounting for more than 87% of the nation's electrical generation in 2022 (EPRA, 2023). Renewable energy sources, especially geothermal (47%), hydropower (23%) and wind (13%) account for the majority of Kenya's energy mix (IEA, 2025). Despite this enormous role played by renewable energy, fossil fuels still play a critical role in industries in supporting production and transportation activities (GoK, 2023) hence renewable energy alone may not be sufficient to lower total emissions if other sectors, such as transport and informal settlements remain heavily reliant on fossil fuels.

Problem Statement

Climate change continues to pose a significant challenge to sustainable development, with rising carbon dioxide (CO_2) emissions remaining one of the principal drivers of global warming (IPCC, 2022). For developing countries such as Kenya, the challenge lies in sustaining economic growth while reducing environmental degradation. Through Kenya Vision 2030, the country seeks to accelerate industrialization, agricultural transformation, and expansion of the service sector to achieve upper-middle-income status, while its Nationally

Determined Contributions (NDCs) commit to reducing greenhouse gas emissions by 32% by 2030 relative to the business-as-usual scenario (Government of Kenya, 2007; Government of Kenya, 2020). Achieving these development and climate objectives requires a clear understanding of how economic growth contributes to carbon emissions.

Kenya's economy grew by 4.7% in 2024, with the service sector accounting for 61.3% of GDP, followed by agriculture (21.8%) and industry (16.9%) (KNBS, 2025). Although these sectors are central to employment, income generation and economic transformation, they differ considerably in their production technologies, energy use and carbon intensity. Industrial activities are generally more energy intensive and directly associated with CO_2 emissions, while the service sector contributes indirectly through transport, commercial activities, and increasing electricity demand. Conversely, agriculture contributes relatively less to carbon dioxide emissions, although it remains a major source of other greenhouse gases such as methane and nitrous oxide (IPCC, 2018; IEA, 2024). These differences suggest that the environmental implications of sectoral growth cannot be adequately understood using aggregate measures of economic performance alone.

Kenya's economy is dominated by the service sector, followed by agriculture and industry. Despite their contribution to economic growth, these sectors differ considerably in production technologies, energy requirements and carbon intensity. Consequently, analysing aggregate GDP alone may obscure sector-specific effects on carbon dioxide emissions. Table 1 summarizes the relative economic importance of each sector and their expected implications for CO_2 emissions.

Table 1: Kenya's Economic Structure and Sectoral Contributions to Carbon Dioxide (CO_2) Emissions in 2024

Economic Sector	Contribution to GDP (%)	Principal Economic Activities	Expected Implications for CO_2 Emissions
Agriculture	21.8	Crop production, livestock, forestry and fisheries	Agriculture has relatively low direct CO_2 emissions compared with industry because much of its emissions arise from biological processes. However, mechanization, agro-processing and increased fossil fuel use contribute to CO_2 emissions. The sector remains the largest source of methane (CH_4) and nitrous oxide (N_2O), which are outside the scope of this study.
Industry	16.9	Manufacturing, mining, quarrying, construction and utilities	Industry is expected to contribute the highest direct CO_2 emissions due to energy-intensive manufacturing processes, cement production, industrial fuel combustion and construction activities.
Services	61.3	Transport, trade, finance, information and communication technology (ICT), tourism, education, health and public administration	Although generally less carbon intensive than manufacturing, the expansion of transport services, commercial buildings and electricity consumption contributes indirectly to increasing

Sources: Kenya National Bureau of Statistics (KNBS, 2025); International Energy Agency (IEA, 2024)

As shown in Table 1, the three sectors contribute differently to Kenya's economic output and exhibit distinct emission characteristics. While industry is generally expected to generate the highest direct CO_2 emissions because of its energy-intensive activities, the service sector contributes indirectly through transport, commercial activities and electricity consumption. Agriculture, although a major contributor to greenhouse gas emissions through methane and nitrous oxide, has comparatively lower direct CO_2 emissions. These differences support the argument that aggregate GDP may mask sector-specific environmental effects, reinforcing the need for a disaggregated analysis of agricultural, industrial and service sector value added.

Existing empirical studies have identified economic growth, energy consumption, trade openness, foreign direct investment, urbanization, financial development and natural resource utilization as important determinants of carbon emissions (Stern, 2004; Bekun *et al.,* 2019; Usman *et al.,* 2022). However, most studies conducted in Kenya and other African economies have relied on aggregate GDP as a proxy for economic growth, implicitly assuming that all sectors exert similar effects on carbon emissions. Consequently, limited attention has been given to examining how agricultural, industrial, and service sector value added individually influence carbon dioxide emissions, despite their distinct economic characteristics and environmental impacts. Moreover, empirical evidence on whether positive and negative changes in sectoral value added have asymmetric effects on carbon emissions remains particularly scarce within the Kenyan context.

Understanding which sectors contribute most to carbon emissions, and whether increases and decreases in sectoral output affect emissions differently, can support more targeted and effective climate policies. Therefore, this study employs the Nonlinear Autoregressive Distributed Lag (NARDL) model to examine the asymmetric effects of agricultural, industrial, and service sector value added on carbon dioxide emissions in Kenya. By providing sector-specific evidence, the study contributes to the literature on economic growth and environmental sustainability while informing the implementation of Kenya Vision 2030, the National Climate Change Action Plan (2023-2027), and Kenya's Nationally Determined Contributions (NDCs) through more targeted low-carbon development strategies.

Materials and Methods

This study employs longitudinal time series research design by utilizing annual time series data for the respective variables covering the period 1990-2021 which was obtained from World Banks' World Development Indicators Database. Empirical analyses and econometric estimations were conducted using Stata version 15.0 and EViews version 9. The study was guided by the Environmental Kuznets (EK) theory which states that an inverse U relationship exists between carbon emissions and income (Grossman and Krueger, 1991). The EK theory postulates that environmental degradation increases at lower levels of per capita income and tends to decline at higher level of per capita income.

The early stages of development are associated with pollution resulting from increasing production and extraction of natural resources. This is called the scale effect of production on environment which results in the upward trend of an EKC (Mäler, 2013). However, when production shifts from primary to industrial production, economic expansion gives rise to the establishment

of information-based industry and services (composition effect) as well as improvement in production techniques or adoption of cleaner technology (technique effect) (Aboagye and Alagidede, 2016). Both composition and technique effects can overcome the scale effect and generate the downward trend of an EKC curve (Panayotou, 2003).

Unit root test

Given that many economic time series data are non-stationary, some transformation such as differencing is typically needed to make them stationary. In the presence of non-stationary variables, a spurious regression might be the result (Musibau *et. al.,* 2021). The order of integration was determined by use of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit-root tests. For ADF test equation 1 is estimated for each of the variables;

$$\Delta Y_t = \alpha_0 + \beta_0 T + \gamma Y_{t-1} + \sum_{i=1}^{k} \alpha_1 \Delta Y_{t-i} + \varepsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where Y represents each of the variables, β is the coefficient on time trend T, Y_{t-i} are lagged values for the variables and k is the lag. The lag length is set by use of Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC) and Schwartz Bayesian Information Criterion (SBIC) (Kong and Khan, 2019).

The ADF tests the null hypothesis that $H_0: \gamma = 0$; that is the variable in question contains a unit root against the alternative that $H_1: \gamma < 0$; that is, the variable in question is stationary. If the t-statistic exceeds the DF or MacKinnon critical values, the null hypothesis is rejected. The Phillips Perron (PP) Unit Root Test modifies the ADF test to accommodate serial correlation. The null hypothesis is that the variable contains unit root against the alternative that the variable is stationary. It involves fitting the regression in equation 2:

$$y_i = \alpha + \rho y_{i-1} + \epsilon_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\

series while y_t is the observed time series and δ is the size of the outlier.

The IO on the other hand is a type of observation where the outlier has its origin in the underlying noise process. Assuming an AR (1) structure with drift, innovational outlier (IO) model is specified as:

$$y_t = \mu + \frac{1}{1-\rho L}\delta I_t\,[t = T_{IO}] + z_t; z_t = \rho z_{t-1} + \varepsilon_t \quad \ldots\ldots\ldots\

Once the variables are decomposed into their respective positive and negative partial sums a shown in equations (3) to (8), the nonlinear ARDL specification becomes:

$$\Delta lnCO_{2t} = \gamma_o + \gamma_1 lnCO_{2t-1} + \gamma_2^+ lnAGDP_{t-1}^+ + \gamma_3^- lnAGDP_{t-1}^- + \gamma_4^+ lnSGDP_{t-1}^+ + \gamma_5^- lnSGDP_{t-1}^- + \gamma_6^+ lnIGDP_{t-1}^+ + \gamma_7^- lnIGDP_{t-1}^- + \gamma_8 lnRNE_{t-1} + \sum_{i=1}^{n1} \lambda_1 \Delta lnCO_{2t-i} + \sum_{i=0}^{n2} \lambda_2 \Delta lnAGDP_{t-i}^+ + \sum_{i=0}^{n3} \lambda_3^- \Delta lnAGDP_{t-i}^- + \sum_{i=0}^{n4} \lambda_4^+ \Delta lnSGDP_{t-i}^+ + \sum_{i=0}^{n5} \lambda_5^- \Delta lnSGDP_{t-i}^- + \sum_{i=0}^{n6} \lambda_6^+ \Delta lnIGDP_{t-i}^+ + \sum_{i=0}^{n7} \lambda_7^- \Delta lnIGDP_{t-i}^- + \sum_{i=1}^{n8} \lambda_8 \Delta lnRNE_{t-i} + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (14)$$

Where γ_0 is the intercept term, Δ is the first difference operator, $\gamma_{1,..,8}$ are the long run coefficients which capture the long run impact of explanatory variables on CO_2 emissions, $\lambda_{1,...,8}$ are the short run coefficients, $n_{1,..,8}$ are the optimum lag orders selected by AIC and SBIC criteria and all other variables are as previously defined. Testing for cointegration uses the null hypothesis: $H_0: \gamma_1 = \gamma_2^+ = \gamma_3^- = \gamma_4^+ = \gamma_5^- = \gamma_6^+ = \gamma_7^- = \gamma_8 = 0$ against the alternative hypothesis that: $H_1: At\ least\ one\ of\ \gamma_1, \gamma_2^+, \gamma_3^-, \gamma_4^+, \gamma_5^-, \gamma_6^+, \gamma_7^-, \gamma_8 \neq 0$. If cointegration is confirmed by use of bounds test, then the long run and short run relationship between the respective variables and CO_2 is examined. If cointegration is not confirmed, then only the short run form of the nonlinear ARDL model is estimated.

Wald Asymmetry Test

Following the estimation of the NARDL model and confirmation of a long-run relationship through the bounds testing procedure, the study employed the Wald test to determine whether positive and negative changes in sectoral value added exert asymmetric effects on carbon dioxide (CO_2) emissions. Consistent with Shin *et al.* (2014), the Wald test examines whether the coefficients associated with the positive and negative partial sum decompositions are statistically different in both the long run and the short run.

The null hypothesis for the long-run asymmetry test is specified as: $H_0: \gamma_i^+ = \gamma_i^-$ against the alternative hypothesis:$H_1: \gamma_i^+ \neq \gamma_i^-$.

Where γ_i^+ and γ_i^- denote the long-run coefficients associated with positive and negative changes in the respective explanatory variable.

Similarly, the short-run asymmetry was examined by testing the equality of the cumulative short-run coefficients associated with the positive and negative partial sums. The hypotheses are specified as: $H_1: \lambda^+ = \lambda^-$ against $H_1: \lambda^+ \neq \lambda^-$.

Where λ_{ij}^+ and λ_{ij}^- represent the cumulative short-run coefficients associated with positive and negative changes in the explanatory variable, respectively.

The Wald statistics follow an asymptotic chi-square (χ^2)distribution. Rejection of the null hypothesis indicates the presence of asymmetry, implying that positive and negative changes in sectoral value added exert significantly different effects on carbon dioxide (CO_2) emissions. Conversely, failure to reject the null hypothesis suggests that the effects are symmetric (Shin *et al.,* 2014).

Diagnostic Tests

Diagnostic tests are important in empirical analysis since they are used to test the robustness of the model. Such tests include stability tests, normality tests, heteroscedasticity tests and serial correlation tests (Ssekuma, 2011). The diagnostic tests are Breusch-Godfrey LM test for serial correlation, Jarque-Bera test for normality, autoregressive conditional heteroskedasticity test and white heteroskedasticity test for heteroskedasticity, Ramsey RESET test for

the functional form and cumulative sum of recursive residuals (CUSUM) and cumulative sum of squares of recursive residuals (CUSUMSQ) for model stability.

Normality Test:

Jarque-Bera test measures whether the series follows a normal distribution or not (Jarque and Bera, 1980). In the Jarque-Bera test, the null and alternative hypotheses are set as follows:

H_0: *The variable is normally distributed*

H_1: *The variable is not normally distributed*

The JB test statistic is defined as:

$$JB = \frac{N-k}{6}\left[S^2 + \frac{(K-3)^2}{4}\right]$$

Where k is the number of estimated parameters S, K and N denote the sample skewness, the sample kurtosis and the sample size respectively. This test statistic is compared with a χ^2 (chi square) distribution with $N-k$ degrees of freedom. The null hypothesis of normality is rejected if the calculated test statistic exceeds a critical value from the χ^2 distribution.

Serial Correlation

Serial correlation is the relationship between a given variable and a lagged version of itself over various time intervals. It may be caused by non-stationarity of variables, data manipulation (averaging, interpolation and extrapolation) and incorrect functional form. This study used Breusch-Godfrey test for serial correlation. Breusch and Godfrey (1978) autocorrelation test is more flexible, covering autocorrelation of higher orders and applicable whether or not the regressors include lags of the dependent variable. Serial correlation causes the estimated variances of the regression coefficients to be biased thus leading to unreliable hypothesis testing.

The null and alternative hypotheses are stated as:

H_0: *No Autocorrelation*

H_1: *Autocorrelation exists*

Breusch (1978) and Godfrey (1978) proved that if the following auxiliary regression model is fitted

$\hat{\mu}_t = \alpha_1 + \alpha_2 X_t + \hat{\rho}_1\hat{\mu}_{t-1} + \hat{\rho}_2\hat{\mu}_{t-2} + \cdots + \hat{\rho}_p\hat{\mu}_{t-p} + \varepsilon_t$, and R^2 is obtained, then the Chi square statistic (χ_p^2) is obtained as $(n-p)R^2$.

The $\hat{\mu}_t$ represent sample residuals, n number of observations, p is the lag order and to test the null hypothesis of no autocorrelation the Chi square statistic (χ_p^2) is compared with the critical value that is if the $\chi_p^2 > \chi_{crit}^2$ then the null hypothesis is rejected. Alternatively, the F-statistic can be used. If $F_{Cal} > F_{Crit}$ then the null hypothesis is rejected.

Heteroskedasticity

Heteroskedasticity occurs when the variance of the disturbance term is not constant. Hence, the t-values for the estimated coefficients cannot be trusted. A Breusch-Pagan test was used to test for heteroskedasticity. The null hypothesis is that homoskedasticity (or constant variance) exists and the alternative hypothesis is that heteroskedasticity exists.

H_0: *Homoscedasticity exists* (Constant variance)

H_1: *Heteroscedasticity exists* (Variance is not constant)

The Chi-Square test statistic is calculated as nR^2 where n is the number of observations, and R^2 is the coefficient of determination of the augmented residual regression. The null hypothesis is rejected if the p-value is less than the level of significance.

Ramsey RESET Test

To identify whether the functional form of the model is wrongly specified, Ramsey Regression Equation Specification Error Test (RESET) is used. The test identifies if there exists any omitted variable bias and data transformation bias (taking logs, power and interactions). The

null hypothesis of correct specification is tested against the misspecification (as alternate hypothesis). If the null hypothesis is not rejected, then a good functional form of the model is inferred.

Results and Discussion

The descriptive statistics results are presented in table 2. Based on the empirical results in table 2, a comparison of mean values for sector value added to GDP reveal that service sector GDP has the highest mean followed by agriculture and finally industry. The parameter skewness for all the variables is less than 1 which shows that the variables are moderately skewed. The Jarque-Bera normality test results show that all the variables except renewable energy conform with normality.

Table 2: Descriptive Statistics (ln)

Variables	Mean	Std. Dev.	Median	max	min	skewness	kurtosis	JB	p-value
lnCO_2	9.216	.456	9.082	10.045	8.676	.474	1.829	3.026	0.2202
lnRNE	4.354	.06	4.371	4.472	4.210	-.585	3.267	1.921	0.3828
lnAGDP	23.076	.243	23.098	23.466	22.694	-.034	1.755	2.074	0.3545
lnIGDP	22.894	.35	22.810	23.537	22.477	.429	1.692	3.263	0.1956
lnSGDP	23.812	.626	23.905	24.7	22.401	-.543	2.397	2.057	0.3576

Source: Study Findings (2024)

Unit Root Analysis

In this study unit root tests were conducted with and without structural breaks. For unit root tests without structural breaks ADF and PP tests were done whereas Clemente-Montanes-Reyes (CMR) test was used for testing for unit roots with two structural breaks. For ADF, the optimal lag has to be established. The maximum lag length was therefore established at 4 lags from which the optimal lag based on AIC, SBIC and HQIC was obtained. The PP test does not require setting an optimal lag length. The optimal lags for the respective variables are as shown in table 3.

Table 1: Optimal Lag Length for Respective Variables

VARIABLE	LAG LENGTH
CO_2	1
RNE	1
AGDP	0
SGDP	2
IGDP	3

Source: Study Findings (2024

The results for non-structural break stationary test (ADF and PP) are shown in table 4 for intercept and intercept and trend conditions. The results indicate that all variables are first difference stationary at 5% level of significance. As such the order of integration is one that is I(1).

The critical values at 5% for both ADF and PP tests for model with intercept at level and first difference and for intercept and trend for various lags are as shown in table 4. The lag order selection for ADF is by AIC, SBIC and HQIC.

Table 2: ADF and PP Unit Root Test Results

		ADF		PP		Conclusion
		T	P value	T	P value	
CO_2	Intercept First Diff	1.743	0.9982	2.522	0.9991	N
	I&T	-4.191	0.0007	-6.517	0.0000	S
	First Diff	0.975	0.9474	-1.080	0.9324	N
		-5.506	0.0000	-8.840	0.0000	S
RNE	Intercept	0.254	0.9752	0.961	0.9938	N
	First Diff	-4.470	0.0002	-4.602	0.0001	S
	I&T	-1.344	0.8767	-1.254	0.8988	N
	First Diff	-5.639	0.0000	-5.368	0.0000	S
AGDP	Intercept First Diff	0.978	0.9940	1.252	0.9963	N
	I&T	-4.307	0.0004	-6.961	0.0000	S
	First Diff	-3.314	0.0639	-3.809	0.0161	N/S
		-4.419	0.0020	-7.514	0.0000	S
IGDP	Intercept First Diff	1.673	0.9981	2.652	0.9991	N
	I&T	-5.499	0.0000	-5.500	0.0000	S
	First Diff	-1.147	0.9207	-0.875	0.9587	N
		-6.671	0.0000	-7.630	0.0000	S
SGDP	Intercept First Diff	2.658	0.9991	4.641	1.0000	N
	I&T	-6.146	0.0000	-6.549	0.0000	S
	First Diff	0.051	0.9947	1.399	1.0000	N
		-8.705	0.0000	-8.575	0.0000	S

Note: *The null hypothesis is that the time series has a unit root or non-stationary. If the absolute value of the ADF or PP is lower than their critical statistics, the study fails to reject the null hypothesis of non-stationarity. The p-values also provide a basis for rejection of the null hypothesis. First Diff. denotes first difference; I&T represents intercept and trend. S denotes stationary, N denotes non-stationary, N/S denotes stationary under PP but not under ADF and S/N denotes stationary under ADF and not under PP.*

Source: Study Findings (2024)

After testing for unit root using the traditional ADF and PP procedure, the Clemente-Montanes-Reyes ((CMR) structural break test was conducted. The results for Clemente-Montanes-Reyes are presented in table 5 and table 6 where Table 5 present results for additive outliers and 6 present results for the innovative outliers. This study adopts the IO results since in the IO model the assumption is that structural changes take place gradually and allows for a break in both the slope and the intercept of the model. All variables were first difference stationary in both the AO and IO cases.

Table 5: Clemente-Montañes-Reyes Additive Outliers Unit Root Test Results

	Test Statistic	Level SB1	SB2	Conclusion	Test Statistic	First Diff. SB1	SB2	Conclusion
CO_2	-3.441	2006(0.000)	2013(0.000)	Not stationary	-6.542	2001(0.420)	2010(0.463)	Stationary
AGDP	-2.706	2002(0.000)	2012(0.000)	Not stationary	-5.988	1999(0.471)	2007(0.910)	Stationary
SGDP	-2.704	2004(0.000)	2015(0.000)	Not stationary	-9.945	2006(0.212)	2015(0.120)	Stationary
IGDP	-3.031	2007(0.000)	2015(0.000)	Not stationary	-8.201	2003(0.302)	2010(0.300)	Stationary
RNE	-4.948	2011(0.000)	2016(0.000)	Not stationary	-6.753	2001(0.313)	2003(0.116)	Stationary

Source: Study Findings (2024)

In the AO model the assumption is that structural changes is rapid and allow for a break in only the slope. H_0: The series are not stationary with structural breaks and H_1: The series are stationary with break. SB1 and SB2 denote the structural break dates, values in brackets are the p-values for respective break dates. The critical value at 5% is -5.490.

Table 6: Clemente-Montañes-Reyes Innovative Outliers Unit Root Test Results

Variable	Test Statistic	Level SB1	SB2	Conclusion	Test Statistic	First Diff. SB1	SB2	Conclusion
CO_2	-0.827	2002(0.044)	2014(0.121)	Not stationary	-6.327	2007(0.020)	2018(0.477)	Stationary
AGDP	-1.983	1996(0.052)	2009(0.054)	Not stationary	-9.072	1993(0.007)	2008(0.176)	Stationary
SGDP	-2.704	2008(0.447)	2013(0.139)	Not stationary	-6.241	2007(0.000)	2014(0.000)	Stationary
IGDP	-0.161	2004(0.001)	2011(0.001)	Not stationary	-5.790	2004(0.000)	2013(0.005)	Stationary
RNE	-2.990	2011(0.001)	2018(0.080)	Not stationary	-6.527	2002(0.051)	2014(0.170)	Stationary

In the IO model the assumption is that structural changes take place gradually and allows for a break in both the slope and the intercept of the model. H_0: The series are not stationary with structural breaks and H_1: The series are stationary with structural break. SB1 and SB2 denote the structural break dates, values in brackets are the p-values for respective break dates. The critical value at 5% is -5.490.

Source: Study Findings (2024)

The IO results in table 6 indicate that the variables are first difference stationary. The structural break dates SB1 and SB2 are usually associated with major economic, political and institutional or policy changes in the economy hence understanding these breaks is crucial for accurate economic analysis and policy formulation (Lean & Smyth, 2014). In 2002, a notable structural break in CO_2 emissions coincided with a peaceful political transition that spurred economic recovery and industrial growth, leading to increased emissions (UNFCCC, 2021). For the second structural break that is in 2014, the implementation of Vision 2030 projects, focusing on infrastructure development, further elevated industrial activities and urbanization, contributing to higher CO_2 levels (KNBS, 2023).

From the results, Agriculture sector value added to GDP (AGDP) experienced structural breaks in 1996 and 2009. The 1996 break could be associated with drought and economic policies which affected agricultural productivity (FAO, 2022). In 2009, severe drought conditions experienced in the country led to reduced agricultural output, highlighting the sector's sensitivity to climatic variations (ADB, 2022). The spillover effects of the 2007-2008 post-election violence which led to displacement of people could be another possible factor contributing to the 2009 break.

The service sector value added to GDP saw breaks in the years 2008 and 2013 whereby the 2008 disruption is possibly linked to post-election violence, which affected services like tourism and finance (Brookings Institution, 2020). Also, the global financial crisis of 2007/2008 could have contributed to this break. By 2013, growth in financial services, including mobile banking innovations like M-Pesa, marked a positive structural change (IMF, 2023). The industry sector value added to GDP (IGDP) experienced shifts in 2004 and 2011. The 2004 break corresponds with industrial expansion and increased manufacturing activities given the economic recovery after the 2002 elections and the new government putting in place policies that led to economic growth (KNBS *et. al*, 2023). In 2011, government infrastructure projects spurred growth in the construction sector, reflecting targeted policy interventions (World Bank, 2023).

The structural break analysis identified break dates in 2011 and 2018, indicating important shifts in Kenya's renewable energy consumption. The 2011 break coincides with the implementation of Kenya Vision 2030, which prioritised renewable energy development through increased investment in geothermal power and other indigenous energy sources (Government of Kenya, 2007; Kiplagat *et al.,* 2011). The 2018 break corresponds to a period of continued renewable energy expansion following the adoption of the National Energy Policy of 2018 and increased investment in geothermal and wind energy projects, reinforcing Kenya's transition towards a cleaner energy system (Government of Kenya, 2018; IEA, 2023).

Bounds Cointegration Test

After testing for stationarity, the study proceeded by conducting bounds test for cointegration so as to determine whether cointegration exists or not. Because the NARDL model is sensitive to lag specification, the maximum lag length was restricted to two, consistent with Hamuda *et.al* (2013). This approach was adopted to obtain a parsimonious model suitable for the annual data and the relatively small sample size. The final NARDL specification was selected from the candidate models generated within the specified maximum lag and was subsequently subjected to the bounds test for cointegration, Wald tests for

asymmetry and a series of post-estimation diagnostic tests to ensure the adequacy of the estimated model. Table 7 presents the NARDL Bounds test results.

Table 7: Non-linear ARDL Bounds Test Results

Sample: 1992 2021		
Null Hypothesis: No long-run relationships exists		
F-statistic	**4.707**	
	Critical Value Bounds	
Significance	**I(0)**	**I(1)**
10%	2.030	3.130
5%	2.320	3.500
2.5%	2.600	3.840
1%	2.960	4.260

The bounds test was conducted under Case III (unrestricted intercept and no deterministic trend) using $k = 4$ long-run regressors. (0) and I(1) are lower bound and upper bound respectively. H_0: no levels relationship. Accept H_0 if F < critical value for I(0) regressors and reject if F > critical value for I(1) regressors.

Source: Study Findings (2024)

From the bounds test results, the F statistic (4.707) is greater than the upper bound, I(1) bounds value of 3.500 at 5% significance level hence the null hypothesis of no levels relationship is rejected. The results show that there exists a long run relationship among the variables hence the study proceeds by estimating the Nonlinear ARDL cointegrating relationship. Following the selection of a maximum lag length of two, the optimal specification was identified as NARDL (1,1,1,1,1,1,2,1). The lag structure corresponds to one lag for $\ln CO_2$, $\ln AGDP^+$, $\ln AGDP^-$, $\ln SGDP^+$, $\ln SGDP^-$, $\ln IGDP^+$ and lnRNE and two lags for $\ln IGDP^-$ as presented in table 8.

Table 8: NARDL Regression Estimates

NARDL(1,1,1,1,1,1,2,1) Regression				
Sample: 1993 - 2021		**Number of obs. = 29**		
ΔlnCO_2	**Coef.**	**Std.Err.**	**t**	**P>t**
ECT	-0.904	0.149	-6.069	0.000
Long Run				
$\ln AGDP^+$	2.734	0.754	3.630	0.003
$\ln AGDP^-$	-1.800	0.942	-1.910	0.077
$\ln SGDP^+$	-0.213	0.098	-2.170	0.049
$\ln SGDP^-$	0.594	0.210	2.820	0.014
$\ln IGDP^+$	-0.727	0.316	-2.300	0.039
$\ln IGDP^-$	5.486	1.903	2.880	0.013
lnRNE	-5.036	1.231	-4.090	0.026
Short Run				
$\Delta\ln AGDP^+$	0.321	0.098	3.280	0.047
$\Delta\ln AGDP^-$	-1.444	0.411	-3.510	0.039
$\Delta\ln SGDP^+$	0.199	0.058	3.410	0.005
$\Delta\ln SGDP^-$	-0.354	0.127	-2.800	0.015
$\Delta\ln IGDP^+$	0.372	0.325	1.150	0.273

ΔlnIGDP⁻	-1.729	1.158	-1.490	0.159
ΔlnIGDP⁻(-1)	-4.065	1.305	-3.120	0.008
ΔlnRNE	-3.755	0.284	-13.230	0.000
Constant	-2.007	0.389	-5.160	0.000
R-squared	0.9883	Adj R-squared	0.9727	
F-Statistic	27.76	Durbin-Watson stat.	2.0352	
Prob(F-statistic)	0.0000	Jarque Bera	2.3515	
Heteroskedasticity Test: Breusch-Pagan-Godfrey (0.6744)		Ramsey RESET F-statistic	0.53	
F-statistic	0.09 (0.7673)			
Breusch-Godfrey Serial Correlation LM Test				
F-statistic	0.045 (0.8319)			

Source: Study Findings (2024)

Error Correction Term (ECT)

The results in table 8 the estimated error correction term (ECT) is negative and statistically significant (−0.904, $p < 0.01$), confirming the existence of a stable long-run relationship between carbon emissions and sector value added to GDP. The coefficient suggests that about 90.4% of short-run disequilibria are eliminated within one year, indicating that carbon emissions tend to return quickly to their long-run equilibrium after temporary disturbances. While the estimated adjustment speed is relatively high, the negative and significant ECT provides evidence that the model converges to its long-run equilibrium.

Short-Run Estimates

The short-run results show that changes in sector value added to GDP are associated with different responses in carbon emissions. Positive changes in agricultural value added ($\Delta lnAGDP^{+}$) have a positive and significant relationship with carbon emissions ($\beta = 0.321$, $p = 0.047$), while negative changes ($\Delta lnAGDP^{-}$) are associated with a decline in emissions ($\beta = -1.444$, $p = 0.039$). This pattern suggests that periods of agricultural expansion are accompanied by activities such as increased mechanization, fertilizer application and land conversion, all of which are likely to raise emission levels. Similar evidence was reported by Appiah *et al.* (2018), who found that agricultural production contributed to rising carbon emissions in emerging economies. Agboola and Bekun (2019) also observed that agricultural value added can worsen environmental quality where production depends on carbon-intensive practices.

A similar pattern is observed in the service sector. Positive changes in service sector value added ($\Delta lnSGDP^{+}$) are associated with higher carbon emissions ($\beta = 0.199$, $p = 0.005$), whereas negative changes ($\Delta lnSGDP^{-}$) are linked to lower emissions ($\beta = -0.354$, $p = 0.015$). A possible explanation is that expansion of Kenya's service sector continues to rely heavily on transport, trade and other commercial activities that consume fossil-fuel-based energy. This contrasts with findings from some developed economies, where growth in knowledge-based services has been associated with lower carbon emissions as economies become less dependent on energy-intensive production.

The results for the industrial sector are less straightforward. Although positive changes in industrial value added

(ΔlnIGDP^{+}) have a positive coefficient, the effect is not statistically significant (β = 0.372, p = 0.273), suggesting that increases in industrial output do not immediately translate into changes in carbon emissions. However, the lagged effect of a decline in industrial value added is negative and significant (ΔlnIGDP^{-}(-1): β = –4.065, p = 0.008), indicating that lower industrial activity is followed by reduced emissions after about one year. This differs from the findings of Bekun *et al.* (2019), who reported industrialization as a major contributor to carbon emissions but complies with that of Fida and Saeed (2023). One possible explanation is Kenya's increasing reliance on cleaner electricity sources, particularly geothermal energy.

Renewable energy consumption is negatively and significantly related to carbon emissions in the short run (β = –3.755, p < 0.001). While the estimated coefficient is relatively large, the direction of the relationship is consistent with earlier studies. This is in agreement with the assumption that increased use of renewable energy improves the environment as it uses cleaner energy sources (Adebayo *et.al.,* 2021). Aydoğan and Vardar (2020), Dauda *et al.* (2023) and Wang *et al.* (2023) similarly found that greater use of renewable energy contributes to lower carbon emissions. In Kenya, continued investment in geothermal, wind and other renewable energy sources may partly explain this relationship by reducing dependence on conventional fossil fuels.

Long-Run Estimates

The long-run estimates show that sector value added to GDP is associated with carbon emissions in different ways across the three sectors. With the exception of the negative partial sum of agricultural value added, which is significant at the 10% level, all long-run coefficients are statistically significant at the 5% level. The positive changes in agricultural value added (lnAGDP^{+}) have a positive and significant association with carbon emissions (β = 2.734, p = 0.003), while the coefficient for agricultural decline (lnAGDP^{-}) is negative but only weakly significant (β = –1.800, p = 0.077). The positive coefficient indicates that sustained growth in the agricultural sector tends to coincide with higher carbon emissions. This outcome is not unexpected given the continued expansion of cultivated land, increased use of agricultural inputs and mechanization.

Comparable results were reported by Appiah *et al.* (2018), who found that agricultural production contributed to higher carbon emissions in emerging economies. Agboola and Bekun (2019) reached a similar conclusion, arguing that agricultural value added can increase environmental pressure where production systems remain carbon intensive. These findings underline the importance of improving agricultural productivity through sustainable farming practices rather than expanding production at the expense of environmental quality.

A different pattern emerges for the service sector. Positive changes in service sector value added (lnSGDP^{+}) are associated with lower carbon emissions (β = –0.213, p = 0.049), whereas declines in the sector (lnSGDP^{-}) are associated with higher emissions (β = 0.594, p = 0.014). This suggests that as Kenya's economy gradually shifts towards service-based activities, the long-run environmental impact may become less pronounced. Similar observations were made by Seri and de Juan Fernández (2023), who found that expanding service-oriented economies can ease environmental pressure over time. Perera (2025) likewise reported that improvements in

technology and energy efficiency strengthen the environmental benefits associated with service sector growth. In Kenya, this may reflect the gradual transition away from more energy-intensive activities alongside increased adoption of cleaner technologies.

The industrial sector presents a less conventional result. Positive changes in industrial value added ($\ln IGDP^{+}$) are negatively associated with carbon emissions ($\beta = -0.727$, $p = 0.039$), while reductions in industrial output ($\ln IGDP^{-}$) are positively associated with emissions ($\beta = 5.486$, $p = 0.013$). This contrasts with the findings of Bekun *et al.* (2019) and Usman *et al.* (2022), who reported that industrial expansion generally contributes to higher carbon emissions. One possible explanation is that industrial growth in Kenya has increasingly relied on relatively cleaner electricity sources, particularly geothermal energy, together with gradual improvements in production efficiency. Even so, this result differs from much of the existing empirical evidence and should therefore be interpreted with caution.

Renewable energy consumption retains a negative and statistically significant relationship with carbon emissions in the long run ($\beta = -5.036$, $p = 0.026$), reinforcing the short-run results. Rather than focusing on the magnitude of the coefficient, the important result is its direction, which indicates that greater reliance on renewable energy is associated with lower emission levels over time. This is consistent with the findings of Adebayo *et al.* (2021), Chunyu *et al.* (2021), and Ozcan and Ozturk (2019), all of whom reported that renewable energy plays an important role in reducing carbon emissions. Kenya's continued investment in geothermal, wind and other renewable energy sources may partly explain this long-run relationship.

Taken together, the long-run results suggest that the relationship between sectoral growth and carbon emissions is not uniform across the economy. Agricultural expansion remains closely associated with higher emissions, while sustained growth in the service sector appears to support better environmental outcomes. The industrial sector exhibits a relationship that departs from the dominant evidence in the literature and therefore calls for further investigation. In contrast, renewable energy consistently emerges as an important factor associated with lower carbon emissions in Kenya. Once the short run and long run relationship between the sector value added to GDP and carbon emissions was established, it was necessary to check for the presence of asymmetry both in the short run and long run. To achieve this, Wald test was conducted.

Wald Test Results

After establishing the short-run and long-run relationships between sector value added to GDP and carbon emissions, the Wald test was used to determine whether positive and negative changes in sectoral output have symmetric or asymmetric effects on carbon emissions. The results are presented in Table 9.

Table 9: Wald Test Results

Sector	Long-Run p-value	Long-Run Asymmetry	Short-run p-value	Short-Run Asymmetry
AGDP	0.0920	No (weak at 10%)	0.0349	Yes
SGDP	0.0098	Yes	0.0037	Yes
IGDP	0.0174	Yes	0.3325	No

Source: Study Findings (2024)

The results show that the degree of asymmetry differs across sectors. In agriculture, short-run asymmetry is evident (p = 0.0349), implying that increases and decreases in agricultural output do not have the same immediate effect on carbon emissions. In contrast, the evidence of long-run asymmetry is relatively weak (p = 0.0920), indicating that the effects of agricultural expansion and contraction become less distinct over time. This may be because adjustments in land use, farming practices and production systems occur gradually. From a policy perspective, the findings suggest that efforts to reduce emissions from agriculture are likely to be more effective when they target periods of rapid expansion rather than long-term structural changes.

The service sector displays a different pattern. The Wald test confirms significant asymmetry in both the short run (p = 0.0037) and the long run (p = 0.0098), implying that increases and decreases in service sector activity influence carbon emissions differently. This finding supports the long-run estimates, where service sector growth was associated with lower emissions while sectoral decline had the opposite effect. One possible explanation is that continued expansion of relatively less energy-intensive service activities gradually reduces the economy's carbon intensity, whereas contraction shifts economic activity towards sectors with higher emissions. These results reinforce the need to sustain growth in cleaner and more efficient service industries.

For the industrial sector, asymmetry is only evident in the long run (p = 0.0174), while the short-run test is statistically insignificant (p = 0.3325). This suggests that industrial expansion and contraction have comparable effects on carbon emissions in the short term, but their environmental impacts become more pronounced over time. The result is in line with the long-run coefficient estimates and highlights the importance of considering the long-term environmental consequences of industrial policy rather than focusing only on immediate outcomes.

Overall, the Wald test provides further evidence that the relationship between sector value added and carbon emissions is nonlinear. The findings support the use of the NARDL approach proposed by Shin et al. (2014), which allows positive and negative changes in the explanatory variables to influence the dependent variable differently. They also indicate that a single policy approach is unlikely to achieve the same outcome across all sectors, given the differences in how carbon emissions respond to sectoral expansion and contraction.

Diagnostic Tests

The diagnostic test results indicate that the estimated NARDL model satisfies the key assumptions required for reliable inference. The Durbin-Watson statistic (2.035) together with the Breusch-Godfrey LM test (p = 0.8319) provides no evidence of serial correlation in the residuals. Likewise, the Breusch-Pagan-Godfrey test (p = 0.7673) suggests that the variance of the residuals is constant, indicating the absence of heteroskedasticity. The Ramsey RESET test is also statistically insignificant (p = 0.6744), implying that there is no evidence of functional form misspecification. Overall, these diagnostic results suggest that the estimated model is stable and that the reported coefficient estimates can be interpreted with confidence.

Conclusion

This study examined the asymmetric relationship between sectoral value added to GDP and carbon dioxide (CO_2) emissions in Kenya using the

nonlinear autoregressive distributed lag (NARDL) model. The results provide evidence of a stable long-run relationship between sectoral economic activity, renewable energy consumption and carbon emissions. The significant error correction term (-0.904) further indicates that departures from the long-run equilibrium are corrected at a fast rate, supporting the existence of a long-run equilibrium relationship among the variables.

The analysis demonstrates that the relationship between sectoral growth and carbon emissions is not uniform across sectors. Agricultural expansion is positively associated with carbon emissions, whereas the service and industrial sectors exhibited asymmetric responses, indicating that increases and decreases in sectoral output are associated with emissions differently over time. The evidence of long-run asymmetry for agriculture was comparatively weaker than that observed for the service and industrial sectors. It is also worth noting that the negative long-run association between industrial growth and carbon emissions differs from the conventional expectation in much of the existing literature. This may reflect Kenya's changing economic structure, continued investment in cleaner energy sources and improvements in production efficiency. This relationship nevertheless warrants further empirical investigation.

Renewable energy consumption was consistently associated with lower carbon emissions, reinforcing its role in supporting Kenya's transition towards a low-carbon economy. More broadly, the findings show that examining sectoral value-added offers insights that would be overlooked when economic growth is represented only by aggregate GDP. Recognizing these sector-specific differences is therefore essential for designing climate and development policies that are both effective and responsive to Kenya's economic structure.

Policy Recommendations

The results suggest that climate and economic policies should reflect the differing relationships between individual sectors of the economy and carbon emissions. In agriculture, greater emphasis should be placed on climate-smart agricultural practices, sustainable land management, efficient fertilizer use and the adoption of low-carbon production technologies. These measures would support agricultural productivity while contributing to Kenya's commitments under the Climate Change Act (2016), the National Climate Change Action Plan and the Nationally Determined Contributions (NDCs).

The asymmetric behaviour observed in the service sector highlights the need to distinguish between short-run and long-run policy priorities. While service sector expansion may be accompanied by temporary increases in emissions, the long-run relationship suggests opportunities to promote sustainable growth through investments in green transport systems, digital technologies and environmentally sustainable urban infrastructure. Although industrial growth was associated with lower long-run carbon emissions, this finding should be interpreted with caution until confirmed by further evidence. Continued investment in cleaner production technologies, energy-efficient manufacturing and renewable energy use within industry remains important for sustaining economic growth while limiting environmental impacts.

The findings also reinforce the importance of expanding renewable energy as part of Kenya's low-carbon development strategy. Achieving this objective will require more than increasing installed renewable energy

capacity. Addressing financing constraints, strengthening electricity transmission infrastructure, encouraging private sector investment and improving access to affordable clean energy technologies will be equally important if renewable energy is to make a meaningful contribution to achieving Kenya Vision 2030 and the country's climate commitments.

Study Limitations and Future Research

The analysis relied on annual secondary data obtained primarily from the World Bank's World Development Indicators, which remain one of the most widely used international data sources but are subject to periodic revisions and the limitations associated with long-term macroeconomic datasets. The study intentionally focused on the asymmetric effects of sectoral value added on carbon emissions to isolate sector-specific dynamics. Consequently, broader macroeconomic factors such as population, urbanization and fossil fuel energy consumption were not incorporated. Structural break analysis was undertaken before estimating the model to account for major changes in the data over time. Nevertheless, the relatively small sample size calls for cautious interpretation of the estimated coefficients.

In addition, the unexpected long-run association between industrial growth and carbon emissions differs from the dominant findings reported in much of the Environmental Kuznets Curve literature and should therefore be interpreted carefully. The bounds test was also based on the asymptotic critical values available in the estimation software; future studies may examine the robustness of the results using finite-sample critical values. Integrating sectoral value added with selected macroeconomic variables in a broader modelling framework may also provide a more comprehensive understanding of the drivers of carbon emissions while preserving the sectoral perspective.

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