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## Article

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## Symmetric Impact of Carbon Emissions on Poverty in South Africa: New Evidence from ARDL Bounds Test

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### ABSTRACT

The purpose of this study is to investigate the relationship between poverty and carbon emissions in South Africa covering the period between 1994 and 2020. The study employed the ARDL bounds test to assess the existence of a long run relationship between the variables. The results evidenced existence of a long run relationship between poverty, carbon emissions, economic growth and renewable energy consumption in South Africa. The results are such that carbon emissions have a positive and a significant effect on poverty in the long run. Therefore, with CO<sub>2</sub> emissions having a positive influence on poverty, causes more losses in the socioeconomic system and reduces the ability of the population to cope with poverty. Therefore, it is recommended that the government should promote the growth of the South African carbon market, increase enterprise involvement through acceptable price and quota allocation, and work in tandem with other environmental measures to promote sustainable development. This will help alleviate poverty in South Africa.

**Keywords:** Poverty, Carbon Emissions, Autoregressive Distributed Lag Test, South Africa

**JEL Classifications:** O13, O4, Q43

### 1. INTRODUCTION

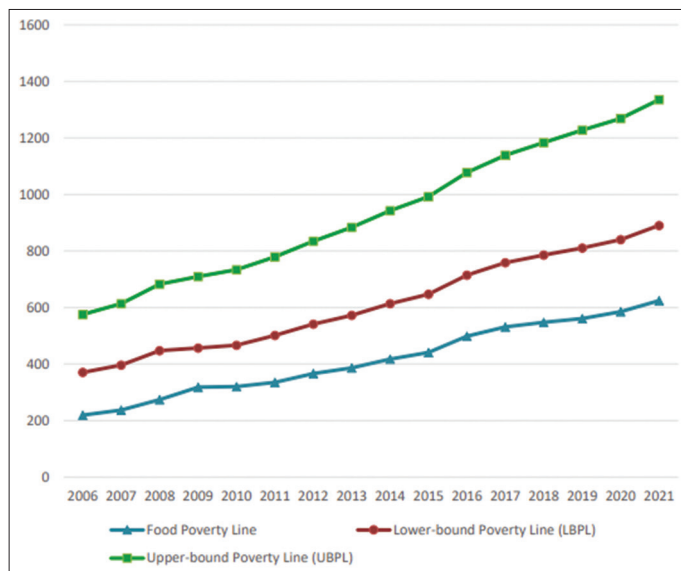
South Africa is a country with a long and tumultuous past. Since the end of apartheid in 1994, the government has struggled to address persistent poverty and unemployment with 25-30% of the workforce unemployed. The Statistics South Africa defines poverty with three categories: The food poverty line, the lower bound poverty line and the upper bound poverty line. The food poverty line (the level below which individuals cannot secure enough food) is R531 per month, according to data from Stats SA, and the upper bound poverty line (the level below which individuals cannot secure food and non-food items) is R1, 138 per month (BusinessTech, 2018). Around 20% of the population is food insecure, meaning they can't buy food that satisfies a minimal calorie need. A total of 55.5% of the population (30.3 million people) lives in poverty at the national upper

poverty line (ZAR 992), while 13.8 million individuals (25%) live in food poverty.

Figure 1 displays the series of inflation-adjusted poverty lines from 2006 to 2019. It can be learned from Figure 1 that South Africa has been experiencing increases in the levels of poverty over the period 2006-2021. These increase has been steeper from 2015 indicating that poverty levels have increased more in those years than in the years before 2015. Following the recent war of Ukraine and Russia leading to increase in oil prices together with the covid-19 pandemic, there is a possibility that poverty will continue to increase.

The dependence of fossil fuels in producing energy has led to discussions about the sustainability of current energy consumption in many countries. Burning of fossil fuels releases large amounts of

**Figure 1:** Inflation-adjusted national poverty lines, 2006-2021 (per person per month in Rands).



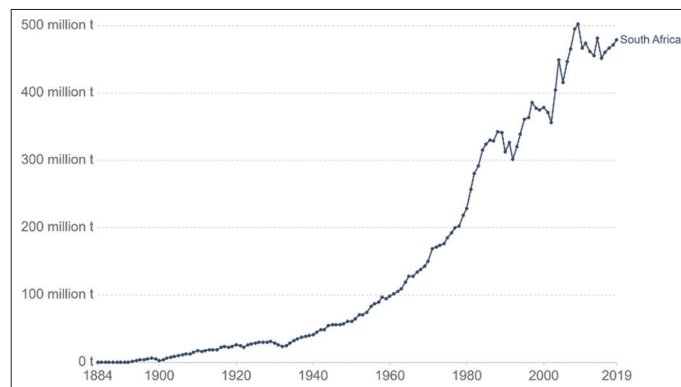
Source: Statistics South Africa 2021

carbon dioxide, a greenhouse gas, into the air. This results in global warming as the greenhouse gases will trap heat in the atmosphere. One subject that has grabbed attention of many researchers is examining the effect of climate changes on human activities aspects. This is on account that as population and industrialisation increase, energy usage also increases which triggers an increase in greenhouse gas emissions (Sarkidie and Strezov, 2019). Research has evidenced that a condition of climate change has an extensive effect on the functionality of contemporary human societies (Burke et al., 2018). The continuous increases in the Greenhouse gas emissions has led to extreme weather conditions evidenced by the droughts, cold, heat waves, floods and natural disasters experienced in both developing and developed countries.

Sanctions imposed by the international community on the apartheid state led to military industrialisation, which constituted a fundamental component of South Africa's economic basis before the dawn of democracy. The government played a key role in paving the road for industry. Much of this was concentrated on heavy industries such as coal and iron-ore mining. In the process of industrialisation, the firms ignored the environmental problems. Carbon dioxide ( $\text{CO}_2$ ) gas, which is created during the combustion process in the industrial sector, is hazardous when inhaled. Even when  $\text{CO}_2$  levels are higher than 10%, it can produce blurred vision, hearing loss, and trembling, leading to fainting (Supardi, 2003).

Figure 2 below shows that trends of carbon emissions in South Africa over the period from 1884 to 2019. It can be realised that around the 1884 to the early 1900s the carbon emissions were close to net-zero. These are times of the early starts of industrialisation in South Africa emanating from the discovery of gold on the Witwatersrand. From 1930 to early 2000s there has been a steep increase in the carbon emissions and then experienced a slight decrease till around 2015 when the Paris agreement was imposed on South Africa to keep emissions low. Since then the

**Figure 2:** Year on year change in  $\text{CO}_2$  emissions (Absolute annual change in carbon dioxide, measured in tonnes). Ritchie (2020)



country has experienced a slight decrease in the carbon emissions (Figure 2).

Governments and businesses all over the world are aiming to attain net-zero greenhouse gas emissions. South Africa is committed to addressing climate change based on science and equity, as stated in the Conference of the Parties to the United Nations Framework Convention on Climate Change decisions 1/CP.19 and 1/CP.20 (DEA, 2015). South Africa, like other developing countries, is particularly sensitive to its effects, especially in terms of water and food security, as well as health, human settlements, infrastructure, and ecosystem services. According to DEA (2015). South Africa is committed to working with others to keep temperature rises well below  $2^\circ\text{C}$  above pre-industrial levels, in terms of a long-term solution to the global challenge of climate change, which could include a further revision of the temperature goal to below  $1.5^\circ\text{C}$  in light of new science, noting that a global average temperature increase of  $2^\circ\text{C}$  translates to up to  $4^\circ\text{C}$  for South Africa by the end of the century.

A vast majority of the current studies that focused on the Greenhouse gas emissions delved much into the impact of carbon emissions on economic growth without considering its impact on poverty. The current study fills in this gap by using the ARDL bounds test to determine the relationship between carbon emissions and poverty. The annual data for South Africa is going to be used for the period between 1994 and 2020.

The rest of the paper is structured as follows: Section 2 reviews the existing literature followed by section 3 which focuses on methodology and data collection. Section 4 analyses the results while section 5 concludes and gives recommendation.

## 2. LITERATURE REVIEW

Over the years since environmental quality has begun to decline owing to economic activity, the worries about sustainable development have continued to increase. Poverty reduction and environmental transformation are the main focus for sustainable development goals (SDGs). The developed nations and developing nations together, they have decided to free mankind from poverty and offer the clean environment for future generations

(Maji, 2019). Developing nations, in particular, promote their economic activities by boosting industrialization and levels of output to increase their economies and alleviate poverty. But economic activities that promote economic growth also raise energy consumption, resulting to increased carbon dioxide (CO<sub>2</sub>) emissions, harming human welfare and sustainable development (Danish, 2020). The relationship between CO<sub>2</sub> emissions, poverty levels and economic growth had been extensively research in the last decades. Although, the results in the literature reveals mixed directions of causality, this could be due to different methodologies, variables and countries used to test the relationship. In the framework of the South African economy, this study will examine the link between poverty, CO<sub>2</sub> emissions and economic growth. The literature review shows that the linkages between CO<sub>2</sub> emissions, poverty levels and economic growth can broadly be classified into three research clusters. The first cluster is focusing on the linkage between CO<sub>2</sub> emissions and economic growth. The second cluster will be focusing on the linkage between CO<sub>2</sub> emissions and poverty levels. The third cluster will be focusing on the linkage between poverty level and economic growth.

## 2.1. CO<sub>2</sub> Emissions and Poverty

Regions with significant poverty decreases, particularly in East Asia, the Pacific and South Asia, have shown increased carbon emissions of almost 200%. In sub-Saharan Africa, the only area which reduced its carbon emissions over this period has nearly doubled the population living in extreme poverty (Goldstein, 2015; Dagume, 2021; Magwedere et al., 2022). Steinberger et al. (2012) found that human development depends on economic expansion, and, in turn, national economic expansion needs more energy utilization and thus more greenhouse gas emissions. This implies that when mitigating CO<sub>2</sub> emissions, the contribution of Carbon-emissions industries to the economic growth, and unemployment reduction must not be neglected.

From 2007 to 2014, Jin et al. (2018) measured CO<sub>2</sub> emissions and the poverty-alleviation index using socioeconomic and energy consumption statistics data from 286 municipal cities in China, analysed relationships between CO<sub>2</sub> emissions, employment rate, and poverty alleviation index using simultaneous equations, and interpreted the mechanism by which CO<sub>2</sub> emissions influence social poverty at the municipal level. According to the findings, there was a positive relationship between poverty alleviation and CO<sub>2</sub> emissions during the period from 2007 to 2014.

Bruckner et al. (2022) served to examine the effects of poverty reduction on domestic and international carbon emissions. The results show that the reduction of poverty can lead to a more than two-fold increase in carbon emissions in low- and lower-middle-income nations in sub-Saharan Africa. High-emitting nations must significantly reduce their emissions if they are to assure global progress in eradicating poverty without exceeding climate targets.

Baloch et al. (2020) investigated the relationship between income inequality, poverty, and carbon dioxide (CO<sub>2</sub>) emissions in 40 Sub-Saharan African nations from 2010 to 2016. According to the Driscoll Kray regression estimator's findings, rising income inequality relates to rising CO<sub>2</sub> emissions. Furthermore, rising

poverty has a negative impact on environmental degradation in Sub-Saharan African countries.

Khan (2019) used panel data from ASEAN states from 2007 to 2017 to investigate the effect of poverty and logistical operations in the context of environmental deterioration. Because of the presence of endogeneity, the system-generalized method of moments (GMM) was used. According to the findings, poverty and logistical operations have a strong and positive link with increased environmental degradation. Because impoverished people lack skills, they are forced to utilize natural resources in novel and unsustainable ways for survival and profit, resulting in increased deforestation.

Using panel data from 30 Chinese regions between 2005 and 2019, Yu and Liu (2021) investigated the nonlinear linkage between poverty and CO<sub>2</sub> emissions. The autoregressive distributed lag (ARDL) model is initially employed in this investigation. Results show that while inclusive financing has both positive and negative effects on CO<sub>2</sub> emissions, poverty has a short-term negative impact and a long-term favourable effect.

Islam et al. (2017) used econometric techniques to evaluate the influence of energy consumption (EC), economic growth, population, poverty, and forest area on CO<sub>2</sub> emissions in Malaysia, Indonesia, and Thailand. Time series data from 1991 to 2010 were used in this study, which spanned a 20-year period. Several tests, including the Panel unit root test, cointegration test, and Granger causality test, were carried out. They discovered that the variables had several panel unit root tests based on the empirical findings. The co-integration test also demonstrated that in the variables there were at least four co-integrating equations. For the Granger test, the link between poverty and CO<sub>2</sub> emission was only one-way, whereas the other factors were independent of the CO<sub>2</sub> emission. Tests demonstrated the positive link between EC and economic growth and CO<sub>2</sub> emissions. Population growth rates, on the other hand, had a small effect on CO<sub>2</sub> emissions. Poverty and forest areas, however, showed negative CO<sub>2</sub> emissions relationships.

Khan et al. (2022) purposed to determine the impact of poverty and inequality on environmental degradation in the 18 Asian developing economies covering the period between 2006 and 2017. The findings for the Driscoll-Kraay (D-K) standard error approach established that poverty contributes to the environmental degradation in terms of ecological footprint. The results of this study further support the Environmental Kuznets Curve (EKC-Hypothesis) for the nations that were examined using the D-K approach.

Nabi et al. (2020) investigated the dynamic linkages between population growth, price level, poverty headcount ratio, and carbon emissions in the cross-sectional setting of 98 developed and developing countries using different plausible hypotheses such as "population-induced poverty trap," "welfare-reducing effects," "environmental Kuznets curve," and "pollution haven." For empirical analysis, the study employed cross-sectional regression and a switching regression regime. The findings reveal a positive correlation between price changes and carbon

emissions, confirming “welfare-reducing effects,” whereas there is a negative relationship between population growth and poverty at various poverty thresholds, supporting the “Gary Becker human capital theory.” Furthermore, across nations, there is a positive link between poverty rates and carbon emissions. The findings supported the “pollution haven” theory, owing to a rise in pollution as a result of financial liberalization policies. In a particular time, span, there is a U-shaped link between economic growth and carbon emissions.

Zhang and Zhang (2020) assessed the poverty alleviation impact of China’s pilot carbon emissions trading schemes (ETS) at the provincial level before and after the program, which ran from 2007 to 2017. They specifically assess poverty reduction in terms of rural household income growth and rural employment creation. Their research indicates that the emissions trading schemes (ETS) policy resulted in gains in rural residential income and employment by leveraging the quasi-experimental variance in whether provinces were affected by this pilot emissions trading schemes (ETS) program. The findings suggested that the implementation of ETS is helpful to income development and job creation in China’s rural areas, implying that the ETS policy may be useful to poverty reduction in impacted provinces.

## 2.2. Economic Growth and Poverty

Economic growth reduces poverty while increasing income inequality, although the effect is less than that of poverty reduction. As a result, greater income inequality is not a trade-off for poverty reduction, and economic development is helpful in reducing poverty (Ravallion, 1995). Nevertheless, rural agriculture expansion has a significant impact on poverty reduction in rural regions. This suggests that, agricultural expansion in rural areas continues to play an important role in poverty reduction (Suryahadi et al., 2009). In decreasing poverty, strong macroeconomic policies and global economy openness can be essential. These policies largely have an impact on economic growth and are increasingly developing nations with stronger macroeconomic policies and this growth alleviates poverty (Roemer and Gugerty, 1997). The empirical evidence on the effect of economic growth on poverty is largely examined in the existing economic literature.

Tanchangya and Ayoungman (2022) served to examine the both symmetric and asymmetric effect of poverty, inequality and population on carbon emissions in Bangladesh for the period from 1980 to 2020. The study employed both Autoregressive distributed Lag (ARDL) and Non-linear Autoregressive distributed Lag (NARDL). It was observed that poverty, inequality and population have short run effect on carbon emissions in Bangladesh.

For instance, Garza-Rodriguez (2018) used a cointegration analysis with structural change to examine the link between poverty and economic growth in Mexico from 1960 to 2016. The Gregory-Hansen cointegration test revealed the presence of a long-term equilibrium link between poverty reduction and economic growth, both in the short and long run. Using a vector error correction model (VECM), they discovered that a 1% rise in economic growth leads to a 2.4% increase in per capita consumption, which finally leads to poverty alleviation.

Okoroafor and Nwaeze (2013) studied and assessed the influence of poverty on Nigerian economic growth from 1990 to 2011. Data were obtained from secondary sources, and the ordinary least squares (OLS) approach was used in this study to assess the influence of the poverty and discomfort index on Nigeria’s economic growth using a multiple regression model. Contrary to economic predictions, empirical results from the single equation regression model reveal a zero-correlation between poverty, discomfort index, and economic growth in Nigeria. None of the parameter estimates for the Human Development Index (HDI) and the Discomfort Index are statistically significant in explaining Nigeria’s economic growth.

In the instance of Pakistan, Afzal et al. (2012) used time series data on education, poverty, physical capital, and economic growth from 1971-72 to 2009-10. The ARDL model findings indicate that the short-run and long-run effects of physical capital on economic growth are both positive and significant. Only in the long run does education have a positive and significant impact on economic growth. Poverty and economic growth are negatively and strongly connected in the long run. The Toda-Yamamoto Augmented Granger Causality Test results indicate bi-directional causality between education and economic growth, economic growth and poverty, and poverty and education.

Afzal et al. (2013) studied the relationships between education, poverty, and economic growth in Bangladesh, India, Pakistan, and Sri Lanka. Panel data from 1995-96 to 2012-13 were utilized. They used a Fixed Effects model. The findings supported a positive correlation between education and economic growth, whereas poverty was shown to be inversely connected to economic growth in these South Asian nations.

Stevens and Sessions (2008) discovered that the influence of GDP growth on poverty growth has either reduced or stayed constant over time in their ongoing study of the impact of economic growth on poverty, and that economic expansion in the 1980s in the United States had no effect on poverty. They discovered, using a formal error-correction model, that gains in economic growth are significantly related to declines in the poverty rate for all households. GDP growth, in particular, was found to have a greater impact on poverty throughout the expansionary periods of the 1960s, 1970s, 1980s, 1990s, and 2000s.

Zhao et al. (2022) examined the impacts of carbon pricing on poverty and inequality under the long-term climate target in China covering the period during the transition to carbon neutrality and in pursuit of the long-term objectives of the Paris Agreement. It was discovered that attempts to mitigate climate change would not significantly impede China’s efforts to reduce poverty, with the number of people living in poverty in 2050 in most cases being <0.3 million.

Nansadiqa et al. (2019) investigated the impacts of economic growth and unemployment on poverty reduction in Indonesia from 1990 to 2017. They also used the vector error correction model to investigate the multivariate dynamic causal connection between poverty, unemployment, and economic growth. According to the

study, economic growth and unemployment have a long-term detrimental impact on poverty levels. A bidirectional Granger causal relationship between poverty and economic growth, as well as a unidirectional causal impact running from unemployment to poverty, were also found. Their findings emphasized the necessity of a poverty reduction program that promotes inclusive economic growth.

Using the dynamic panel threshold framework, Aye and Edoja (2017) studied the influence of economic growth on CO<sub>2</sub> emissions. The study is based on information from a panel of 31 developing nations. According to the findings, economic expansion has a negative influence on CO<sub>2</sub> emissions in the low growth regime but a positive effect in the high growth regime, with the marginal effect being greater in the high growth regime. As a result, their discovery does not support the Environmental Kuznets Curve (EKC) theory, but rather establishes a U-shaped relationship. Energy consumption and population were also discovered to have a positive and significant impact on CO<sub>2</sub> emissions.

### 2.3. CO<sub>2</sub> Emissions and Economic Growth

According to the Environmental Kuznets Curve (EKC) theory introduced by Grossman and Krueger (1991), continuing economic growth ultimately reverses the environmental damage caused during the early stages of economic development. The pioneers of energy consumption and economic growth are Kraft and Kraft (1978). Who examined the causal relationship between economic growth and energy consumption, also CO<sub>2</sub> emissions were incorporated in the study as these strands are inter-related and should be studied together. Their results found that there is negative relationship between economic growth and CO<sub>2</sub> emissions. However, the relationship between CO<sub>2</sub> emissions and economic growth is further investigated in the existing literature.

Duong and Flaherty (2022) purposed to determine the impact of economic growth on poverty taking into consideration the role of income inequality and carbon emissions. Using the generalized method of moments Estimators, the study discovered that while economic progress lessens poverty, carbon emissions (from carbon-intensive growth) combined with inequality actually make poverty worse. It was further discovered that, in terms of eradicating poverty, impoverished nations are adversely affected by both carbon emissions and income disparity, whereas rich countries are largely affected by the latter.

Borhan et al. (2012) investigated the effect of CO<sub>2</sub> on Asean+8 economic growth. From 1965 to 2010, income levels per capita were assessed using gross domestic product per capita. For empirical investigation, a three-equation simultaneous model was developed in this work. The Environmental Kuznets Curve link was discovered in the pollution indicator CO<sub>2</sub> in Asean+8.

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Albiman et al. (2015) carried a study to examine the relationship between economic growth per capita, energy consumption and CO<sub>2</sub> emissions in Tanzania from the periods 1975-2013. The study used non-causality technique of Toda and Yamamoto. The results of the study reveal that there is unidirectional causality that runs from energy consumption and economic to CO<sub>2</sub> emissions.

Acheampong (2018) empirically examined the causal relationship between Economic growth and CO<sub>2</sub> emissions in 116 countries by employing panel vector autoregression (PVAR) and generalized method of moment (GMM) for the period 1990-2014. By using the multivariate approach, the results of the study firstly reveals that economic growth does not cause energy consumption at global and regional levels, secondly, economic growth has no causal effect on carbon emissions, thirdly, carbon emissions positively cause economic growth and lastly, energy consumption positively causes economic growth. The impulse response functions reveal evidence of Environmental Kuznets Curve (EKC).

Odhiambo (2012) examined the causal relationship between economic growth and CO<sub>2</sub> emissions in South Africa by utilizing ARDL bound testing approach by using annual time series data for the period from 1970 to 2007. The study incorporated energy consumption in a bivariate setting between economic growth and CO<sub>2</sub> emissions by creating trivariate model. The empirical results of the study reveal that there is a unidirectional causal that runs from economic growth to CO<sub>2</sub> without feedback in South Africa. The results further show that energy consumption granger causes CO<sub>2</sub> emissions and economic growth. The results failed to find the causal run from CO<sub>2</sub> emissions to either energy consumption or economic.

## 3. METHODOLOGY

### 3.1. Model Specification

The empirical analysis of the study will employ four variables, where poverty is dependent variable and carbon emissions, economic growth and renewable energy consumption are the independent variables. This study will employ and modify the study conducted by Chen et al (2019), Khan, Yahong and Zeeshan (2022) to understand the impact between CO<sub>2</sub> emissions and poverty in South Africa. All the variables are transformed to logarithmic form, it helps the variables to be in the same unit of measurement and therefore minimise heteroscedasticity.

The model is specified as:

$$IPOV = \beta_0 + \beta_1 LCO_2 + \beta_2 LGDP + \beta_3 LREC + \epsilon_t \quad (1)$$

Where LCo2 represents the log form CO<sub>2</sub>e per capita, LPov represents poverty, LGDP represents gross domestic product, and LREC represents renewable energy consumption.

### 3.2. Data Collection

The present study used annual data series for the period 1994–2020. The data for empirical analysis has been collected from various data source, below is the list of data and the collection site as illustrated in Table 1 below. The data for carbon emissions and poverty were sourced from Wold Bank database, while Renewable energy consumption and Gross Domestic Product data were collected from International Energy Agency and South African Reserve Bank, respectively. All the variables are transformed to logarithmic form it helps the variables to be in the same unit of measurement and therefore minimise heteroscedasticity.

### 3.3. Unit Root

The study utilized unit root tests to determine the stationarity in each series before examining the model's long- and short-run dynamics. Multiple tests for stationarity have been proposed in previous research; however, in the current analysis, the most generally used unit root tests, namely Phillips-Perron (PP), Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). We checked the level of stationarity of all the variables at the “level” (I[0]) and the “first difference” (I[1]).

### 3.4. Co-Integration Test

The ARDL bounds testing procedure is used in this study to investigate the long run relationship between poverty, CO<sub>2</sub> emissions, GDP and renewable energy consumption in South Africa. Pesaran and Shin (1999) pioneered the ARDL bounds approach, which was later expanded by Pesaran et al. (2001). For the research, the ARDL technique was chosen over conventional models such as Engle and Granger (1987) and Johansen (1988) for the following reasons: Firstly, unlike the traditional Johansen test, which employs a system of equations, the ARDL technique examines the long term relationship of the variables using a single reduced form of equation. Secondly, it is appropriate for testing co-integration when a small sample size is used. Thirdly, it is not necessary for the underlying variables to be of similar order, e.g. integrated of order zero I(0), integrated of order one I(1), or fractionally integrated, for it to be applicable.

## 4. THE ARDL MODEL CAN BE SPECIFIED AS FOLLOWS

Base on the advantages of the selected time series data of the ARDL model, in this study we will proceed with a similar method to inspect the influence of poverty, GDP, and renewable energy consumption on CO<sub>2</sub> emissions in South Africa. The ARDL model is specified as follows:

**Table 1: Data sources**

| Variable                                   | Data source                 |
|--|-----------------------------|
| Carbon emission (CO <sub>2</sub> emission) | World Bank database         |
| Poverty                                    | World Bank database         |
| Renewable energy consumption               | International Energy Agency |
| Gross domestic product                     | South African Reserve bank  |

Source: Own calculation

$$\begin{aligned} \Delta POV = & \beta_0 + \sum_{i=0}^p \beta_i \Delta POV - i + \sum_{i=1}^p \beta_i \Delta CO_2 - i \\ & + \sum_{i=0}^p \beta_i \Delta LGDP - i + \sum_{i=0}^p \beta_i \Delta LREC - i \\ & + \lambda POV - i + \lambda CO_2 - i + \lambda LGDP - i + \lambda LREC - i + \varepsilon_t \end{aligned} \quad (2)$$

Equation2 represent the ARDL bounds testing approach under the unrestricted error correction model, where represent variable difference values like wise  $\lambda$  indicate the dynamic relationship in the long run and p explain the lag length of each variable. To check if there is a co-integration relationship, the ARDL bounds testing approach uses F-statistics for a joint significance test. In order to execute statistical diagnostic tests on the model's stability and estimate the short-and long-term coefficients, equation 3,  $\theta$  explains the adjustment speed of the equilibrium after some short-run economic shocks

$$\begin{aligned} \Delta POV = & \beta_0 + \sum_{i=0}^p \beta_i \Delta POV - i + \sum_{i=1}^p \beta_i \Delta CO_2 - i \\ & + \sum_{i=0}^p \beta_i \Delta LGDP - i + \sum_{i=0}^p \beta_i \Delta LREC - i + \theta POV - i \\ & + \lambda POV - i + \lambda CO_2 - i + \lambda LGDP - i + \lambda LREC - i + \varepsilon_t \end{aligned} \quad (3)$$

It is critical to examine if the variables are co-integrated before drawing conclusions or making judgments about the calculated coefficients. This is accomplished through the use of a joint null hypothesis of non-differenced variables (Shin et al., 2013). The bound's critical value is then compared to Pesaran et al. critical 's values in scenario one (2001).

Case one was chosen because each of the one model specifications include constants, and the constants are unlimited. “K” represents the number of long-run regressors before decomposing variables. If the Wald tests F-statistics are bigger than the upper critical values, there is evidence of co-integration, according to intuition. If the F-statistics are smaller, there is no correlation.

### 4.1. Diagnostic Tests

It's crucial to do a set of tests to ensure that the nonlinear ARDL model is stable. Serial correlation, normality tests and heteroscedasticity are among them. For this model, the null hypothesis of no serial correlation, homoscedasticity, or normalcy cannot be rejected. This suggests that the model is free of serial correlation and heteroscedasticity (variance of errors that does not remain constant).

### 4.2. Stability Tests

The Brown, Durbin, and Evans (1975) model of stability verification is used in the model to perform a stability check. The CUSUM and CUSUM of Squares tests are used to see if the estimated models' coefficients remain constant over time, which is an indicator of model stability.

## 5. FINDINGS OF THE STUDY

### 5.1. Unit Root Tests

After the check of ADF, PP and KSPP it could be concluded that stationarity of the value are at level [I(0)] and the first difference [I(1)]

of all the variables, as shown in Table 2. Both PP, ADF and KSPP unit root testing approaches of stationarity suggest that all variables in the log form are stationary at I(1) and I(0). We can proceed to test for ARDL

## 5.2. Co-integration

It is important to produce the lag length criterion under the Johansen technique before the cointegration test can be performed. The lag length criterion is done using the basis of AIC, SC, LR, FPE, and HQ. Table 3 presents result of the selected lag. As seen from the table above, the lag length selected is 3 and was used throughout the study. This because it has more asterix and lower AIC (Brooks, 2008a).

The estimated F-statistic is 5.204548, which is greater than the Upper bound of 4.35 at a 5% level of significance, as shown in Table 4. As a result, the findings show that there is co-integration between poverty, carbon emissions, the Human Development Index, renewable energy, and GDP.

Table 5 shows the results of the chosen ARDL model's long-run estimation. The data show that CO<sub>2</sub> emissions has a positive impact on poverty, which is considerable at the 1% level. As a result, a 1% rise in LCO<sub>2</sub> emissions will result in a 1.33% increase in poverty. This results are in line with the findings of Jin et al. (2018) who found a positive relationship for China and Islam et al. (2017) for Malaysia, Indonesia and Thailand.

Furthermore, the findings reveal that GDP has a direct negative impact on poverty, which is statistically significant at 1%. This means that, ceteris paribus, a 1% increase in economic growth is associated with a 1.81% fall in poverty. The results are similar to the findings of Garza-Rodriguez (2018) in Mexico; Okaroafor and Nwaeze (2013) for Nigeria and Afzal et al. (2013) for Bangladesh, India, Pakistan and Sri Lanka.

Renewable energy consumption has a negative link with poverty, according to the findings, which are statistically significant at the 1% level of significance. This means that a 1% increase in renewable energy will result in a 14.91% fall in poverty, ceteris paribus. This results are in line with Khobai's (2021) results for South Africa.

The short-term results as shown in Table 6 indicate that the association between carbon dioxide emissions and poverty is negative and statistically insignificant, while the relationship between poverty and GDP is positive and statistically significant in the short run. There is also a negative relationship between poverty and renewable energy but it is statistically insignificant.

Table 7 presents the diagnostic tests results. The LM statistic is 0.292869, having a probability value of 0.8298, which is >0.05% level of significance. As a result, we accept the null hypothesis in this analysis and conclude that the model lacks serial correlation. Heteroscedasticity tests revealed an F-statistic of 0.223399 and a probability of 0.9214, both of which are over the 0.05% level of significance, showing that the model is homoscedastic. The model accepts the null hypothesis of the Normality test and concludes that the residuals are normally distributed, as evidenced by the F-statistic of 0.593734 and probability value of 0.593734, both of which are >5% level of significance. Finally, the diagnostic tests for Langrage Multiplier serial correlation test, Jarque-Bera normalcy test, and Heteroscedasticity test all passed, indicating that the model is stable.

The results of the CUSUM stability test are shown in Figure 3. At a 5% level of significance, the blue line does not cross the red lines, indicating that the model is stable. This test is also used to examine the long-term dynamics of regression.

**Table 2: Unit root tests**

| Integration order | Variables | ADF test    |                        | PP test     |                        | KPSS test   |                        |
|-------------------|-----------|-------------|------------------------|-------------|------------------------|-------------|------------------------|
|                   |           | Coefficient | Coefficient with trend | Coefficient | Coefficient with trend | Coefficient | Coefficient with trend |
| Level             | Lc02      | 0.3701      | 0.7909                 | 0.3701      | 0.7708                 | 0.6840**    | 0.1507**               |
| Difference        | D (Lco2)  | 0.0014***   | 0.0054***              | 0.0014***   | 0.0054***              | 0.2341      | 0.0573                 |
| Level             | LGDP      | 0.0130**    | 0.9996                 | 0.0248**    | 0.9994                 | 0.7304**    | 0.1790**               |
| Difference        | D (LGDP)  | 0.1297      | 0.0554*                | 0.1555      | 0.0554*                | 0.6000**    | 0.1304*                |
| Level             | LHDI      | 0.9561      | 0.8086                 | 0.9646      | 0.8139                 | 0.4891**    | 0.1776**               |
| Difference        | D (LHDI)  | 0.0002***   | 0.0001***              | 0.0002***   | 0.0001***              | 0.4282*     | 0.1011                 |
| Level             | POV       | 0.8310      | 0.8620                 | 0.7411      | 0.8620                 | 0.2593      | 0.1871**               |
| Difference        | D (POV)   | 0.0000***   | 0.0000***              | 0.0000***   | 0.0000***              | 0.1524**    | 0.0818                 |
| Level             | LREC      | 0.0039***   | 0.7581                 | 0.0001***   | 0.6661                 | 0.6484**    | 0.1967**               |
| Difference        | D (LREC)  | 0.0078***   | 0.0037***              | 0.0085***   | 0.0000***              | 0.7821***   | 0.5000***              |

a: (\*) significant at the 10%; (\*\*) significant at the 5%; (\*\*\*) significant at the 1% and (no) Not Significant. b: Lag Length based on SIC. c: Probability based on MacKinnon (1996) one-sided P values. Source: Own calculation. ADF: Augmented Dickey-Fuller

**Table 3: Selection order criteria**

| Lag | LogL     | LR        | FPE       | AIC        | SC         | HQ         |
|-----|----------|-----------|-----------|------------|------------|------------|
| 0   | 62.33402 | NA        | 5.85e-08  | -5.303093  | -5.104722  | -5.256363  |
| 1   | 166.5730 | 161.0967  | 1.98e-11  | -13.32482  | -12.33296* | -13.09117  |
| 2   | 175.0450 | 10.01235  | 4.66e-11  | -12.64046  | -10.85511  | -12.21988  |
| 3   | 208.5627 | 27.42359* | 1.57e-11* | -14.23298* | -11.65415  | -13.62548* |

Source: Own calculation

**Table 4: ARDL Co-integration test**

| K  | Critical value bound of the F-statistic |       |          |       |          |       |
|--|---|-------|----------|-------|----------|-------|
|  | 10% level                               |       | 5% level |       | 1% level |       |
|  | I (0)                                   | I (1) | I (0)    | I (1) | I (0)    | I (1) |
| 3  | 2.72                                    | 3.77  | 3.23     | 4.35  | 4.29     | 5.61  |
| Calculated F-statistics                        |   |       |          |       |          |       |
| LPOV (GDP, LREC, LCO <sub>2</sub> ) = 5.204548 |   |       |          |       |          |       |

Source: Own calculations. ARDL: Autoregressive distributed lag

**Table 5: Long run results**

| Dependent variable=LPOV |              |                |              |        |
|-------------------------|--------------|----------------|--------------|--------|
| Long term results       |              |                |              |        |
| Variable                | Coefficients | Standard error | T-statistics | Prob.  |
| LCO <sub>2</sub>        | 1.333370     | 1.641583       | 6.812247     | 0.0013 |
| LGDP                    | -1.814142    | 0.240612       | -7.539687    | 0.0000 |
| LREC                    | -14.917095   | 2.239537       | -6.660794    | 0.0000 |
| C                       | -3.948743    | 6.184893       | -0.638450    | 0.5343 |

Source: Own calculations

**Table 6: Short run analysis**

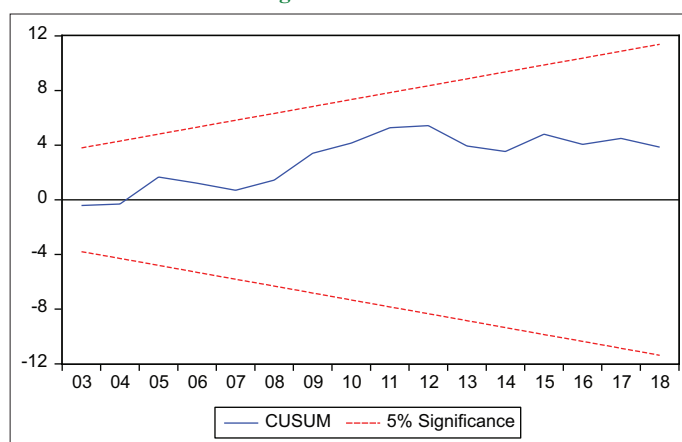
| Variable       | Coefficient | Standard error | T-statistics | Prob.  |
|----------------|-------------|----------------|--------------|--------|
| D (LC02[-3])   | -1.119216   | 1.531655       | -0.730724    | 0.4755 |
| D (GDP[-3])    | 0.097262    | 2.210730       | 0.043995     | 0.9655 |
| D (LREC[-3])   | -7.217154   | 2.530847       | -2.851676    | 0.0115 |
| ECM(-3)        | -0.409831   | 0.147345       | -2.781433    | 0.0133 |
| R <sup>2</sup> | 0.352202    |                |              |        |
| D.W test       | 1.761488    |                |              |        |

\*, \*\*, \*\*\* represent 1%, 5% and 10% significance levels, respectively. Source: Own calculation

**Table 7: Short-run diagnostics**

| Short run diagnostics |              |          |
|-----------------------|--------------|----------|
| Test                  | F-statistics | P-value  |
| Normality             | 0.593734     | 0.593734 |
| Heteroskedasticity    | 0.223399     | 0.9214   |
| Serial correlation    | 0.292869     | 0.8298   |

Source: Own calculation

**Figure 3: CUSUM**


## 6. CONCLUSION

The purpose of this study was to investigate the relationship between poverty and carbon emissions in South Africa covering the period between 1994 and 2020. The study employed the ARDL bounds test to assess the existence of a long run relationship between the variables. Economic growth and renewable energy

consumption were added as intermittent variables to form a multivariate framework.

The results evidenced existence of a long run relationship between poverty, carbon emissions, economic growth and renewable energy consumption in South Africa. The results are such that carbon emissions has a positive and a significant effect on poverty in the long run. Therefore, with CO<sub>2</sub> emissions having a positive influence on the poverty, causes more losses in the socioeconomic system and reduces the ability of the population to cope with poverty. It was also established that economic growth and renewable energy consumption have a negative and significant effect on poverty in the long run, such that when economic growth and renewable energy increase, poverty reduces. There short run results were found to be insignificant.

It is recommended that the government should promote the growth of the South African carbon market, increase enterprise involvement through acceptable price and quota allocation, and work in tandem with other environmental measures to promote sustainable development. This will help alleviate poverty in the country. It is also important to invest more in renewable energy as it reduces carbon emissions and reduces poverty.

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