TESTING FOR LONG-RUN ELASTICITIES IN THE PRESENCE OF STRUCTURAL CHANGE: EVIDENCE FROM CLIMATE CHANGE FOR SOUTH AFRICA

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ABSTRACT

This study uses Dynamic Ordinary Least Squares (DOLS) developed by Stock and Watson (1993), Fully Modified Ordinary Least Squares (FMOLS) developed by Phillips and Hansen (1990), and Canonical Cointegrating Regression (CCR) developed by Park (1992) methods to provide insights into the responsiveness of climate change to changes in energy consumption, urbanization, and economic growth over a significant period. The DOLS, FMOLS, and CCR methods serve as supplementary robustness checks to the existence of a long-term relationship ascertained among the stated variables under study (Auwal, 2024). The study detects a structural change in the long run in the effect on the South African economy from 1971 to 2022, using the least squares method and Bai & Perron's (2003) tests, which necessitates the use of a dichotomous variable to represent the categorical data periods of investigation. The findings from the DOLS, FMOLS, and CCR models revealed are three-fold. On energy consumption, climate change significantly and positively responds to changes in coal and oil consumption by 0.85% to 1.1% and 0.25% to 0.27%, respectively. While the degree of responsiveness of climate change to gas consumption is significantly negative between 0.04% and 0.15%, the climate change response to changes in urbanization and economic growth was insignificant. The study concludes that while urbanization can create localized climate changes, it is not considered to be a significant direct contributor to climate change in South Africa on a large scale. Similarly, its economic activity alone doesn't significantly influence the progression of climate change in South Africa.

JEL Code: C13, L16, Q54
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1. INTRODUCTION

Climate change is already altering South African ecosystems, economies, and livelihoods. Since 1990, the national average temperature has increased twice as fast as global temperatures (USAID, 2024). It has experienced a growing demand for energy following the economic growth post-apartheid era characterized by a persistent increase in urbanization as evident in the urbanization index. Although coal has been subjected to a mix of trends since 2003 but has dominated the energy supply with hydroelectricity contributing the least to the energy supply, crude oil and gas experienced a series of fluctuations in trend (Department of Energy, 2009), coal has traditionally dominated the energy supply sector in South Africa. Approximately 85 percent or 42,000MW, of the nation's electricity is generated via coal-fired power stations. South Africa's dependence on coal as a primary fuel source for electricity generation makes it one of the world's top 15 greenhouse gas (GHG) emitters (USAID, 2024). Despite environmental concerns, coal will continue to provide most of South Africa's power for the next decade, although the share from renewables will grow rapidly. Non-hydro renewables are predicted to develop faster than the market, with 8.7GW of additional renewable energy capacity planned to be installed between 2023 and 2032 (ITA, 2024).

Despite their mixed effects on air quality, human health, wildlife, and climate change, South Africa's major primary energy suppliers had remained Coal and crude oil. It is ranked 6th (Department of Energy, 2009) and 8th (British Petroleum, 2024) among the world's largest recoverable coal reserves in 2006 and 2016[1] respectively, 7th in both global rankings on coal production and consumption in 2016. The South African economy is a major emitter of carbon dioxide (CO2) emissions and its CO2 emissions are principally due to a heavy reliance on coal (McSweeney & Timperley, 2018). It is the 12th among the top 15 largest emitters in the world, the world's 14th largest emitter of GHGs (Carbon Brief, 2024), and the world's 14th largest emitter of GHGs in 2018 (McSweeney & Timperley, 2018).

Generally, the increasing concern about GHGs emissions has motivated many researchers to investigate the relationship between energy consumption, CO2 emission, and economic growth in different countries and regions (Khobai & Roux, 2017). However, this relationship has rarely been examined in South Africa, even though its energy consumption and carbon emissions have more than doubled in the last two decades. While there are studies carried out in the international literature to investigate the relationship between CO2 emission, energy consumption, urbanization, and economic growth, available literature shows very few focus on South Africa and focused on energy consumption and economic growth (Okafor, 2012; Wolde-Rufael, 2009; Odhiambo, 2010), CO2 emission and economic growth (Sibanda & Ndlela, 2020; Shikwambana et al. 2021), urbanization and energy consumption (Nathaniel et al., 2019), energy consumption, CO2 emission and economic growth (Khobai & Roux, 2017; Tagwi, 2022). However, South Africa's energy utilization is highly dependent on low-cost and abundantly available coal. A large amount of crude oil is imported into the country, while a small amount of renewable energy is used (ITA, 2024).

This study contains two fundamental aspects that reflect the central contributions to the existing literature. First, it establishes and analyzes the relationship and effects of urbanization, economic growth proxy by gross domestic product (GDP), and disaggregated energy consumption: coal, gas, and oil consumption. This aspect of the contribution of the inclusion of urbanization in the energy–growth relationship has not been extensively and exhaustively

[1]In 2016, South Africa had 35,053 million tons of proven coal reserves, which was about 3% of the world's total coal reserves (British Petroleum, 2024). The Directorate of the South African Coal Sector Report estimated that South Africa had 66.7 billion tons of recoverable coal reserves, which was about 7% of the world's total.

investigated in the South African economy. Some studies have initially focused on the bivariate relationship of any combination of environmental effects, the economy, and energy consumption aspects (See Shahani & Raghuvansi, 2019; Soile, 2015; Majeed et. al, 2021). The second aspect provides insights into the stability of the relationship among the variables by considering the length of the sample size employed. This restriction appears unrealistic due to the presence of possible historical events that have modified the trends and have necessitated re-estimation of the nexus by admitting the presence of break(s).

The remainder of the study is organized as follows: while Section 2 provides the received, Section 3 describes the data, methodology, and analytical framework. Section 4 presents the empirical results and discussion. The last but not the least, Section 5 presents the conclusions and provides some policy recommendations.

2. LTERATURE REVIEW

Several research studies in developing, emerging, and advanced countries revealed urbanization as a significant factor influencing carbon dioxide emissions (Sadorsky, 2014; Zhang, Yu, & Chen, 2017). The population shift from rural to urban areas is primarily caused by the absence of transportation[2] and the presence of high job prospects, which include the perception of higher levels of income as well as the provision of better infrastructure[3] (Obi-Ani & Isiani, 2020; Horn et al., 2021). As a result, the rate of urbanization continues to rise, even though resources are few, and urbanization has led to a series of challenges, which include the growing number of cars on the highways, which results in carbon emissions (Zhou et al., 2019). Today, more than half of the global population lives in urban areas, up from around one-third in 1950 and projected to increase to around two-thirds in 2050 (UN, 2024). In this view, economic growth and development with the urbanization effects have increased energy consumption that has generated an increased amount of carbon dioxide (CO_2) emission, which is noted to be the dominant contributor to global warming and the GHG effect (Bakirtas & Akpolat, 2018; Heidari et el., 2015; Wang et al., 2018).

However, from the existing available literature reviewed, it is evident that there are several gaps. The first has to do with an absence of studies that estimate the long-run elasticities or degree of responsiveness of climate change to changes in economic growth, urbanization, and disaggregated energy consumption for the South African economy despite the economy's potential position in the African continent and the world economy at large. For example, Musakwa & Odhiambo (2024) examined the causal relationship between urbanization, energy consumption, and economic growth in South Africa. The study employed autoregressive distributed lag (ARDL) to cointegration and error correction model (ECM)- based Granger causality test using annual data from 1990 to 2021. The study found unidirectional causal flow from energy consumption to urbanization in the short run and long run, unidirectional causality from urbanization to economic growth, and bidirectional causality between economic growth and electricity, while no causality was confirmed when total energy consumption was used. Fasanya & Arek-Bawa (2024) assess the relationship between CO2 and urbanization as well as the role of world uncertainty in this association in a South African context, focusing on yearly data from 1968 to 2020. Using the autoregressive distributed lag (ARDL) approach, the results revealed that urbanization's effect on CO2 emissions is only significant when it is augmented with world uncertainty. And that the effect is negative. Shikwambana et al. (2021) used linear correlation coefficient and the environmental Kuznets curve (EKC) hypothesis test to

[2]The absence of affordable and reliable transport often prevents access to education, health services and employment opportunities (Horn et al., 2021).

[3]Such as educational institutions, hospitals, and transportation systems in large cities that are not or scarce in remote regions.

determine the relationship between economic growth and emission levels for pollutants (namely carbon dioxide (CO2), black carbon (BC), sulfur dioxide (SO2), and carbon monoxide (CO)) in South Africa, and sequential Mann–Kendall (SQMK) test to study the trends for the period from 1994 to 2019. The overall results indicate that emission levels are generally correlated with economic growth.

Nathaniel et al. (2019) explore the relationship between ecological footprint, urbanization, and energy consumption by applying the ARDL estimation technique to data spanning 1965–2014 for South Africa. The finding revealed the existence of a long-run relationship and was further confirmed to be robust by the fully modified OLS (FMOLS), dynamic OLS (DOLS), and the canonical cointegrating regression (CCR) estimates. The findings also revealed that economic growth and financial development exact a deteriorating impact on the environment in the short run, but the same was not true for both energy use and urbanization. Sibanda & Ndlela (2020) investigate the relationship between carbon emissions, agricultural output, and industrial output in South Africa by applying the Autoregressive Distributed Lag (ARDL) technique to annual data from 1960 to 2017. The finding shows evidence that carbon emissions are not influenced by agricultural and industrial output, but conversely, agricultural output is influenced by carbon emissions and industrial output.

Khobai & Roux (2017) investigate the relationship between energy consumption, carbon dioxide (CO2) emission, economic growth, trade openness, and urbanization in South Africa using annual data for the period between 1971 and 2013. While the Johansen test of co-integration results show that there is a long-term relationship between energy consumption, CO2 emission, economic growth, trade openness, and urbanization in South Africa, the vector error correction model (VECM) Granger causality indicates that there is bidirectional causality flowing between energy consumption and economic growth in the long run, and a unidirectional causality flowing from CO2 emissions, economic growth, trade openness and urbanization to energy consumption and from energy consumption, CO2 emissions, trade openness and urbanization to economic growth.

Tagwi (2022) employed the ARDL Bounds test econometric technique to evaluate the short and long-term impact of carbon dioxide emissions (CO2), renewable energy usage, and climate change on South Africa's agricultural sector from 1972 to 2021. The findings indicated that, in the short run, climate change reduces agricultural economic growth, and carbon dioxide emissions increase as agricultural economic growth increases. The use of renewable energy was insignificant in the short and long run, and Carbon dioxide emissions granger cause temperature and renewable energy to be unilateral.

3. METHODOLOGY

3.1 Data Description and Sources

Table 1 provides a detailed explanation of the data included in a dataset covering the period from 1971 to 2022, along with where that data originated from - it provides context about the information and its origin, allowing for better understanding and interpretation of the data the study intends to use for analysis.

Table 1: Description of the dataset

Variable Description	Key	Data Source
Climate change It is proxied by a primary driver of climate change, CO2 emission.	CO2	Global Carbon Budget (2024): Carbon dioxide (CO□) emissions from fossil fuels and industry. Land-use change is not included
Gross Domestic Product (GDP),	GDP	World Bank and OECD (2025): This data is expressed in constant 2015 US$.
Urbanization (urban expansion)	UR	United Nations, Department of Economic and Social Affairs, Population Division (2018); HYDE (2023)
Energy consumption (Fossil fuel – coal, gas, and oil)	CC	Energy Institute - Statistical Review of World Energy (2024) - terawatt-hours (TWh).
	GC	
	OC	

Source: Authors' compilation

3.2. Preliminary Data Analysis

Empirically, using time-series data requires understanding the time properties of the variables to determine the most appropriate econometric techniques. To achieve this, the study employs descriptive analysis and unit root tests to determine the stationarity of time series data and identify the order of integration[4] before examining the relationship between the variables and estimating the long-run elasticities. The study employs the Augmented Dickey-Fuller (ADF) test to determine the level of stationary and ensure that none of the series is stationary at the second difference I(2) and to avoid spurious regression.

3.2 Model Specification

Theoretically, the environmental Kuznets curve (EKC)[5] hypothesis connects climate change, energy consumption, urbanization, and economic growth. EKC hypothesis suggests that as the economy develops, environmental degradation initially increases with economic growth, but eventually reaches a turning point where further economic growth leads to a decrease in environmental damage, potentially due to increased adoption of cleaner technologies and environmental regulations; however, this relationship is complex and heavily influenced by factors such as energy consumption and urbanization patterns, where increased urbanization can lead to higher energy consumption and associated emissions (Zou & Chau, 2023), thus contributing to climate change. To estimate the long-run degree of responsiveness of climate change to changes in GDP, UR, CC, GC, and OC in South Africa, the functional form of the relationship is expressed as:

$$CO2\ Emission = f\ (GDP, UR, CC, GC, CC\ )$$

Empirically, estimations made by ignoring the presence of structural breaks may result in biased parameter values (Çamalan et al., 2024)[6]. This study employed the least squares method and multiple structural breaks[7], investigating whether structural breaks exist before the model

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[4]Usually, the order of integration indicates the number of times a variable needs to be differenced to become stationary, meaning its statistical properties do not change over time.

[5] EKC-related studies started with Kuznets (1955), who examined the relationship between income inequality and economic growth. Then, it continued with Grossman & Krueger (1991), who analyzed the link between economic growth and environmental pollution.

[6] Structural breaks are considered permanent changes in a series or a relationship between two or more series mainly because of shocks, policy changes, and global crises.

[7] The Bai & Perron (2003) test is used in time series analysis to test for whether the true coefficients in two linear regressions on different data sets are equal in the presence of a structural break.

estimation. To estimate the long-run elasticities, the study employed three different but complementary estimation techniques: dynamic OLS, fully modified OLS, and canonical cointegrating regression (CCR) approaches.

3.3 Model Estimation Techniques

3.5.1 Structural Break Test

Models for testing structural breaks are an important modeling technique that should be considered as part of any thorough time-series analysis. The break tests help in the determination of when and whether there is a significant change in data as well as relationships. Bai & Perron (1998 & 2003) considered theoretical issues related to the limiting distribution of estimators and test statistics in the linear model with multiple structural changes. This study uses the procedure to identify whether there is a single or multiple structural breaks in the relationship between the time series under investigation. To detect multiple breakpoints in a time series where the relationship between variables might shift at different points in time, not just one break as in traditional structural break tests.

The purpose of conducting the test involves estimating a regression model with potential breakpoints at unknown locations, then searching for the breakpoints that minimize the sum of squared residuals across different regimes.

3.5.2 The DOLS estimates

The DOLS adopts a parametric approach to estimating a long-run relationship in a model in which the variables are integrated in a different order but are still cointegrated (Masih & Masih, 1996). This model deals with simultaneity bias and small sample bias by including leads and lags (Kurozumi & Hayakawa, 2009). The estimators of DOLS can be obtained from least-squares estimates, and these estimators are unbiased and asymptotically efficient even in the presence of the endogenous problem. The parameters also adjust the possible autocorrelation and residual non-normality (Herzer et al., 2006b; Stock & Watson, 1993).

$$y_t = \alpha + \beta X_t + \sum_{i=-k}^{i=k} \phi_i \Delta X_{t+i} + \varepsilon_t \quad (1)$$

In equation (1), β is the long-run elasticity. The term ø's are the coefficients of leads and lags differences of I(1) regressors. These coefficients are considered nuisance parameters, and they adjust for possible endogeneity, autocorrelation, and non-normal residuals (Herzer & Nowak-LehmannD, 2006a; Herzer et al., 2006b).

3.3.2 The FMOLS Estimates

FMOLS adopts the semi-parametric approach to estimate long-run parameters[8]. The technique has certain advantages, such as: (i) it provides consistent parameters even in the small sample size and overcomes the problems of endogeneity, serial correlation, omitted variable bias, and measurement errors and allows for heterogeneity in the long-run parameters[9]; (ii) estimates a single cointegrating relationship with a combination of I(1) variables[10]; (iii) concentrates on the transformation of both data and parameters[11]. Amarawickrama & Hunt (2007) pointed out that the FMOLS method makes appropriate corrections to the inference problems in the traditional EG cointegration technique, and therefore, estimated t-statistics for the long-run estimates are valid. Following Adom et al. (2015) the FMOLS estimator can be obtained as follows.

[8] See Adom et al. (2015); Fereidouni et al. (2014)
[9] See Agbola (2013); Bashier & Siam (2014); Fereidouni et al. (2014)
[10] See Bashier & Siam (2014)
[11] See Park (1992)

$$\hat{o}_{FME} = \left(\sum_{t=1}^{T} Z_t Z_t'\right)^{-1} \left(\sum_{t=1}^{T} Z_t Y_t^{+} - T \begin{bmatrix} \lambda_{12'}^{+} \\ o \end{bmatrix}\right) \quad (2)$$

In equation (2) Y_t^{+} and λ_{12}^{+} terms correct the endogeneity and serial correlation. The FMOLS estimator is asymptotically unbiased and has a fully efficient mixture-normal asymptotic distribution, which allows for standard Wald tests using the asymptotic chi-square statistical inference (Adom et al., 2015).

3.3.3 The CCR Estimates

This method also can be used for testing cointegrating vectors in a model with the integrated process of I (1). This model is too similar in the sense to FMOLS; however, the difference is that CCR concentrates on only data transformation while FMOLS focuses on the transformation of both data and parameters (Adom et al., 2015; Park, 1992). Further, CCR is a single equation regression in which we can also apply multivariate regression without modification and losing the efficiency (Park, 1992). Following Adom et al. (2015) the CCR estimator is obtained as in equation (3).

$$\hat{o}_{CCR} \left(\sum_{t=1}^{T} Z_t^{*} Z_t^{*1}\right)^{-1} \sum_{t=1}^{T} Z_t^{*} Y_t^{*} \quad (3)$$

To ensure the goodness of fit of the model, diagnostic and stability tests are also conducted. The diagnostic test examines the serial correlation, functional form, normality, and heteroscedasticity associated with the selected model.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1 The Existence of Structural Breakpoint

Tables 2 and 3 present the result of the estimated regression as well as the structural breakpoint test. The least squares method results show that except for GC, all the coefficients appeared statistically significant at 5% levels. The post-estimation diagnostic test also supports the existence of structural breaks. The multiple breakpoint test (Bai & Perron, 2003)[12] also suggests the rejection of the null hypothesis of no structural break, detecting a statistically significant breakpoint in 2004.

Table 2: OLS Estimation

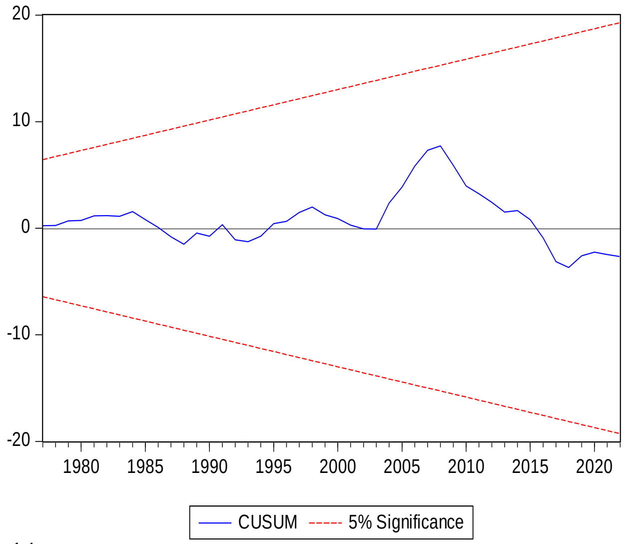
Dependent Variable: CO2				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
GDP	3.65E-05	1.01E-05	3.621608	0.0007
UR	-5670826.	1428919.	-3.968614	0.0003
CC	353453.6	19822.96	17.83052	0.0000
GC	-62352.54	314961.6	-0.197969	0.8439
OC	277748.4	87585.65	3.171163	0.0027
C	2.14E+08	53003779	4.045544	0.0002
R-squared	0.988126	Mean dependent var		3.51E+08
Adjusted R-squared	0.986835	S.D. dependent var		97989257
F-statistic	765.6012	Durbin-Watson stat		1.198052
Prob(F-statistic)				0.00000

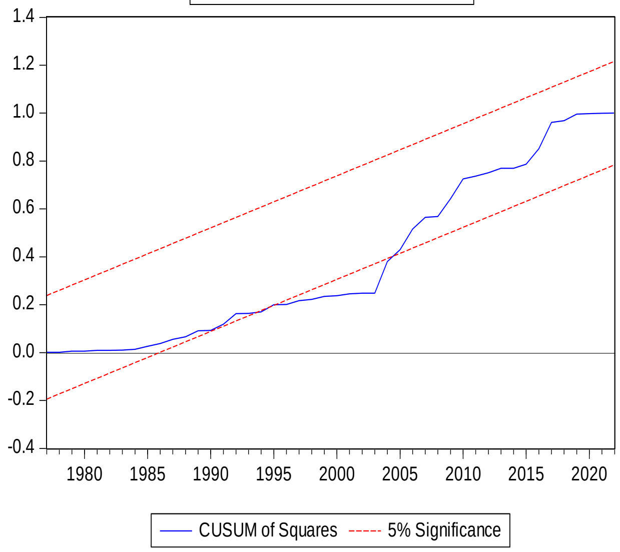
[12] The Bai Perron method is based on having no a priori reasoning, and is extracted from the correlation behavior of the time series to identify when the breaks occur. It is an algorithm for efficiently finding a linear regression model's least squares break points.

Post-estimation Diag. Tests				
Test Statistic	**F-statistic**	**P-Value**	**Null Hypothesis (H_0)**	**Decision Rule**
Normality Test	0.232174	0.890398	Normally distributed Residuals	Fail to reject H_0
Heteroskedasticity	2.257804*	0.0643	Constant variance	Fail to accept H_0
Serial Correlation	3.722928**	0.0321	no serial correlation	Fail to accept H_0
Ramsey RESET	6.766693***	0.0027	Misspecification	Fail to accept H_0
CUSUM	Stable**			
CUSUMSQ	Unstable			
Note: The asterisks ***, **, and * are respectively the 1%, 5%, and 10% significance levels.				

Source: Authors' Computation

Figure 1: Plot of CUSUM and CUSUMQ Graphs





Existence of Multiple Breakpoints in the Model

The results for the multiple breakpoint tests in which model specification details and test statistics are reported in Table 3. From Table 3, the number of breaks allowed by the Bai-Perron model is five at most, with a trimming set at $\varepsilon = 0.15$ to adjust the estimates with a minimum of 52 observations. The date the breakdown occurs is identified, i.e., 2004, as the year the break commenced. This was initially confirmed in Figure 1 of the post-estimation diagnostic test of CUSUM of squares.

Table 3: Bai–Perron Multiple structural breaks test

Sequential F-statistic determined breaks:			**1**
Break Test	**F-statistic**	**Scaled F-statistic**	**Critical Value****
0 vs. 1 *	6.915162	41.49097	20.08
1 vs. 2	3.147943	18.88766	22.11
Break dates:			
	Sequential	Repartition	
1	2004	2004	
* Significant at the 0.05 level.			

Source: Authors' computation

4.2 The Spurious Regression Issue

From Table 2, some statistically significant coefficients were obtained but the post-estimation diagnostic test confirmed nonsense a spurious regression phenomenon that occurs for a wide range of data-generating processes (DGP)[13].

4.3 Preliminary Tests of the Variables

4.3.1 Data Presentation and Analysis

Table 4 presents the results of the descriptive statistics with the average, minimum, and maximum value, skewness, and Kurtosis, as well as the Jarque-Bera test, among others given. Table 4 also shows that the skewness value for GDP, UR, GC, and OC is positive and close to zero, which indicates a right-skewed (longer right tail) and symmetrical distribution, respectively. On the other hand, the values for CO2 and CC are negative and close to one, which revealed a left-skewed (longer left tail) distribution, respectively. Kurtosis values of less than 3 for all the variables indicate that the distribution is flatter with lighter tails (platykurtic), which suggests fewer extreme values. Except for GC, the low Jarque-bera value suggests that the data is more likely to be normally distributed.

Table 4: Descriptive Statistics

Statistic	**CO2**	**GDP**	**UR**	**CC**	**GC**	**OC**
Mean	3.51E+08	2.99E+12	56.02269	796.2276	18.63287	234.5183
Median	3.63E+08	2.64E+12	55.21000	832.4707	12.74615	250.5550
Maximum	4.95E+08	4.63E+12	68.34000	1091.169	44.10787	347.1934
Minimum	1.68E+08	1.55E+12	47.87000	340.1753	0.614787	112.9051
Std. Dev.	97989257	1.02E+12	6.769596	227.0458	16.93626	71.53393
Skewness	-0.477672	0.362516	0.310517	-0.657420	0.393077	-0.139814
Kurtosis	2.080304	1.617925	1.711681	2.289740	1.458440	1.566421
Jarque-Bera	3.810130	5.277571	4.431805	4.838757	6.487964	4.622235
Probability	0.148813	0.071448	0.109055	0.088977	0.039008	0.099150
Observations	52	52	52	52	52	52

Source: Authors' computation

[13] Differencing the series may not always prevent spurious estimates; nor should the $R^2 > DW$ rule-of-thumb be seen as an adequate rule to identify a spurious regression.

4.3.2 Stationarity and Unit Root Tests

From Table 5, the ADF test results revealed that except LUR, which is stationary at level, GDP, GC, CC, OC, and CO2 have unit roots and are stationary after the first difference[14]. This means that the DOLS, FMOLS, and CRR models can be used to test for the long-run coefficients in the relationships among these variables.

Table 5: Augmented Dickey-Fuller test (ADF) Results

Variable	Test Method & Critical Values		@Level		@ 1st Difference	
			t-Statistic	Prob.*	t-Statistic	Prob.*
CO2	ADF test statistic		-0.746818	0.9637	-7.775280	0.0000
	Test critical values:	1% level	-4.148465	-4.152511	-4.152511	
		5% level	-3.500495	-3.502373	-3.502373	
		10% level	-3.179617	-3.180699	-3.180699	
GDP	ADF test statistic		-1.387239	0.8530	-5.936588	0.0000
	Test critical values:	1% level	-4.148465		-4.152511	
		5% level	-3.500495		-3.502373	
		10% level	-3.179617		-3.180699	
LUR	ADF test statistic		-3.981245	0.0157		
	Test critical values:	1% level	-4.152511			
		5% level	-3.502373			
		10% level	-3.180699			
CC	ADF test statistic		-0.932486	0.9440	-7.962866	0.0000
	Test critical values:	1% level	-4.148465		-4.152511	
		5% level	-3.500495		-3.502373	
		10% level	-3.179617		-3.180699	
GC	ADF test statistic		-2.462198	0.3448	-6.593721	0.0000
	Test critical values:	1% level	-4.148465		-4.152511	
		5% level	-3.500495		-3.502373	
		10% level	-3.179617		-3.180699	
OC	ADF test statistic		-1.353774	0.8626	-8.186229	0.0000
	Test critical values:	1% level	-4.148465		-4.152511	
		5% level	-3.500495		-3.502373	
		10% level	-3.179617		-3.180699	

Source: Authors' computation

4.3.3 Optimum Lag Selection

Empirical modeling and estimation required optimum lag to be determined prior to estimating models such as the DOLS, FMOLS, and CCR models that are for the long-run coefficients, among the variables. The results are illustrated in Table 6. The study selects the optimum lag to be 2, based on the outcomes from all the criteria used.

Table 6: Lag Order Selection Criteria

Endogenous variables: CO2 GDP UR CC GC OC						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-2951.215	NA	1.31e+46	123.2173	123.4512	123.3057
1	-2593.731	610.7014	2.02e+40	109.8221	111.4594	110.4409
2	-2521.938	104.6984*	4.88e+39*	108.3308*	111.3715*	109.4798*
3	-2502.604	23.36192	1.18e+40	109.0252	113.4693	110.7046
4	-2467.972	33.18931	1.88e+40	109.0822	114.9297	111.2919

[14] The study employed the ADF test at the level and first difference with trend and intercept included in the equation using the Schwarz information criteria for automatic selection and the results.

*Indicates lag order selected by the criterion. LR: Sequential modified LR test statistic (each test at 5%), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

Source: Authors' computation

4.4 The Long-Run Elasticities Models

Table 7 presents the estimation results for the DOLS, FMOLS, and CCR models. Except for the case of GDP and urbanization, the coefficients or long-term elasticities obtained are statistically significant. While the findings revealed a significant positive degree of responsiveness of climate change to changes in coal and oil at 0.85% to 1.1% and 0.25% to 0.27%, respectively, the response of climate change to changes in gas is significantly negative at 0.04% to 0.15%. Additionally, the response of climate change to changes in urbanization and economic growth was statistically insignificant.

Although the estimated coefficients are adequate only if the model is statistically viable, the diagnostic test of the three models, as provided in the bottom panel of Table 7, revealed that the model's overall performance is sound. To this end, it is obvious that all the variables of interest, except for GDP and urbanization, revealed a statistically significant influence on climate change in South Africa.

Table 7: DOLS, FMOLS, & CCR Estimation Results

Dependent Variable: CO2						
Variable	**DOLS**		**FMOLS**		**CCR**	
	Coefficient	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
LGDP	0.113005	0.352088	0.018187	0.176090	-0.003474	0.152069
LUR	-0.615050	-1.214152	-0.341565	-1.560170	-0.319408	-1.770376
LCC	1.088877***	6.333094	0.853926***	21.11638	0.855651***	23.17609
LGC	-0.151830***	-4.393248	-0.041290***	-4.267904	-0.042336***	-2.808679
LOC	0.252910*	2.051498	0.268233***	4.541409	0.277933***	4.049165
Dummy	0.167025**	2.830448	0.086307***	3.544614	0.091022***	3.453045
C	10.49950	1.673853	13.43157***	6.441740	13.90011***	1.807972
R^2	0.999340		0.992472		0.992385	
Adj. R^2	0.996964		0.991445		0.991346	
S.E. of reg.	0.015732		0.028579		0.028744	
LR variance	0.000145		0.000706		0.000706	
F-statistic	200.1788***		1110.558***		1272.775***	
J-B test	5.523136**		0.367544**		0.335943**	
Note: The asterisks ***, **, and * are respectively the 1%, 5%, and 10% significance levels.						

Source: Authors' computation

5. CONCLUSIONS AND RECOMMENDATIONS

This study employed DOLS, FMOLS, and CCR to estimate the long-run elasticities, in the presence of structural change, of climate change in South Africa to changes in urbanization, economic growth, coal consumption, gas consumption, and oil consumption from 1971 to 2022. The structural break test results identified 2004 as the date the breakdown occurred, the year the break commenced. The date may not be unconnected to the fact that average manufacturing tariffs were cut from 28% in 1990 to 23% in 1994 and 8% by 2004 (Edwards & Winkel, 2005).

The findings revealed a significant positive degree of responsiveness of climate change to changes in coal and oil, negative to natural gas, and insignificant to changes in urbanization and economic growth. The study concludes that increased burning of fossil fuels directly leads to higher carbon dioxide levels in the atmosphere due to the carbon released during combustion in South Africa. Secondly, switching to natural gas as an energy source can help mitigate climate change to some extent on the South African economy. Thirdly, economic activity alone does not significantly influence the progression of climate change in South Africa, primarily because the main driver of climate change is GHG emissions, which are not directly proportionally tied to economic growth. Lastly, while urbanization can create localized climate changes, it is considered not to be a significant direct contributor to South Africa climate change on a large scale; the primary driver of climate change remains GHG emissions from human activities like burning fossil fuels (coal, gas, and oil).

Given South Africa's vulnerability to climate change and regarding the use of energy consumption according to the estimation results, there should be an accelerating transition towards cleaner and renewable energy sources. Also, developing and deploying renewable energy technologies should be prioritized to reduce dependence on fossil fuels and promote sustainable energy practices in South Africa.

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