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Connection between urbanization and CO_2 emissions in South Africa: does global uncertainty matter?

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Abstract

Purpose – Given the interest in sustainable development, this study aims to assess the relationship between CO_2 and urbanization as well as the role of world uncertainty in this association in a South African context.

Design/methodology/approach – This study focuses on yearly data from 1968 to 2020. To do this, the authors use the autoregressive distributed lag (ARDL) approach.

Findings – The authors find that urbanization's effect on CO_2 emissions is only significant when it is augmented with world uncertainty. Moreover, this effect is negative (referring to a reduction in CO_2 emissions). Meanwhile, the authors find that GDP has a positive (that is, increasing) and significant effect on CO_2 emissions. Overall, policymakers should focus on decoupling economic growth from traditional fossil fuels that produce greenhouse gas emissions.

Originality/value – The existing body of research contains numerous studies examining the relationship between urbanization and CO_2 emissions. However, the dearth of research on the impact of global uncertainty on this connection is weak. Hence, this study aims to fill this gap and make a significant contribution to the field.

Keywords ARDL, Uncertainty, CO_2 emissions, Renewable energy, Urbanization, Ecological footprint, Augmented STRIPAT framework

Paper type Research paper

1. Introduction

Urbanization has been linked to economic growth, with 80% of the wealth of the world generated from urban areas (World Bank Group, 2020). Urbanization can result from the movement from rural to urban areas, emigration, increased births from the urban population or reclassification of rural to urban areas (United Nations, 2018). It oft occurs under unprepared circumstances where the resources available cannot sustain the rate at which the urban population is growing (Zurich, 2015). Even though the African continent is mainly rural, the rate at which it is urbanizing is the fastest in the world. Moreover, it is projected to double over the next 30 years (Moriconi-Ebrard et al, 2020). Urbanization has the potential of benefiting the growth of many economies by reducing poverty and inequality as well as increasing job opportunities, quality of education and health (United Nations, 2020).

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Meanwhile, in the case of South Africa, coal is intertwined with most of the economic growth. The country is the 14th greatest CO_2 emitter, the 7th largest coal producer in the world and the 5th largest coal exporter. As a result of reduced coal reserves and the issues with climate change, South Africa is aiming to reduce its dependence on coal (McSweeney and Timperley, 2018). Consequently, South Africa's high levels of CO_2 emissions are threatening the country's long-term growth, and quality policies are needed to address this. Theoretically, urbanization has an increasing relationship with energy consumption due to transportation and increased living standards (Salim *et al.*, 2017). In South Africa, the prime energy source is coal, and the country is currently urbanizing at a rate of 2.02%. Therefore, more energy is required as the proportion of urban citizens to rural continues to grow (World Bank Group, 2022). However, despite these local circumstances, in recent years, there has been a push to shift the global economy toward greater sustainability. This can be seen in the Paris agreement of 2015 which aimed to "reduce greenhouse emissions" and "curve the effects of climate change" (Yang *et al.*, 2021). The aim was to limit the global temperature rise below 2 degrees Celsius while actively limiting it to 1.5 degrees and provide countries (mainly developing countries) with the resources to deal with the impact of climate change (European Commission, 2019).

To address the knowledge gap on the determinants of greenhouse gas emissions, literature on the impact of urbanization on CO_2 emissions has sprung up (see, e.g. Wang *et al.*, 2020; Sufyanullah *et al.*, 2022; Rehman and Rehman, 2022; Hashmi *et al.*, 2021; Xue *et al.*, 2022). However, the present study may be viewed as an extension of Bekun's (2023) analysis. Specifically, Bekun (2023) examined the effect of several variables (e.g. GDP and fossil fuel consumption) on CO_2 emissions in South Africa. We extend the work of Bekun (2023) by considering the role of urbanization on CO_2 emissions in a South African context. The present study is especially connected that of Wang *et al.* (2021). Their study assessed the effect of urbanization on CO_2 emissions in OECD countries. Certainly, to the best of our knowledge, few or no studies have undertaken to assess the impact of urbanization with a focus on South Africa. This is a significant contribution because the idiosyncrasies of a country (incl. economic development) expectedly affect the nature of the urbanization–CO_2 nexus. Results uncovered from such an examination will improve our understanding of these phenomena. In addition, analyzing the role of the World Uncertainty Index (WUI) in the relationship between urbanization and CO_2 emission will allow us to see how spikes in the global plane will impact our reliance on CO_2 emission (Ahir *et al.*, 2022). The WUI measures the uncertainty of the country by how consumers and the public perceive the nation (Ahir *et al.*, 2022). We may thus be able to answer questions like "in the presence of great uncertainty in the political and economic climate, will the economy go toward sustainable growth and development that creates carbon dioxide emissions?" Against this background, this study examines the influence of urbanization on CO_2 emissions in South Africa with relevance to the role of WUI.

The rest of the paper is organized as follows. In Section 2, we provide a review of related works of literature, while the theoretical foundation is explained in Section 3. We describe the methodology in Section 4 while the data and preliminary analysis of the paper as well as empirical results are presented in Section 5. Finally, Section 6 concludes with some policy implications.

2. Literature review

There is a large body of literature that has assessed the relationship between urbanization and the environment (especially CO_2 emissions). For example, Wang *et al.* (2020) investigated the impact of economic policy uncertainty using the WUI as a proxy. The paper used the autoregressive distributed lag (ARDL) method and found that an increase in the level of WUI in the past will increase the CO_2 emission is the present, due to the relationship between the lagged WUI and the CO_2 emission. Anser *et al.* (2021) looked at the impact of economic policy uncertainty on the connection between urbanization and CO_2 emission. The paper followed the STRIPAT framework using panel ARDL. It focused on the top ten biggest emitters of CO_2. Like other studies, they used WUI as a proxy to mitigate the limits of economic policy uncertainty. Anser *et al.* (2021) discovered contradictory results in the long- and short-run relationships between global uncertainty and CO_2 emissions. It reduces CO_2 emissions in the short term while increasing emissions in the long run. According to the findings, GDP per capita follows the environmental Kuznets curve (EKC).

On the contrary, Adebayo and Odugbesan (2020) used the ARDL approach but incorporated "new wavelet coherence techniques" in South Africa, Africa's greatest provider of CO_2 emissions. They found evidence of cointegration amongst economic growth, financial development and CO_2 emission. Both ARDL and wavelet coherence techniques using the STRIPAT framework found that in the long and short run economic growth positively influences CO_2 emission and the long-run impact is greater than short run. Subsequently, Xue *et al.* (2022) discovered a small but significant positive association between economic growth and CO_2 emissions, indicating that their country's economic progress will inevitably result in more CO_2 emissions. The study supported the EKC. The findings were supported by Wang *et al.* (2020) and Salahuddin *et al.* (2018). Specifically, Salahuddin *et al.* (2019) used the ARDL approach to investigate both urbanization and globalization impact on CO_2 emission in South Africa. The study used the STRIPAT model. The study discovered cointegration between the variables and demonstrated a negative relationship between urbanization and CO_2 emissions in both the short and long run. In a recent study, Sufyanullah *et al.* (2022) used the ARDL approach in their study, the study found that urbanization had a strong positive relationship with CO_2 emissions in the short run which was attributed to the excessive amount of automobiles used. The study was done in the context of Pakistan, a country that is urbanizing at a rapid rate. The paper uncovered that there is a direct relationship between rapid urbanization and CO_2 emission. The paper used ARDL techniques and found that in the long run that there is a strong direct relationship between urbanization and CO_2 emission.

Unlike the other studies, Rehman and Rehman (2022) used the grey system analysis and found a direct causal relationship between carbon emission and environmental damage. The method was used because they wanted to focus on a group with common characteristics that being increasing population growth rate. The variables were urbanization, population growth, GDP and energy consumption, which are all factors that are linked to the growth of a country. The paper focused on the five most populous countries in Asia and found there was a positive link between population growth and the CO_2 emissions the country produced. More specifically, the growth of the urban sector of the population. The paper found that population growth and urbanization played a massive role in the CO_2 emissions of a country. India and Pakistan both ranked number one when looking at the relationship between population growth and urbanization on CO_2 emissions. But China managed to sustain its urbanization even though its population growth was high and had a lower impact on CO_2 emissions than countries whose urban population was increasing. This shows that the growth of a country's urban population leads to CO_2 emissions. The study demonstrated that the growing urban population of the country has a causality relationship with CO_2 emissions (Rehman and Rehman, 2022). Despite the significant work done to better understand the connection between urbanization and CO_2 emissions, few or no studies have yet examined how the dynamics of this relationship may be affected by the role of uncertainty due to global events. Therefore, the present study contributes to the literature by addressing this gap in the literature.

Meanwhile, in a study looking at the association between greenhouse gas emissions and agricultural income on several European countries, Zafeiriou *et al.* (2018) found a significant decreasing effect (from agricultural income) in the case of France, Germany, Greece, Spain and the UK. Meanwhile, for Bulgaria, there was an increasing effect. Interestingly, in a study looking at satisfaction with the national climate response in Greece, Zerva *et al.* (2018) found that Greek citizens were not satisfied with the government's response to climate change and that this dissatisfaction has only worsened over time. This is instructive for policymakers as it shows that environmental concerns are likely to gain greater support as extreme weather events are observed and as citizens become aware of the consequences of failing to curtail some of the excesses of the traditional economy.

It is therefore evident from the preceding review that there need to assess the association between urbanization and CO_2 emissions in a South African context. Moreover, following other studies, we also include the WUI in our analysis.

3. Theoretical foundation

The Ecological Modernization Theory (EMT), which emerged in the 1980s as a means of connecting economics and innovation, serves as the foundation for this study (see inter alia, Glynn *et al.*, 2017). By including people in the notion, it enables the utilization of their social roles to get the best environmental results for the world. It also emphasizes the use of policies by society as a whole to influence and implement laws about climate change (Buttel, 2000). The idea may be applied in a social and political and economic context. EMT states that at low urban development or modernization, the impact on the environment is high (Hashmi *et al.*, 2021). Although as urban development increases, environmental issues become important, EMT has been used to influence environmental issues (Hashmi *et al.*, 2021). The urban environmental theory also supports EMT by stating that the stages of economic development correlate with the environmental conditions (Poumanyvong and Kaneko, 2010).

Following this, a "Stochastic Impacts by Regression on Population, Affluence and Technology" (STIRPAT) model is defined to characterize the effect of different factors on the environment as defined by Dietz and Rosa (1997). The STIRPAT model that will be used for this paper is defined in equation (1).

$$I_t = aP_t^b A_t^c T_t^d \mu_t \tag{1}$$

In the model, (I) is the dependent variable and represents the environmental impact. The independent variables are affluence (A), population (P) and technology (T). The constant term is represented by a and the elasticities of "population, affluence and technology" are denoted by b, c and d, respectfully. Urbanization is used as a measure for population due to the influence urbanization has on CO_2 emission.

4. Methodology and data

4.1 Methodology

A modified version of the long-run STIRPAT model above, this paper explore the connection between urbanization and CO_2 and how global uncertainty impacts the relationship. Equation (1) can be written as Model 1 without interaction with global uncertainty:

$$LCO2_t = \beta_0 + \beta_1 LGDP_t + \beta_2 LRNW_t + \beta_3 LURB_t + \beta_4 LWUI_t + \sum_{t=1}^{s} D_r B_{rt} + \mu_t \tag{2}$$

The dependent variable carbon dioxide emission (CO_2) is a proxy variable for the impact on the environment. The independent variables are GDP per capita (Constant 2010) which is a proxy for affluence, renewable energy consumption (RNW) which is a proxy for technological advancement, and urban population (U) % of the total population which is a proxy for the population and (WUI) which represent world uncertainty. As shown in equation (2), the breaks are captured with the inclusion of $\sum_{r=1}^{s} D_r B_{rt}$ where B_{rt} is a dummy variable for each of the breaks defined as $B_{\mathrm{rt}} = 1$ for $t > \mathrm{T_B}$, otherwise $B_{\mathrm{rt}} = 0$. The time period is represented by t; T_{B} are the structural break dates where $r = 1, 2, 3, \ldots, k$ and D_{r} is the coefficient of the break dummy. As earlier noted, the Bai and Perron's (2003) test that determines breaks endogenously is used. This test is relevant when dealing with models with probable multiple structural changes over time. Apart from computational simplicity, the test allows for up to five breaks in the regression model and is therefore considered a more general framework for detecting multiple structural changes in linear models.

To examine the role of world uncertainty on the relationship between urbanization and CO_2 emission in South Africa, we create Model 2 (equation) with an interactive term of world uncertainty and urbanization. Equation (1) can be written as Model 2 with interaction:

$$LCO2_t = \beta_0 + \beta_1 LGDP_t + \beta_2 LRNW_t + \beta_3 (LURB_t * LWUI_t) + \beta_4 LURB_t + \sum_{t=1}^{s} D_r B_{rt} + v_t \tag{3}$$

To empirically analyze the relationship between urbanization and CO_2 emissions, the ARDL model specification popularly known as bound test is used to show both the short- and long-run relationships. This method is adopted for this study for three reasons. First, compare to other multivariate cointegration methods (i.e. Johansen and Juselius, 1990), the bounds test is a simple technique because it allows the cointegration relationship to be estimated by OLS once the lag order of the model is identified. Second, adopting the bound testing approach means that pretest such as unit root is not required. That is the regressors can either I(0), purely I(1) or mutually cointegrated. Third, the long-run and short-run parameters of the models can be simultaneously estimated. The ARDL method estimates $(p + 1)^k$ number of regressors to obtain the optimal lag length for each variable, where p is the maximum number of lags to be used and k is the number of variables in each equation. An appropriate lag selection based on the Schwarz Information Criteria and Akaike Information Criteria is used. The statistic underlining this procedure is the familiar Wald or F-statistic in a generalized Dickey–Fuller type regression, which is used to test the significance of lagged levels of the variables under consideration in a conditional unrestricted equilibrium error correction model (ECM) (Pesaran *et al.*, 2001). The ARDL model specification in functional form is:

$$\begin{aligned}\Delta LCO2_t = \alpha_0 &+ \sum_{k=1}^{p} \beta_1 \Delta(LCO2)_{t-k} + \sum_{k=0}^{q1} \beta_2 \Delta(LGDP)_{t-k} + \sum_{k=0}^{q2} \beta_3 \Delta(LRWN)_{t-k} \\ &+ \sum_{k=0}^{q3} \beta_4 \Delta(LURB)_{t-k} + \sum_{k=0}^{q4} \beta_5 \Delta(LWUI)_{t-k} + \alpha_1 (LCO2)_{t-1} \\ &+ \alpha_2 (LGDP)_{t-1} + \alpha_3 (LRWN)_{t-1} + \alpha_4 (LURB)_{t-1} \\ &+ \alpha_5 (LWUI)_{t-1} + \sum_{t=1}^{s} D_r B_{rt} + \mu_t \end{aligned} \tag{4}$$

The bound test approach for the long-run relationship between the urbanization and CO_2 emissions is based on the Wald test (F-statistic) by imposing restrictions on the long-run estimated coefficients of one period lagged level of the urbanization and CO_2 to be equal to zero, that is, the null hypothesis of no cointegration states that H_0: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = 0$, is tested against the alternative hypothesis of H_0:$\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq 0$. Then the calculated F-statistic is compared to the tabulated critical value in Pesaran *et al.* (2001). They compute two critical values bounds for any significance level: a lower value that assumes all variables are I(0), and an upper value that assumes all variables are I(1). If the calculated F-statistic is greater than the upper bound, there is cointegration; if it is less than the lower bound, there is no cointegration and if it lies in between the two bounds, then the test is considered inconclusive.

Introducing an interactive term into the ARDL framework, we extend equation (4) to include the relevant interactive variable (WUI).

$$\begin{aligned}\Delta LCO2_t = \alpha_0 &+ \sum_{k=1}^{p} \beta_1 \Delta(LCO2)_{t-k} + \sum_{k=0}^{q1} \beta_2 \Delta(LGDP)_{t-k} + \sum_{k=0}^{q2} \beta_3 \Delta(LRWN)_{t-k} \\ &+ \sum_{k=0}^{q3} \beta_4 \Delta(LURB)_{t-k} + \sum_{k=0}^{q4} \beta_5 \Delta(LURB * LWUI)_{t-k} + \alpha_1(LCO2)_{t-1} \\ &+ \alpha_2(LGDP)_{t-1} + \alpha_3(LRWN)_{t-1} + \alpha_4(LURB)_{t-1} \\ &+ \alpha_5(LURB * LWUI)_{t-1} + \sum_{t=1}^{s} D_r B_{rt} + v_t \end{aligned} \tag{5}$$

To ensure the goodness of fit of model, the diagnostic and stability tests are also conducted, the diagnostic test examines the serial correlation, functional form, normality and heteroscedasticity associated with selected model. Pesaran and Pesaran (1997) suggested using cumulative (CUSUM) and cumulative sum of squares (CUSUMSQ). The CUSUM and CUSUMSQ statistics are updated recursively and plotted against the break points. If the plots of CUSUM and CUSUMSQ statistics stay within the critical bonds of 5% level of significance, the null hypothesis of stable coefficients in the given regression cannot be rejected.

4.2 Data description and sources

The annual data is collected from Our World in Data (2022), The World Bank Group (2022) and Global Footprint Network (2022) from the period of 1968 to 2020 (see Table 1). The period is chosen based on the availability of information of WUI. The results in Table 2 show that there is no multicollinearity because the values of the variance inflation factor (VIF) in both models is less than 10 which is important for the tests going forward (Salahuddin *et al.*, 2019). All the data series are in logged form.

5. Empirical results and discussion

5.1 Preliminary analysis

Table 3 displays the descriptive statistics for each variable. The global uncertainty index (LNWUI) had the lowest mean value at −1.902, and the highest mean value was gross domestic product per capita (LNGDP) at 8.593. The world uncertainty rating is generally low, indicating that it is a relatively secure nation. The world uncertainty index (LNWUI), which is used to assess uncertainty, has the largest difference between the mean and median by 0.088, which displays symmetry between the mean and median.

Table 1. Data description and sources

Variable	Proxy	Explanation	Notation	Source
Carbon dioxide	CO_2 emissions (metric tons per capita)	Impact on the environment	CO_2	Our World Data (https://ourworldindata.org/co2/country/south-africa)
Gross domestic product per capita	GDP per capita (constant 2015 US$)	Affluence	GDP	World data bank (https://data.worldbank.org/country/ZA)
Renewable energy	Renewable energy consumption (% equivalent primary energy)	Technological advancement	RWN	Our World Data (https://ourworldindata.org/co2/country/south-africa)
Urban population	Urban population (percentage of total population)	Population	URB	World data bank (https://data.worldbank.org/country/ZA)
World uncertainty	World uncertainty index for South Africa, index, annual		WUI	World uncertainty index (https://worlduncertaintyindex.com/data/)
Ecological footprint	Ecological footprint biocapacity (gha per person)		EF	Global footprint network (https://www.footprintnetwork.org/)

Source: Authors' compilation (2024)

Table 2. Variance inflation factor (VIF)

Model 1	VIF	Tolerance	Model 2	VIF	Tolerance
LN_URB	1.820	0.549	lnGDP	1.680	0.595
LNGDP	1.770	0.564	lnURB*lnWUI	1.510	0.663
INWUI	1.750	0.572	ln_RWN	1.250	0.800
LN_RWN	1.290	0.774			
Mean VIF	1.660		Mean VIF	1.480	

Source: Authors' computation (2024)

Table 3. Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min.	Median	Max.
LN_CO2	53	2.129	0.109	1.885	2.139	2.298
LNGDP	53	8.593	0.095	8.430	8.576	8.746
LN_RWN	53	−0.886	1.128	−4.174	−0.683	1.147
LNWUI	53	−1.902	1.1420	−4.370	−1.814	0.295
LN_URB	53	4.002	0.116	3.863	3.989	4.210

Source: Authors' computation (2024)

Pearson's correlation coefficient results in Tables 4 and 5 demonstrate a moderate correlation between the variables. Except for the WUI, most of the correlations are positively connected. This suggests that a rise in CO_2 emissions has a moderately negative influence on the degree of world uncertainty. This demonstrates that a rise in CO_2 promotes political and economic certainty. When urbanization and world uncertainty are regarded as interacting factor in Model 2, CO_2 emissions and the interactive term are negatively associated, implying that WUI influences urbanization's connection with CO_2. In both models, the connection between GDP and CO_2 follows the EKC, with a positive association between the variables; however, it is a weak relationship at 0.198 (Model 1) and 0.174 (Model 2). When the interaction component is present, the correlation between the variables weakens, indicating the influence of the WUI on the model (Table 5).

The results in Table 6 were obtained by comparing the augmented Dickey–Fuller and Phillips–Perron tests for stationarity. The augmented Dickey–Fuller test for stationarity suggests that LNCO2, LNGDP, LNWUI and LNEF have unit roots and are stationary after the first difference. While LNRWN and LNURB are fixed and integrated at I(0). Except for LNWUI, which was stationary at levels and integrated at 1, the Phillips–Perron test provided identical results as the augmented Dickey–Fuller test (0). Because the variables are not fully integrated at I(1), Pesaran *et al.* (2001) use the ARDL bound test to test for cointegration among the variables.

According to the Bai and Perron's (2003) test in Table 7, the model had many structural breaks, but only 1980 was significant in both models. The test results indicate that the structural break happened in 1980, which can be linked back to the apartheid era when citizens and international governments were actively attempting to eliminate the apartheid regime through economic distribution via boycotts and penalties (Jones and Inggs, 2012). Attempts to end the apartheid rule began to have a financial impact on the country in the 1980s.

Table 4. Pearson's correlation coefficient: Model 1 without interaction

Model 1	ln_CO_2	lnGDP	ln_RWN	lnWUI	ln_URB
ln_CO2	1.000				
lnGDP	0.198	1.000			
ln_RWN	0.303	0.440	1.000		
lnWUI	−0.107	0.556	0.301	1.000	
ln_URB	0.362	0.560	0.395	0.597	1.000

Source: Authors' computation (2024)

Table 5. Pearson's correlation coefficient: Model 2 with interaction

*Model 2**	ln_CO_2	lnGDP	ln_RWN	lnUrb * lnWUI	ln_URB
ln_CO2	1.000				
lnGDP	0.174	1.000			
ln_RWN	0.239	0.467	1.000		
lnUrb*lnWUI	−0.093	0.597	0.384	1.000	
ln_URB	0.293	0.578	0.468	0.686	1.000

Source: Authors' computation (2024)

Table 6. Unit roots test

	AUGMENTED DICKEY–FULLER			PHILLIPS–PERRON:		
	Level *t*-statistics	Difference *t*-statistics	I(d)	Level *t*-statistics	Difference *t*-statistics	I(d)
LN_CO2	−2.491	−4.490***	I(1)	−2.490	−7.056***	I(1)
LNGDP	−0.987	−4.054***	I(1)	−0.791	−4.297***	I(1)
LN_RWN	−3.587***	–	I(0)	−3.032**	–	I(0)
LNWUI	−2.096	−8.546***	I(1)	−3.741***	–	I(0)
LN_URB	−4.097**	–	I(0)	2.858*	–	I(0)
LNURB*LNWUI	−3.409**	–	I(0)	−3.402**	–	I(0)
LNEF	−1.207	−9.869***	I(1)	−1.316	−11.266**	I(1)

Notes: Let ***, ** and * denote 1, 5 and 10% level of significance. The Schwarz Information Criterion was used to select the appropriate lags for each variable of both models
Source: Authors' computation (2024)

Table 7. Bai–Perron tests of multiple structural breaks

			Bai and perron critical values		
Test date	Break test	*F*-statistic	1%	5%	10%
1980	0 vs 1	34.390	4.480	3.650	3.230
(Model 1)	1 vs 2	3.260	4.880	3.980	3.630
1980	0 vs 1	40.630	4.480	3.650	3.230
(Model 2)	1 vs 2	2.810	4.880	3.980	3.630

Source: Authors' computation (2024)

5.2 Cointegration analysis

Table 8 displays the results of the ARDL bound test, which is used to determine whether there is a long-run link between the variables by testing for cointegration. The *F*-statistics are used to compare the upper and lower critical value boundaries. The null hypothesis is rejected if the *F*-statistics exceed the upper bound and accepted if the *F*-statistics fall below the lower bound. The *F*-statistics for Model 1 was greater than the upper bound for a 5% level of significance at 4.176, resulting in the rejection of the null hypothesis in favor of variable cointegration. Model 2 without cointegration produced the same result because the *F*-statistics was more than the upper bound for 5% level of significance, which was 4.356. As a result, there was considerable cointegration for both models.

5.3 Model estimation and interpretation

According to the results from Table 9, which depict the long- and short-run estimate for the model without interaction, all the explanatory variables of the long-run estimate are significant except for LN_URB. There is a positive strong relationship between CO_2 emission and economic growth. A 1% increase in gross domestic product per capita (LNGDP) results in 0.87% increase in CO_2, given other variables remain constant. In Table 10, the relationship between CO_2 emission and economic affluence in the model with the interaction mirrors that Table 9 where a 1% increase in LNGDP results in a 0.85% increase in LNCO2. One difference

Table 8. Bound test for cointegration

Bound test for cointegration	*F*-statistics	*t*-statistics
Model 1	4.176**	−3.827
Model 2	4.356**	−3.887
Model 1: critical values	**Lower bound, I(0)**	**Upper bound (1)**
1% level of significance	3.410	4.680
5% level of significance	2.620	3.790
10% level of significance	2.260	3.350
Model 2: critical values	**Lower bound, I(0)**	**Upper bound (1)**
1% level of significance	3.410	4.680
5% level of significance	2.620	3.790
10% level of significance	2.260	3.350

Notes: Let ** denotes 5% level of significance. The Schwarz Information Criterion was used to select the appropriate lags for each variable of both models
Source: Authors' computation (2024)

Table 9. Model 1 (without interaction) long-run and short-run estimates

Variable	Long-run			Short-run			
Dependent variable: lnCO2	Coeff	*t*-stat	(Prob.)	Variable	Coeff	*t*-stat	Prob
LNGDP	0.872***	4.530	(0.000)	ΔLNGDP	−0.114	−0.320	(0.748)
LN_RWN	−0.033*	−2.030	(0.051)	ΔLN_RWN	0.009	0.970	(0.341)
LNWUI	−0.060**	−2.500	(0.018)	ΔLNWUI	0.026	1.540	(0.133)
LN_URB	−0.394	−1.590	(0.122)	ΔLN_URB	5.248	0.580	(0.567)
Dummy	0.121*	1.900	(0.066)	Dummy	−0.062	−1.140	(0.263)
				Constant	−2.710	−1.820	(0.078)
				ECM_{t-1}	−0.660	−3.830	(0.001)
				R^2		0.604	
				Adjusted R^2		0.400	

Note: Let ***, ** and * denotes 1, 5 and 10% level of significance
Source: Authors' computation (2024)

noted between Model 1 and Model 2 estimates is that the coefficients of the variables in the Model 1(without interaction) is higher than in Model 2 (with interaction). This shows that the interaction variable (LNWUI) impacts the variables by reducing their influence on carbon dioxide emission. Therefore, WUI has an impact on the relationship between urbanization and CO_2. These results are supported by the studies of Xue *et al.* (2022) while Pata (2018) refuted the claim that CO_2 emission as a positive impact on CO_2 emission. The Pearson's correlation coefficient (Tables 3 and 4) and the significant positive relationship between the variables LNCO2 and LNGDP in the long-run support the EKC theory that there is a positive relationship between carbon dioxide and economic growth. This finding is also consistent with the results uncovered in Bekun (2023). Expectedly, rising GDP leads to improved infrastructure (e.g. roads, telecommunications and power stations) as well as a rising proportion of the population who have access to such things as vehicles and access to electricity. The result is an increase in CO_2 emissions being produced within the country.

Table 10. Model 2 (with interaction): long-run and short-run estimates

Variable Dependent variable: lnCO2	Long-run Coeff	*t*-stat (Prob)	Variable	Short-run Coeff	*t*-stat Prob
lnGDP	0.857***	4.680 (0.000)	*Δ*LNGDP	−0.089	−0.28 (0.780)
ln_RWN	−0.030*	−2.010 (0.052)	*Δ*LN_RWN	0.008	0.900 (0.377)
lnURB*lnWUI	−0.057**	−2.370 (0.024)	*Δ*LNURB*LNWUI	0.024	1.480 (0.148)
LN_URB	−0.338	−1.370 (0.179)	*Δ*LN_URB	5.062	0.570 (0.572)
Dummy	0.128*	2.030 (0.050)	Dummy	−0.066	−1.240 (0.224)
			Constant	−2.579	−1.780 (0.085)
			ECM_{t-1}	−0.659	−3.890 (0.000)
			R^2	0.607	R^2
			Adjusted R^2	0.417	Adjusted R^2
			Constant	−2.579	−1.780 (0.085)
			ECM_{t-1}	−0.659	−3.890 (0.000)
			R^2	0.607	
			Adjusted R^2	0.417	

Notes: Let ***, ** and * denote 1, 5 and 10% level of significance. The values in bracket are the *p*-values
Source: Authors' computation (2024)

The relationship between urbanization and carbon dioxide emissions is not significant in both the long run and the short run for both models, although the coefficients are both negative in the long run and positive in the short run. This supports the EMT that there is change in the relationship between urbanization and environmental issues as the urban development increases (Hashmi *et al.*, 2021). But when urbanization is interacted with WUI in Model 2, the variable becomes significant at a 5% level in the long run. In Model 2, at a 5% level of significance a 1% increase in the interactive term will result in a 0.057% decrease in CO_2 while other variables remain constant. This indicates that the role of WUI is significant in the model and that WUI is important in the relationship between urbanization and CO_2 emission.

In both models, renewable energy consumption has a negative impact on CO_2 emission at a 10% level of significance. The coefficients −0.033 are −0.030 respectively for Model 1 and Model 2. Considering renewable energy accounts for less than 5% of total energy consumption in South Africa, the impact on coal's market share will be minimal, which explains the low coefficients (Roser and Ritchie, 2020). The fact that it is relevant in the long term implies that, even if the influence is minimal, it is still present.

The short-run coefficients are nonsignificant in both models in Tables 9 and 10. Which is a common case in literature, with studies like Xue *et al.* (2022), Adebayo and Odugbesan (2020) and Wang *et al.* (2020) presenting similar results, although other papers managed to produce significant short-run models such as Sufyanullah *et al.* (2022), Pata (2018) and Ali *et al.* (2016). The variables not reaching the level of significance have little effect on the outcomes because the divergence from equilibrium is addressed by the error correcting term (ECM) in Models 1 and 2. Both ECM are statistically significant at a 1% level and are negative. The ECM is lagged over a year, which means that after a year, the short-run model will converge to the long-run model. This demonstrates that the impacts of carbon dioxide emissions are not yet considerable but will be shortly.

5.4 Diagnostic analysis

The diagnostic tests in Table 11 show the posttest that the ARDL models are subjected to after estimation to verify the stability of the models. The outcome of the test showed that, in both models, the *p*-values for the tests are not significant except for the *F*-statistics. This indicates that there is no serial correlation (Breusch–Godfrey LM test), no heteroscedasticity (ARCH test), the models are normally distributed (Jarque–Bera test) and there are no misspecification errors (Ramsey RESET test). The CUSUM and CUSUMQ, which are shown in Figure 1, verified the model's coefficient is stable at a 5% level of significance by being in the middle of the upper and lower bound of the test.

5.5 Causality test

After the model estimation and the diagnostic test, the Toda–Yamamoto causality test was performed for both models. The results in Table 12 show that there is a bidirectional relationship between carbon dioxide emissions (LN_CO2) and world uncertainty for South Africa (lnWUI). Table 13 supports the causal relationship between carbon dioxide emissions and WUI for South Africa because when WUI interacts with urbanization the interactive variable (LNURB*LNWUI) has a bidirectional relationship with LN_CO2. The role that WUI plays is evident with WUI creating a bidirectional relationship between carbon dioxide emissions and urbanization. This suggests that there is a strong link between the variables; therefore, lowering the uncertainty index for South Africa will have an influence on the country's carbon emissions. Moving away from nonrenewable energy sources, on the contrary, will lower the country's uncertainty and the volatility of the economy (Ahir *et al.*, 2022). This lends credibility to the notion that WUI plays a role in the link between urbanization and CO_2 emissions.

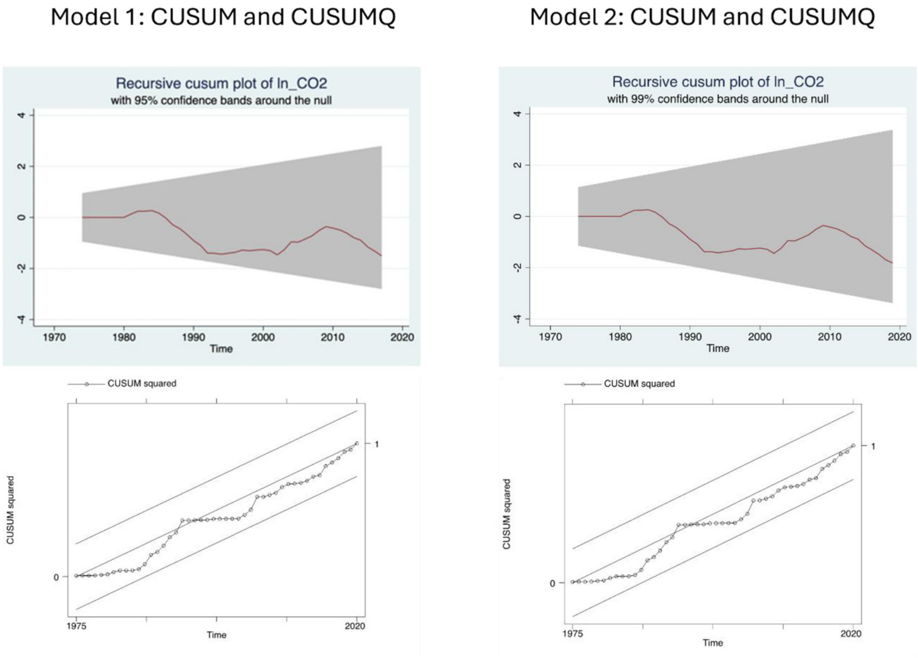
6. Conclusion and implication for policy

This study looked at the link between urbanization and CO_2 emissions from 1968 to 2020. Specifically, the study used the ARDL bound test and revealed that there is evidence of long-run cointegration between CO_2 emissions, GDP per capita, renewable energy consumption, urbanization and the WUI. In both models, GDP was the most significant contributing factor to CO_2 emissions in the long run, indicating that as South Africa's economy increases, so will CO_2 emissions. In both long-term models, the WUI had the least influence on CO_2. In the

Table 11. Diagnostic analysis

Diagnostic analysis	Model 1	Model 2
F-statistics	15.75 (0.000)***	16.860 (0.000)***
Normality-JB	0.618 (0.734)	0.746 (0.689)
DW stat	1.904	1.891
ARCH	0.587 (0.4435)	0.422 (0.516)
Ramsey test	0.459 (0.502)	0.460 (0.502)
LM test	0.243 (0.6219)	0.379 (0.538)
Autocorrelation		
CUSUM	Stable	Stable
CUSUMQ	Stable	Stable

Notes: Let *** denotes 1%, level of significance. The values in bracket are the *p*-values
Source: Authors' computation (2024)



Source: Authors computation (2024)

Figure 1. CUSUM and CUSUMQ

Table 12. Model 1 Toda–Yamamoto causality test

Model 1	ln_CO2	lnGDP	ln_RWN	lnWUI	ln_URB
LN_CO2	–	0.692 (0.708)	0.094 (0.954)	23.315 (0.000)***	11.675 (0.003)***
LNGDP	6.724 (0.035)**	–	0.334 (0.846)	15.116 (0.001)***	2.672 (0.263)
LN_RWN	3.042 (0.218)	0.220 (0.896)	–	2.223 (0.328)	0.335 (0.846)
LNWUI	5.206 (0.074)*	1.453 (0.484)	1.151 (0.562)	–	0.143 (0.931)
LN_URB	0.367 (0.832)	7.564 (0.023)**	0.496 (0.780)	17.340 (0.000)***	–
ALL	16.823 (0.032)**	10.394 (0.238)	5.928 (0.655)	41.706 (0.000)***	21.890 (0.005)***

Note: Let ***, ** and * denotes 1, 5 and 10% level of significance
Source: Authors' computation (2024)

short term, the variables had no substantial influence on CO_2, which is not uncommon in this field of study like Xue *et al.* (2022) and Wang *et al.* (2020). The Pearson's correlation coefficient, long-run estimates and Toda–Yamamoto causality test all confirmed WUI played a significant role in the model. When WUI interacted with urbanization to investigate the role of uncertainty, the interactive variable impact on the model became significant. The paper supported both the EMT and EKC hypothesis, recognizing the positive relationship between CO_2 and GDP and as urban levels increased, the relationship between urbanization and CO_2 shifted from a direct to an indirect relationship.

Table 13. Model 2 Toda–Yamamoto causality test

MODEL 2	ln_CO2	lnGDP	ln_RWN	lnUrb*lnWUI	LN_URB
LN_CO2	–	1.232(0.540)	0.102(0.950)	24.390(0.000)***	11.308(0.004)***
LNGDP	7.926(0.019)**	–	0.182(0.913)	15.621(0.000)***	2.708(0.258)
LN_RWN	3.081(0.214)	1.381(0.501)	–	2.686(0.261)	0.129(0.937)
LNWUI* LN_URB	4.730(0.094)*	0.535(0.765)	0.195(0.550)	–	0.139(0.933)
LN_URB	0.435(0.805)	2.712(0.258)	0.693(0.707)	20.479(0.000)***	–
ALL	18.582(0.017)**	5.411(0.713)	7.492(0.485)	45.112(0.000)***	21.717(0.005)***

Notes: Let ***, ** and * denote 1, 5 and 10% level of significance. The values in bracket are the *p*-values
Source: Authors' computation (2024)

Overall, we may infer that it is the improvement in development (infrastructure, specifically) and income levels that lead to better living standard as well as greater environmental footprint. Therefore, the focus of policymakers must be on transitioning to green energy as they pursuit their objectives of economic development. This is especially imperative given the detrimental effects of climate change on human settlements. Moreover, the shift growth toward a sustainable trajectory, implementation of the legislation needs to be immediate. This will also allow South Africa to adhere to the Paris pledge and address the current problem of reduced coal reserves. Technology advancement needs energy, and the rate South Africa is producing energy is impacting the planet negatively. The natural resources used are finite and the impact on the planet is detrimental. Therefore, the country needs to focus on passing the Climate Change Bill introduced by the Department of Forestry, Fisheries and the Environment. This will also help mitigate the effects of the power shortage crisis the country is experiencing.

For future research, it may be of interest to analyze the associations among CO_2 emissions, GDP and urbanization in the context of countries that have a lesser degree of industrialization than South Africa. This may be a fruitful endeavor on account of the fact that these countries have undertaken the journey to development in an environment where greener alternatives are available.

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