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The Causal Relation between Energy Consumption, Carbon Dioxide Emissions, and Macroeconomic Variables in Somalia

Zakarie Abdi Warsame[1,3]*, Maria Mohamed Ali[1], Liban Bile Mohamud[2], Farhia Hassan Mohamed[1]

[1]Faculty of Economics, SIMAD University, Mogadishu, Somalia, [2]Somalia National Bureau of Statistics, Somalia, [3]Kasmotute Insttitute for Technology, Logistics and Economics Research (KITLER), Somalia. *Email: zakariye1968@gmail.com

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ABSTRACT

This study investigated the relationship between energy consumption, carbon dioxide emissions, and macroeconomic variables in Somalia with data spanning from 1990 to 2019 using ARDL model. The study found a negative long-run relationship between carbon dioxide emissions and energy consumption in Somalia, suggesting that improving access to clean energy can reduce the gradual rise of carbon dioxide emissions. The study also found that rising industrial value-added had a significant positive impact on energy consumption. Furthermore, findings from Cholesky's variance decomposition showed that 13.13% of future fluctuations in energy consumption are due to shocks in carbon dioxide emission, 33.63% of future fluctuations in carbon dioxide emissions are due to shocks in energy consumption, 40.63% of future fluctuations in industrialization are due to shocks in energy consumption and 41.23% of future fluctuations in population are due to shocks in energy consumption. There was evidence of a bidirectional causality between: energy consumption and population. The study suggests adding renewable energy technologies to the energy portfolio. This would help reduce reliance on unstable energy sources and reduce the chance that changes in commodity prices will interrupt the energy supply, which eventually would help reduce the effects of climate change.

Keywords: Energy Consumption, Industrialization, Trade Openness, Somalia and ARDL
JEL Classifications: P18, O14, Q53

1. INTRODUCTION

Energy consumption and related services to meet social and economic development and improve human health and welfare are increasing due to the requirement to meet basic human needs and productivity (Edenhofer et al., 2011). The energy development of a country is closely related to the economic development of the country. A country's economic growth is directly influenced by its ability to provide energy to its citizens. Achieving the Millennium Development Goals (MDGs) depends heavily on access to energy. It is undoubtedly evident that energy inadequacies have a close association with poverty indicators, such as illiteracy, life expectancy, infant mortality, fertility rates, and rapid urbanization in developing countries like Somalia; this is because rural residents migrate to urban areas in search of better living conditions and social amenities (Lipton and Ravallion, 1995).

Due to the limited energy supply in Somalia, the rapid growth of the urban population is currently being hampered by energy insecurity. Around 80-90% of all energy consumption in Somalia comes from wood and charcoal (African Development Bank, 2015).

Electricity provision in Somalia has been the primary responsibility of the country's thriving private sector since the collapse of the central government in 1991. As of right now, the total production capacity is around 106 Megawatts. While most utilities still use gasoline power plants to generate electricity, hybrid systems that take advantage of renewable sources like solar and wind are attracting more and more attention and funding. Recent research by the African Development Bank found that Somalia has the greatest resource potential for coastal wind power in Africa, with the capacity to produce between 30,000 and 45,000 Megawatts. Solar panels could generate more than 2,000 kWh/m^2 of energy.

Around one-sixteenth of the population, by some estimates, has access to modern power. Somalia has more expensive taxes than its neighbors, Kenya and Ethiopia (U.S. Agency for International Development).

Somalia consumed 12,100,621,000 BTU (0.001 quadrillion BTU) of energy in 2017, representing 0.00% of global energy consumption. The country produced 156,621,000 BTU (0.00 quadrillion BTU), covering 1% of its annual energy consumption (Somalia Energy Statistics-Worldometer, n.d.).

Despite this, since 1960, carbon dioxide emissions from the combustion of fossil fuels have tripled. Concerns have grown due to the realization that human-caused carbon dioxide emissions significantly contribute to climate change. Emissions of carbon dioxide and models of economic performance may be critical for understanding the connections between population growth and financial performance. Rapid economic growth and demographic expansion contribute to environmental deterioration (Chandia et al., 2018).

Several economic and legal factors are making the environmental situation around the world worse. These factors operate in different areas and have varying degrees of impact and consequences. They include a macroeconomic policy that encourages the overuse of natural resources, an investment policy that prioritizes using natural resources, and a sectoral policy that needs improving, especially in the fuel and energy industry (Shpak et al., 2022).

Somalia's CO_2 emissions are relatively low compared to other countries due to its limited industrialization and low per capita energy consumption. Somalia's energy sector is primarily based on fossil fuels, with oil accounting for about 95% of the country's total energy consumption. However, due to the ongoing civil conflict and lack of infrastructure, energy access is limited, and the country's total CO_2 emissions remain low. According to the (World Bank, n.d.), Somalia's CO_2 emissions in 2018 were estimated to be 0.06 metric tons per capita, which is significantly lower than the global average of 4.8 metric tons per capita. However, it is important to note that Somalia, like other developing countries, is vulnerable to the impacts of climate change, including sea-level rise, droughts, and floods.

Besides, Conservation policies can greatly affect how well the economy does because every economy depends a lot on how much energy is used. So, testing macroeconomic and environmental variables in the real world is important, as it is crucial to clarifying policy implications and recommendations.

Since per capita income is associated with energy consumption, economic growth can also be identified as the primary cause behind the increase in energy consumption over the last decade (Asumadu-Sarkodie and Owusu, 2016a).

Nevertheless, no consensus has been achieved about the pattern of the causal link between rising macroeconomic output and energy consumption in Somalia. In light of this, the study investigates the relationship between macroeconomic variables, carbon dioxide emissions, and energy consumption in Somalia. The research makes an effort to address the gap in the literature on energy-emissions economic analysis, which has been spotty and scarce in Somalia. In order to assess how each random innovation affects energy usage, carbon dioxide emissions, and increased macroeconomic output the research estimates the variance decomposition using Cholesky's approach.

Finally, reliable estimation methods based on Auto Regressive Distributive Lag ARDL, and granger causality test are used to provide more extensive scheme suggestions from Somalia's energy consumption. The paper is structured as follows: Section 2 reviews the relevant literature, Section 3 describes the research methodology and data, Section 4 presents the study's findings, and Section 5 concludes with policy implications.

2. LITERATURE REVIEW

The literature provides ample documentation of the dynamic causal connection between energy consumption and environmental pollution. The primary objective of these investigations was to describe temporal relationships, but bivariate models were used extensively. There appears to be no consensus regarding the dynamic causal relationship between energy consumption and environmental pollution.

Possible causes of inconclusive results include misspecification of estimated models, bias from omitted variables, or failure to select true lag lengths (which are very sensitive to Granger causality).

Table 1 represents a few of the existing literature examined in the study with their subsequent econometric method, the length of the data employed, and the findings of their study.

3. METHODOLOGY

The study examines the causal nexus between energy consumption, carbon dioxide and macroeconomic variables in Somalia. A time series data spanning from 1990 to 2019 were employed from World Bank, SESRIC and World data. Six study variables were used in the study which include EC-energy-consumption (kilogram of oil equivalent per capita); CO_2-carbon dioxide emissions (kt); TO- Trade Openness; IND-industry, value added (Constant 2015 US$), which is a proxy for industrialization; GDPPC-RGDP per capita (Constant 2015 US$); and POP-population.

A linear representation of the relationship between energy consumption, carbon dioxide and macroeconomic variables in Somalia is showed in Eq. (1):

$$InEC_t = F(InCO2_t, InTO_t, InIND_t, InPOP_t, InGDPPC_t) \quad (1)$$

Where $InEC_t$, $InCO_{2t}$, $InTO_t$, $InIND_t$, $lnPOP_t$ and $lnGDPPC_t$ represent a natural logarithmic transformation of CO_2, TO, IND, POP and GDPPC for a more stable data variance.

The empirical specifications for the model can be quantified as:

Table 1: Summary of the related literature

Reference	Time period	Econometric approach	DV	IV	Findings
(Asumadu-Sarkodie and Owusu, 2017)	1960-2013	VECM	EUSE	CO_2, FID, IND, GDPPC, POP	EC↔FD, EC↔IND, EC↔POP, CO_2↔FD, CO_2↔GDPPC
(Warsame, 2023)	1990-2019	ARDL	CO_2	FDI, REC, GDPPC, PG, K	CO_2→PG, REC→PG
(Shahbaz et al., 2015)	1980-2012	VECM	CO_2	EC, FP, TSVA	CO_2↔EC, TSVA↔CO_2, FP→CO_2, FP→EC, FP→TSVA
(Rafindadi and Ozturk, 2015)	1971-2012	ARDL	NGC	GDP, LF	GDP does not Granger-cause NGC
(Warsame and Sarkodie, 2021)	1985-2017	NARDL	DEFO	EC, RGDPC, and PG	PG↔GDP, GDP→PG, GDP→EC
(Warsame et al., 2022)	1990-2017	ARDL	ED	REC, POP. IQ, RGDPC, and K	No causality is observed from renewable energy to environmental degradation and vice versa.
(Lin et al., 2015)	1980-2011	VECM	CO_2	GDP, EC, and POP	Weak long-run causality from EC to CO_2
(Asumadu-Sarkodie and Owusu, 2016b)	1980-2012	VECM	CO_2	GDP, EC, and POP	CO_2↔EC, GDP↔EC, POP→CO_2
(Cerdeira Bento and Moutinho, 2016)	1960-2011	ARDL	CO_2	GDP, REEP, NREEP, and INT	GDP→REEP, NREEP→REEP
(Mohiuddin et al., 2016)	1971-2013	VECM	CO_2	EC and GDP	EC→CO_2
(Chen et al., 2019)	1980-2014	ARDL	CO_2	GDP, R, N, and T	long-run causality from GDP, the square of GDP, REC, N, and T to CO_2.
(Salahuddin et al., 2015)	1980-2012	FMOLS	CO_2	GDP, EC, and FD	Long-run causality from GDP to CO_2
(Dong et al., 2018)	1993-2016	VECM	CO_2	GDP, FF, NU, and RE	Long-run causality among CO_2, FF, NU, and REC

$$InEC_t = \beta_0 + \beta_1 InCO2_t + \beta_2 InTO_t + \beta_3 InIND_t + \beta_4 InPOP_t + \beta_5 InGDPC_t + \varepsilon_t \quad (2)$$

Where $InEC_t$ is the dependent variable, while $InCO2_t$, $InTO_t$, $InIND_t$, $InPOP_t$ and $InGDPPC_t$ are the explanatory variables in year t, ε_t is the error term, and $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ and β_5 are the elasticities to be estimated.

The first step in testing for cointegration is investigating the order of integration of the variables. We apply Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) stationarity tests to determine if the series are cointegrated. Once the series become stationary, we select the lag order and investigate whether there are cointegrating relationships between variables. To examine the long run relationship among the model variables, there are several tests of cointegration. The first one that has been extensively used and discussed in the literature is the popular Engle and Granger test which is applicable only for same order integrated variables. Subsequently, many other approaches have been developed some of which are the Error correction Cointegration technique of Johansen which is more general and flexible than the Engle and Granger approach, Phillips and Ouliaris test, Johansen and Juselius test, the Structural Error Correction Model (ECM) proposed by (Boswijk, 1994), and the test suggested by (Banerjee et al., 1998a) which is based on the t-test for the null hypothesis. However, these standard approaches have been criticized as being highly unreliable in small samples, inconsistent with different order integrated variables, lead to significantly misleading results and biased against the rejection of null hypothesis (no-cointegration) which requires an adjustment for critical values (Shahbaz et al., 2015). Hence, in order to increase the power of test, more robust cointegration technique is employed which is autoregressive distributed lag (ARDL) bounds testing approach.

Following the empirical work of (Sarkodie and Adams, 2018) the ARDL cointegration equation can be written as:

$$\begin{aligned}\Delta InEC_t &= +\alpha_0 + \beta_1 InCO2_{t-1} + \beta_2 InTO_{t-1} + \beta_3 InIND_{t-1} \\ &+ \beta_4 InPOP_{t-1} + \beta_5 InGDPPC_{t-1} + \sum_{i=0}^{q} \Delta\alpha_1 InEC_{t-k} \\ &+ \sum_{i=0}^{p} \Delta\alpha_2 InCO2_{t-k} + \sum_{i=0}^{p} \Delta\alpha_3 InTO_{t-k} + \sum_{i=0}^{p} \Delta\alpha_4 InIND_{t-k} \\ &+ \sum_{i=o}^{p} \Delta\alpha_5 InPOP_{t-k} + \sum_{i=0}^{p} \Delta\alpha_6 InGDPPC_{t-k} + \varepsilon_{t-k} \quad (3)\end{aligned}$$

Where α_0 is the constant, α_1–α_6 are the coefficient of the short-tun variables, β_1-β_5 are the elasticities of long-run parameters, q indicates the explained's optimal lags, p shows the optimal lags of the explanators, Δ is the first difference sign showing short run variables and ε_t is the error term.

The ARDL cointegration approach begins with bound testing, which is then regressed using Ordinary Least Squares (OLS).

The null hypothesis (H_0): $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$ implies variables are not cointegrated in the long-run whereas the alternative hypothesis (H_1): $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq \beta_7 \neq 0$ implies variables are cointegrated in the long-run. The Wald-F statistics and critical values were employed to test the null hypothesis. If the Wald-F statistics exceed the upper bound critical values, the null hypothesis is rejected, indicating that the variables are linked in the long run and vice versa.

4. RESULTS AND DISCUSSION

4.1. Descriptive Analysis and Correlation Matrix

We examined the characteristics of the data series using descriptive statistics presented in Table 2. Results in Table 2 report the mean of Energy Consumption (2.48), Carbon dioxide (12.79), Trade

Table 2: Descriptive statistics of variables

Stats	LEC	LCO_2	LTO	LIND	LPOP	LGDPPC
Mean	2.483004	12.785123	1.435547	7.862481	6.571825	2.474741
Median	2.483861	2.795866	1.411702	7.910259	6.566554	2.461671
Maximum	2.764392	2.863323	2.027635	8.265808	6.852656	2.622711
Minimum	2.357120	2.690196	0.750508	7.434153	6.341225	2.340999
SD	0.076813	0.043834	0.463578	0.272687	0.165930	0.089644
Skewness	1.392708	−0.514309	−0.011466	−0.143373	0.179796	0.129722
Jarque-Bera	31.04760	1.446313	3.062268	2.508708	2.246811	1.833647
P-value	0.000000	0.485218	0.216290	0.285260	0.325171	0.399787

Openness (1.44), Industrialization (7.86), Population (6.57), and GDP per capita (2.47). Besides, Industrialization and Population have the highest maximum values of 8.27, and 6.85 respectively. Energy Consumption, Population, and GDDPC are positively skewed while CO_2, Trade Openness, and Industrialization are negatively skewed.

Furthermore, the correlation of the sampled variables presented in Table 3 shows that Carbon dioxide, Trade Openness, Industrialization, Population, and GDP Per Capita are negatively correlate with Energy Consumption in Somalia.

4.2. Unit Root Test

Testing the unit root properties is a prerequisite in time series modeling, specifically ARDL. Hence, Augmented Dickey-Fuller (ADF) and Philips perron (PP) tests were utilized to circumvent spurious regression results. The unit root analysis reported in Table 4 shows lnEC is stationary at level [I (0)], whereas the remaining series has unit root. However, Table 4 shows that most of the series are integrated at first difference [I (1)] while only lnEC is integrated at [I (0)]. Since none of the variables are stationary at second difference I (2), we proceeded to estimate the bounds test cointegration.

4.3. Cointegration Test

Results of the bounds test presented in Table 5 examine the presence of long-run co-integration between energy consumption and the explanator variables. However, the results show the Wald F-statistics (13.06530) is above the upper bound critical value (3.38) at 5% significance level. This infers the variables are cointegrated in the long run.

4.4. ARDL Long-run and Short-run Results with Diagnostics

The long-run estimations of the ARDL method are presented in Table 6, with some diagnostic test statistics. The results show a negative long-run significant relationship between carbon dioxide emission and energy consumption in Somalia. In other words, carbon dioxide emissions are negatively related to energy consumption in the long run, which has a policy implication in Somalia. It is likely that reducing carbon dioxide emissions through the adoption of renewable and clean energy technologies will eventually improve energy consumption in Somalia in the long run. This finding is in line with the findings of (Asumadu-Sarkodie and Owusu, 2017).

The impact of rising industrial value added also has significant positive impact on energy consumption. The rise in industrial activities requires more energy to contribute to the gross domestic product. A 1% rise in industrial value-added increases energy consumption by 1.34% in the long run.

Population is found to be negatively related to energy consumption in the long run. This implies that a 1% increase in population leads a decrease of 2.040% to energy consumption in the long run. This contradictory finding may be attributable to the fact that a large proportion of the Somali population resides in rural areas and is typically unable to obtain oil or fuel. Finally, the study found that variables of trade openness and GDPPC are insignificant in the long run.

Our results indicating that an increase in industrial value-added leads to increased energy consumption are in line with the findings of (Lovins, 1990), (Shahbaz and Lean, 2011).

Table 3: Correlation matrix

	LEC	LCO_2	LTO	LIND	LPOP	LGDPPC
LEC	1					
LCO_2	−0.0042	1				
LTO	−0.7191	0.3411	1			
LIND	−0.7721	0.2503	0.9797	1		
LPOP	−0.8085	0.2914	0.9754	0.9821	1	
LGDPPC	−0.6198	0.5987	0.9138	−0.8959	0.8948	1

Table 4: Unit root

Variables	T-statistics at level	
	ADF	PP
lnEC	−7.4709***	−6.2445***
$\ln CO_2$	−2.6578	−2.3435
lnTO	−1.1355	−2.9312
lnIND	−2.2516	−2.2305
lnPOP	−2.9307	−2.5392*
lnGDPPC	−2.3044	−2.5738
At first difference		
$\Delta \ln CO_2$	−3.4250*	−3.4618*
ΔInTO	−4.5596***	−4.5596***
ΔInIND	−5.9256***	−5.8817***
ΔInPOP	−4.4759***	−1.6335
ΔInGDPPC	−5.6156***	−5.6063***

***, **, *Indicate the significance level at 1%, 5%, and 10%. Δ denotes first difference operator. The T-statistics reported are the intercept and trend

Table 5: F bounds test

F-statistic	Level of significance (%)	Bounds test critical values	
		I (0)	I (1)
13.06530	1	3.06	4.15
	5	2.39	3.38
	10	2.08	3

Table 6: Long run results and diagnostics

Variables	Coefficient
C	51.3108 (3.3227)**
$lnCO_2$	−5.2763 (−1.9771)*
lnTO	−0.1054 (−1.2831)
lnIND	1.3428 (2.2224)*
lnPOP	2.0407 (−2.7432)**
lnGDPPC	−0.3539 (−0.6727)
Reset test	0.6933 (0.5105)
Serial correlation	2.6739 (0.1478)
Heteroskedasticity	20.6589 (0.6927)
Normality	0.7342 (0.6927)

***, **,* Indicate significance levels at 1%, 5%, and 10%. The T-statistics are reported in (..), p-values are in [..]

Our results indicating the negative effect of population increase on energy consumption are corroborated by numerous studies such as (Kunvitaya and Dhakal, 2017), (Ohlan, 2015), and (Otsuka, 2018) who conclude that population density has a negative impact on energy consumption.

Diagnostic check results show no serial correlation, heteroscedasticity, model misspecification, and normality problems in the ARDL model. Also, the coefficients of the ARDL model are found stable over the sample period according to the CUSUM and CUSUM-square tests, and test results are presented in Figures 1 and 2, respectively.

The short-run elasticities are computed as the estimated coefficients of the first differenced variables. The short-run results are reported in Table 7. Carbon dioxide exerts negative impact on energy consumption marginally. In short-run, energy consumption will decline by 1.4% due to a 1% increase in carbon dioxide emission. The effect of trade openness on energy consumption is negative and highly significant. This indicate that a 1% increase in trade openness leads a decrease of 0.39% to the energy consumption in the short run. The economic activities in industrial sector are positively associated with energy consumption. It is found that 1% increase in industrial value added will cause 0.46% energy consumption rise. Findings also revealed that Population rise is positively affects energy consumption as 1% increase in population leads an increase of 47% to the energy consumption in the short run. The impact of economic growth on energy consumption is positive and highly significant. A 1% rise in economic growth will increase energy consumption by 1.04%. The significance of error correction term implies that change in the response variable is a function of disequilibrium in the cointegrating relationship and the changes in other explanatory variables. The coefficient of ECTt-1 shows speed of adjustment from short-run to long-run and it is statistically significant with negative sign. (Banerjee et al., 1998b) noted that significant lagged error term with negative sign is a way to prove that the established long-run relationship is stable. The deviation of energy consumption from short-run to the long-run is corrected by 12.65% each year.

Figure 1: Assessing parameter stability using CUSUM test

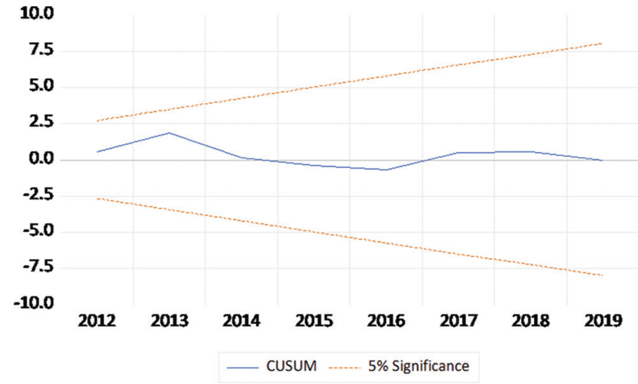

Figure 2: Assessing parameter stability using CUSUM square test

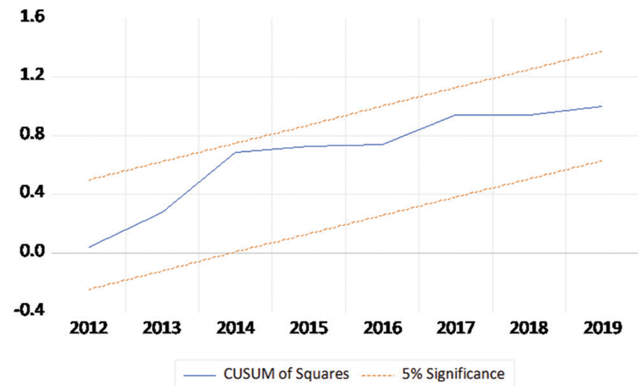

Table 7: Short run ECM results

Variables	Coefficient
$\Delta INEC_{t-1}$	−0.69332 (−7.8215) ***
$\Delta InCO_2$	−1.429 (−8.8308) ***
$\Delta InCO_{2t-1}$	1.2672 (−8.8308) ***
ΔInTO	−0.3945 (−9.6429) ***
$\Delta InTO_{t-1}$	−0.2419 (−5.8585) ***
ΔInIND	0.4623 (9.3141) ***
ΔInPOP	47.8542 (6.9768) ***
$\Delta InPOP_{t-1}$	−106.015 (−8.4944) ***
$\Delta InPOP_{t-2}$	29.5116 (7.3079) ***
ΔInGDPPC	1.0412 (−6.9478) ***
$\Delta InGDPPC_{t-1}$	1.0603 (7.8346) ***
$\Delta InGDPPC_{t-2}$	0.6323 (6.5418) ***
ECT_{t-1}	−0.6583 (−12.6511) ***

***, **,* Indicate significance levels at 1%, 5%, and 10%. The T-statistics are reported in (..), *P* values are in [..]

Table 8: Pairwise granger causality

Null hypothesis	Obs	F-Statistic	Prob.
InCO$_2$ does not granger cause InEC	28	3.69957	0.0405
InEC does not granger cause InCO$_2$	28	1.22018	0.3136
InTO does not granger cause InEC	28	2.04205	0.1526
InEC does not granger cause InTO	28	1.17761	0.3259
InIND does not granger cause InEC	28	1.0382	0.3701
InEC does not granger cause InIND	28	2.03355	0.1537
InPOP does not granger cause InEC	28	2.56318	0.0989
InEC does not granger cause InPOP	28	8.37181	0.0019
InGDPPC does not granger cause InEC	28	0.0409	0.9600
InEC does not granger cause InGDPPC	28	2.40318	0.1128
InTO does not granger cause InCO$_2$	28	5.47321	0.0114
InCO$_2$ does not Granger Cause InTO	28	2.13027	0.1417
InIND does not granger cause InCO$_2$	28	5.33058	0.0125
InCO$_2$ does not granger cause InIND	28	3.47038	0.0482
InPOP does not granger cause InCO$_2$	28	11.7016	0.0003
InCO$_2$ does not granger cause InPOP	28	1.1926	0.3215
InGDPPC does not granger cause InCO$_2$	28	1.90639	0.1714
InCO$_2$ does not granger cause InGDPPC	28	0.25898	0.7741
InIND does not granger cause InTO	28	2.98343	0.0705
InTO does not granger cause InIND	28	4.64893	0.0202
InPOP does not granger cause InTO	28	3.75578	0.0388
InTO does not granger cause InPOP	28	3.04342	0.0672
InGDPPC does not granger cause InTO	28	6.79864	0.0048
InTO does not granger cause lnGDPPC	28	3.48718	0.0476
InPOP does not granger cause InIND	28	15.0648	0.0000
InIND does not granger cause InPOP	28	11.6456	0.0003
InGDPPC does not granger cause InIND	28	11.7177	0.0003
InIND does not granger cause InGDPPC	28	0.40083	0.6744
InGDPPC does not granger cause InPOP	28	19.0959	0.0000
InPOP does not granger cause InGDPPC	28	0.44707	0.6449

4.5. Granger Causality Test

In order to determine the direction of causality between variables, we conducted the Granger causality test shown in Table 8. From CO_2 to energy consumption, trade openness to CO_2, population to CO_2, GDPPC to industrialization, and GDPPC to population we observed unidirectional causation. There are bidirectional causal relationships between population and energy consumption, industrialization and CO_2, industrialization and trade openness, population and trade openness, GDPPC and trade openness, and population and industrialization.

4.6. Variance Decomposition

This section estimates the response of variables to random innovation affecting the variables in the VAR using the Cholesky's method of variance decomposition. Evidence from Table 9 A shows that 13.13% of future fluctuations in lnEC are due to shocks in lnCO_2, 11.43% of future fluctuations in lnEC are due to shocks in lnTO, 5.46% of future fluctuations in lnEC are due to shocks in lnPOP, 3.92% of future fluctuations in lnEC are due to shocks in lnIND, and 0.99% of future fluctuations in lnEC are due to shocks lnGDPPC. As a policy implication for Somalia, carbon dioxide emissions affect energy consumption in the future more than trade openness population, industrialization, and GDP per capita.

Evidence from Table 9 B shows that almost 33.63% of future fluctuations in lnCO_2 are due to shocks in lnEC, 18.73% of future fluctuations in lnCO_2 are due to shocks in lnTO, 16.3% of future fluctuations in lnCO_2 are due to shocks in lnPOP, 3.36%

Table 9: Variance decomposition

A) Variance decomposition of lnEC							
Period	S.E.	INEC	INCO$_2$	INTO	ININD	INPOP	INGDPPC
1	0.037776	100	0	0	0	0	0
2	0.047324	81.74989	7.120279	5.224611	0.222687	5.273605	0.408927
3	0.0576	73.40587	13.42851	6.978587	1.376377	4.473519	0.337144
4	0.061162	71.62573	12.35961	9.294517	2.411826	3.967663	0.340651
5	0.06209	69.58832	12.11219	11.04883	2.903981	4.01573	0.330948
6	0.062742	68.16538	12.45138	10.86428	3.179632	4.819499	0.519825
7	0.063678	66.25832	13.11106	11.0774	3.383104	5.332493	0.83762
8	0.064282	65.38054	13.30776	11.45954	3.603291	5.278576	0.970297
9	0.064652	65.20435	13.20886	11.5053	3.827624	5.28394	0.969932
10	0.064878	65.07637	13.12598	11.42653	3.922963	5.459732	0.988424
B) Variance decomposition of lnCO$_2$							
Period	S.E.	lnEC	lnCO$_2$	lnTO	lnIND	lnPOP	lnGDPPC
1	0.018160	18.98679	81.01321	0.000000	0.000000	0.000000	0.000000
2	0.020924	14.54022	61.0513	0.217973	0.549562	22.00749	1.633451
3	0.028213	32.85115	42.86229	3.161401	0.315152	19.37486	1.435139
4	0.035320	39.48501	32.50462	7.579748	0.598448	17.79076	2.041415
5	0.039651	36.96935	29.0155	15.33211	0.614804	15.64264	2.425601
6	0.041208	35.52213	27.68793	19.21259	0.737222	14.48418	2.355943
7	0.041704	35.06113	27.03512	19.77435	0.837832	14.93328	2.358295
8	0.042176	34.5351	26.63378	19.3365	1.069199	15.7669	2.658517
9	0.042800	34.04188	26.10001	18.98674	1.554874	16.23534	3.081156
10	0.043420	33.62897	25.68895	18.72736	2.298263	16.29576	3.360701
C) Variance decomposition of lnTO							
Period	S.E.	lnEC	lnCO$_2$	lnTO	lnIND	lnPOP	lnGDPPC
1	0.060317	0.097471	14.91304	84.98949	0.000000	0.000000	0.000000
2	0.085146	0.368801	9.412168	66.19750	13.24972	5.954974	4.816833
3	0.115074	7.745887	9.552816	38.76711	22.19934	13.21844	8.516404

(Contd...)

Table 9: ***(Continued)***

Period	S.E.	lnEC	$lnCO_2$	lnTO	lnIND	lnPOP	lnGDPPC
C) Variance decomposition of lnTO							
4	0.144888	10.07868	13.33237	25.56425	28.80558	12.84684	9.372283
5	0.173012	12.94577	14.73421	18.10619	33.18196	11.59211	9.439766
6	0.199343	15.71125	16.61490	1,364,181	34.92462	10.33313	8.774288
7	0.217774	16.50086	19.00609	11.50073	35.44629	9.461863	8.084161
8	0.228622	16.27145	21.09667	10.77755	35.15938	9.075692	7.619251
9	0.234828	15.65524	22.70668	11.27476	34.13013	8.942591	7.290592
10	0.239247	15.13880	23.32543	12.83254	32.88161	8.797875	7.023740
D) Variance decomposition of lnIND							
Period	**S.E.**	**lnEC**	**$lnCO_2$**	**lnTO**	**lnIND**	**lnPOP**	**lnGDPPC**
1	0.053802	51.95368	4.218534	11.05033	32.77745	0.000000	0.000000
2	0.060476	44.20283	12.19904	15.10017	26.56296	1.932907	0.002093
3	0.064266	39.18167	14.51023	14.33457	25.18027	5.842866	0.960392
4	0.070585	32.61441	16.41487	18.64761	20.87722	9.686311	1.759578
5	0.073798	29.86625	16.04012	23.38977	19.10734	9.757484	1.839036
6	0.076304	28.64037	15.04378	26.54260	18.29666	9.735596	1.740986
7	0.080212	29.57774	13.70947	27.97173	17.74547	9.406054	1.589534
8	0.087632	33.72539	11.63210	26.98443	17.65156	8.635057	1.371463
9	0.097614	38.05545	9.435389	25.74610	17.89929	7.743952	1.119817
10	0.107793	40.63962	7.738617	25.20531	18.52484	6.970276	0.921331
E) Variance decomposition of lnPOP							
Period	**S.E.**	**lnEC**	**$lnCO_2$**	**lnTO**	**lnIND**	**lnPOP**	**lnGDPPC**
1	0.000978	29.95410	1.919819	0.520289	5.368368	62.23743	0.000000
2	0.002540	30.70284	2.044221	2.673434	4.960494	58.34512	1.253891
3	0.004913	30.93122	3.410568	10.14105	4.050014	48.75990	2.707250
4	0.007649	30.04796	4.415351	17.55936	3.410027	41.14973	3.417574
5	0.010448	30.31854	4.905000	22.67687	3.106397	35.39828	3.594918
6	0.013174	31.73386	5.126825	25.85679	3.013320	30.82603	3.443170
7	0.015830	33.94238	5.233862	27.49914	3.148990	27.06262	3.113004
8	0.018444	36.54531	5.213597	28.14391	3.512493	23.86276	2.721928
9	0.021002	39.06284	5.026007	28.29266	4.093843	21.17509	2.349561
10	0.023450	41.23321	4.689210	28.24065	4.843619	18.96360	2.029716
F) Variance decomposition of lnGDPPC							
Period	**S.E.**	**lnEC**	**$lnCO_2$**	**lnTO**	**lnIND**	**lnPOP**	**lnGDPPC**
1	0.028245	4.146526	1.049299	9.764113	0.530419	63.62860	20.88105
2	0.042112	4.609519	9.749053	36.46300	4.197690	32.40336	12.57737
3	0.043942	4.401092	11.99666	37.00492	4.043623	30.58769	11.96601
4	0.045385	6.503746	11.98368	37.32893	4.278083	28.67907	1122649
5	0.047393	9.273601	12.79228	36.77025	4.248973	26.59928	10.31562
6	0.050663	15.24251	12.42754	34.66226	5.191256	23.27877	9.197672
7	0.05405	19.39081	10.93782	33.07414	7.875717	20.45694	8.264568
8	0.056983	20.93201	10.10655	32.07623	10.71740	18.49593	7.671884
9	0.059722	21.76906	10.19500	30.18350	13.45841	17.06708	7.326937
10	0.062256	22.65140	10.90741	27.98759	15.46832	15.91398	7.071297

of future fluctuations in $lnCO_2$ are due to shocks in lnGDPPC, and 2.3% of future fluctuations in $lnCO_2$ are due to shocks in lnIND. As a policy implication for Somalia, energy consumption affects carbon dioxide emissions in the future more than trade openness, GDP per capita, industrialization, and population.

Moreover, evidence from Table 9 C shows that, almost 32.88% of future fluctuations in lnTO are due to shocks in lnIND, 23.33% of future fluctuations in lnTO are due to shocks in $lnCO_2$, 15.14% of future fluctuations in lnTO are due to shocks in lnEC, 8.8% of future fluctuations in lnTO are due to shocks in lnPOP, and 7.02% of future fluctuations in lnTO are due to shocks in lnGDPPC. As a policy implication for Somalia, industrialization affects trade openness in the future more than carbon dioxide emission, energy consumption, population, and GDP per capita. Evidence from Table 9 D shows that almost 40.63% of future fluctuations in lnIND are due to shocks in lnEC, 25.21% of future fluctuations in lnIND are due to shocks in lnTO, 7.74% of future fluctuations in lnIND are due to shocks in lnCO2, 6.97% of future fluctuations in lnIND are due to shocks in lnPOP, and 0.92% of future fluctuations in lnIND are due to shocks lnGDPPC. As a policy implication for Somalia, energy consumption affects industrial value added in the future more than trade openness, carbon dioxide emissions, population and GDP per capita.

In addition, evidence from Table 9 E shows that almost 41.23% of future fluctuations in lnPOP are due to shocks in lnEC, 28.24% of future fluctuations in lnPOP are due to shocks in lnTO, 4.84% of future fluctuations in lnPOP are due to shocks in lnIND, 4.69% of future fluctuations in lnPOP are due to shocks in $lnCO_2$, and 2.03% of future fluctuations in lnPOP are due to shocks in lnGDPPC. As a policy implication for Somalia, energy consumption affects industrialization in the future more than trade openness, industrialization, carbon dioxide emissions, and GDP per capita.

Finally, evidence from Table 9 F shows that almost 27.99% of future fluctuations in lnGDPPC are due to shocks in lnTO, 22.65% of future fluctuations in lnGDPPC are due to shocks in lnEC, 15.91% of future fluctuations in lnGDPPC are due to shocks in lnPOP, 15.47% of future fluctuations in lnGDPPC are due to shocks in lnIND, and 10.91% of future fluctuations in lnGDPPC are due to shocks in $lnCO_2$. As a policy implication for Somalia, trade openness affects population in the future more than energy consumption, population, industrialization and carbon dioxide emissions.

5. CONCLUSION AND POLICY IMPLICATIONS

The study examined the causal relationship between energy consumption, carbon dioxide emissions, and macroeconomic variables in Somalia with a data spanning from 1990 to 2019 using the ARDL model. The summary of findings are as follows:

The results show a negative long-run significant relationship between carbon dioxide emission and energy consumption in Somalia. We can say that energy policies aimed at improving access to clean energy consumption in Somalia will reduce the gradual rise of carbon dioxide emission in Somalia.

The impact of rising industrial value added also has significant positive impact on energy consumption. The rise in industrial activities requires more energy to contribute to the gross domestic product. A 1% rise in industrial value-added increases energy consumption by 1.34% in the long run.

Population is found to have a negative long-term relationship with energy consumption. In the long term, a 1% increase in population results in a 2.040% decrease in energy consumption. This contradictory finding may be attributable to the fact that a large proportion of the Somali population resides in rural areas and is typically unable to obtain oil or fuel. Further, the study found that variables of trade openness and GDPPC are insignificant in the long run.

Carbon dioxide emission and trade openness are adversely affected to the energy consumption in the short run. Contrary to this, industrialization, population and GDDPC increase energy consumption in Somalia. ECM's significant error coefficient confirms the existence of a long-run relationship between the variables.

With regards to Granger-causality, there was evidence of a bidirectional causality between: population to energy consumption, industrialization to CO_2, industrialization to trade opennes, population to trade openess, GDPPC to trade opennes, and population to industrialization. Moreover, there was evidence of a unidirectional causality running from CO_2 to energy consumption, trade opennes to CO_2, population to CO_2, GDPPC to industrialization, and GDPPC to population.

Evidence from the Cholesky's method of variance decomposition shows that 13.13% of future fluctuations in energy consumption are due to shocks in Carbon dioxide emissions, 33.63% of future fluctuations in carbon dioxide emissions are due to shocks in energy consumption, 32.88% of future fluctuations in trade openness are due to shocks in industrialization, 40.63% of future fluctuations in industrialization are due to shocks in energy consumption, 41.23% of future fluctuations in population are due to shocks in energy consumption, and 27.99% of future fluctuations in GDPPC are due to shocks in trade openness.

Several policy implications can be drawn based on empirical findings concerning energy consumption in Somalia. To begin with, diversification of Somalia's economic productivity through enhanced technological advancement; innovation; value added to raw materials, goods, and services will broaden the financial base leading to high levels of per capita GDP. Furthermore, diversification of Somalia's energy sector throughout the incorporation of renewable energy technologies into the energy portfolio will reduce reliance on volatile energy sources (fuel, oil, and gas) and the likelihood of interruptions in energy supply due to commodity price volatility, thereby contributing to climate change mitigation efforts.

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