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RESEARCH ARTICLE

Carbon dioxide emissions, GDP, energy use, and population growth: a multivariate and causality analysis for Ghana, 1971–2013

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Abstract In this study, the relationship between carbon dioxide emissions, GDP, energy use, and population growth in Ghana was investigated from 1971 to 2013 by comparing the vector error correction model (VECM) and the autoregressive distributed lag (ARDL). Prior to testing for Granger causality based on VECM, the study tested for unit roots, Johansen's multivariate co-integration and performed a variance decomposition analysis using Cholesky's technique. Evidence from the variance decomposition shows that 21 % of future shocks in carbon dioxide emissions are due to fluctuations in energy use, 8 % of future shocks are due to fluctuations in GDP, and 6 % of future shocks are due to fluctuations in population. There was evidence of bidirectional causality running from energy use to GDP and a unidirectional causality running from carbon dioxide emissions to energy use, carbon dioxide emissions to GDP, carbon dioxide emissions to population, and population to energy use. Evidence from the long-run elasticities shows that a 1 % increase in population in Ghana will increase carbon dioxide emissions by 1.72 %. There was evidence of short-run equilibrium relationship running from energy use to carbon dioxide emissions and GDP to carbon dioxide emissions. As a policy implication, the addition of renewable energy and clean energy technologies into Ghana's energy mix can help mitigate climate change and its impact in the future.

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Abbreviations

Chi^2	Chi square
Parms	Parameter
df	Difference
Prob	Probability
_ce	Co-integrated equation
Coef.	Coefficient
_cons	Constant
Std. Err.	Standard error
L1._ce	Error correction term

Acronyms

VECM	Vector error correction model
ECT	Error correction term
SR	Short run
LRE	Long-run elasticities
LL	Log likelihood
LR	Sequential likelihood ratio
AIC	Akaike information criterion
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
SC	Schwarz information criterion
HQ	Hannan-Quinn information criteria
VIF	Variance inflation factor
LCUs	Local currency units
P	Population
GT	Grubbs' test
GMM	Generalized Method of Moments
FMOLS	Fully-Modified Ordinary Least Squares
DOLS	Dynamic Ordinary Least Squares

Introduction

Access to energy is one of the many ways of achieving higher levels of economic productivity in every technological and advancing country (Owusu and Asumadu-Sarkodie 2016). Energy demand and economic development are increasing due to the requirement to meet basic human needs and productivity (Asumadu-Sarkodie and Owusu 2016a; Edenhofer et al. 2011). However, the quest to meet global energy demand has led to the use environmental unfriendly energy sources that impact climate change due to the emission of greenhouse gases (Asumadu-Sarkodie and Owusu 2016b; Asumadu-Sarkodie and Owusu 2016d; Asumadu-Sarkodie and Owusu 2016e). According to Earth System Research Laboratory (2015), the growth rate of carbon dioxide emissions has increased over the past 36 years (1979–2014), "*averaging about 1.4 ppm per year before 1995 and 2.0 ppm per year thereafter*." As a result of this, the Sustainable Development Goal 13 focuses on actions that help mitigate climate change and its impacts (United Nations 2015). The causal nexus between environmental pollution and energy consumption as well as between economic growth and environmental pollution has become a global interest (Acaravci and Ozturk 2010; Owusu et al. 2016). Nevertheless, it is inconclusive to recommend national policies without empirical evidence to support it. There are a vast number of studies that have employed modern econometric approaches such as autoregressive and distributed lag (ARDL), GMM, DOLS, FMOLS, and vector error correction model (VECM) to analyze both microeconomic and macroeconomic variables. Table 1 shows a few of the compiled studies that have employed modern econometric approaches.

There are conflicting results pertaining to the causal nexus between GDP and energy consumption/intensity or between energy consumption/intensity and carbon dioxide emissions, which we believe depends on the length of data and the particular location for the study. The outcome of studies by Herrerias et al. (2013) and Apergis and Ozturk (2015) maybe misleading since data employed for the study spans from 1995 to 2009 and 1990 to 2011. Using less than 30 observations becomes problematic in making the current inferences for a particular location. Accordingly, employing a lengthy dataset makes it more statistically useful to make the correct inference. Notwithstanding, almost all the studies are done in European countries (Acaravci and Ozturk 2010; Azhar Khan et al. 2014; Caraiani et al. 2015; Fuinhas and Marques 2012; Ohler and Fetters 2014), Asian countries (Apergis and Ozturk 2015; Asafu-Adjaye 2000; Chang 2010; Chen et al. 2007), and the Middle East countries (Azhar Khan et al. 2014; Ozturk and Acaravci 2011; Sadorsky 2011).

Meanwhile, the trend of CO_2 emissions per capita in Africa grew from −7.4 to 6.38 % for the years 1980 and 2008, while per capita income grew from −3.75 to 4.02 % in the same period (Osabuohien et al. 2014). Surprisingly, the debate on CO_2 emissions and its impact in Africa have been neglected for quite a long time; it is therefore necessary to draw inspiration from the African context in order to provide additional perspectives to the global debate.

Our study is in line with Hatzigeorgiou et al. (2011) who did a similar study in Greece where a unidirectional causality was established between GDP and energy intensity (EI) and GDP and CO_2 emissions. They found a bidirectional relationship between CO_2 emissions and EI. Similarly, Hatzigeorgiou et al. (2008) employed a decomposition technique to investigate the factors affecting CO_2 emissions. Their findings show that energy intensity is the main factor responsible for the decrease in CO_2 emissions while income effect contributes to increasing CO_2 emissions.

The causal relationship between carbon dioxide emissions, GDP, and energy use has been sporadic and limited especially in developing countries like Ghana. Ghana's contribution towards climate change mitigation is eminent. Ghana acceded to the Kyoto protocol by the United Nations Framework Convention on Climate Change (UNFCC) in November 2002 and has been listed in non-annex 1 countries that can only contribute in the clean development mechanism as her contribution to reducing emission levels of her greenhouse gases (UNTC 2015). Ghana as a growing economy from lower middle income to a middle income economy has suffered many hitches in the field of health (Asumadu-Sarkodie and Owusu 2015), water management (Asumadu-Sarkodie et al. 2015a; Asumadu-Sarkodie et al. 2015b), energy management, etc. A limitation in scientific research in these areas makes it difficult for local and private investors to make a decisive decision in their investment in Ghana.

Attempts have been made to make known the developmental issues in Ghana in the scientific arena but are still limited in the scope of climate change mitigation. To the best of our knowledge, only Adom and Bekoe (2012) have employed modern econometric approaches like ARDL and partial adjustment model (PAM) to forecast the 2020 electrical energy requirement for Ghana. Their study concluded that domestic electricity consumption is mainly explained by income factor in Ghana. Nevertheless, their study is different from our study.

Against this backdrop, our study investigates the relationship between carbon dioxide emissions, GDP, energy use, and population growth in Ghana by employing data from 1971 to 2013 by comparing VECM and ARDL which are different and absent from the literature listed in the study. The study is worthwhile to Ghana since it will increase the awareness of sustainable development and serve as a reference tool for integrating climate change measures into energy policies, practices, and planning by the Government of Ghana. The rest of the paper are sectioned into "Methodology," "Results and discussion," and "Conclusion" sections with policy recommendations.

Table 1 Compilation of previous studies

Author	Year	Data	Method	Results
Cerdeira Bento and Moutinho (2016)	2016	1960–2010	ARDL	EKC exists
Seker et al. (2015)	2015	1974–2010	ARDL	EKC exists
Apergis and Ozturk (2015)	2015	1990–2011	GMM	EKC exists
Baek (2015)	2015	1980–2009	DOLS and FMOLS	No EKC exists
Herrerias et al. (2013)	2013	1995–2009	VECM	Long-run causality from GDP to EC
Hatzigeorgiou et al. (2011)	2011	1977–2007	VECM	Long-run causality from GDP to EI
Apergis and Payne (2011)	2011	1980–2006	FMOLS	Long-run causality from GDP to EI
Ozturk and Acaravci (2010)	2010	1980–2006	VECM and ARDL	Weak long-run causality from EC to GDP
Salahuddin et al. (2015)	2015	1980–2012	FMOLS	Long-run causality from GDP to CO_2
Lin et al. (2015)	2015	1980–2011	VECM	Weak long-run causality from EI to CO_2

Methodology

The study examines the causal nexus between carbon dioxide emissions, energy use, GDP, and population growth in Ghana by comparing VECM and ARDL. A time series dataset from 1971 to 2013 was employed from the World Bank database (World Bank 2015). Four study variables were used in the study which include CO_2—carbon dioxide emissions (kt), GDP—gross domestic product (current LCU), EU—energy use (kg of oil equivalent per capita), and P—population growth. World Bank (2015) defines energy use as "the primary energy before transformation into other end-use fuels, which is equal to indigenous production plus imports and stock exchange, minus exports and fuels supplied to ships and aircraft engaged in international transport."

Let LCO_2, LEU, LGDP, and LP represent the logarithmic transformation of carbon dioxide emissions, energy use, gross domestic product, and population, since logarithmic transformation leads to a more stable data variance. Following the work of Asumadu-Sarkodie and Owusu (2016c), the VECM for this study can be expressed as

$$\Delta\begin{bmatrix} \mathrm{LCO}_{2t} \\ \mathrm{LEU}_t \\ \mathrm{LGDP}_t \\ \mathrm{LP}_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix} + \sum_{i=1}^{p} \Delta \begin{bmatrix} \beta_{11i}\beta_{12i}\beta_{13i}\beta_{14i} \\ \beta_{21i}\beta_{22i}\beta_{23i}\beta_{24i} \\ \beta_{31i}\beta_{32i}\beta_{33i}\beta_{34i} \\ \beta_{41i}\beta_{42i}\beta_{43i}\beta_{44i} \end{bmatrix} \times \begin{bmatrix} \mathrm{LCO}_{2t-i} \\ \mathrm{LEU}_{t-i} \\ \mathrm{LGDP}_{t-i} \\ \mathrm{LP}_{t-i} \end{bmatrix} + \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \end{bmatrix} [\mathrm{ECT}_{t-1}] + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix} \quad (1)$$

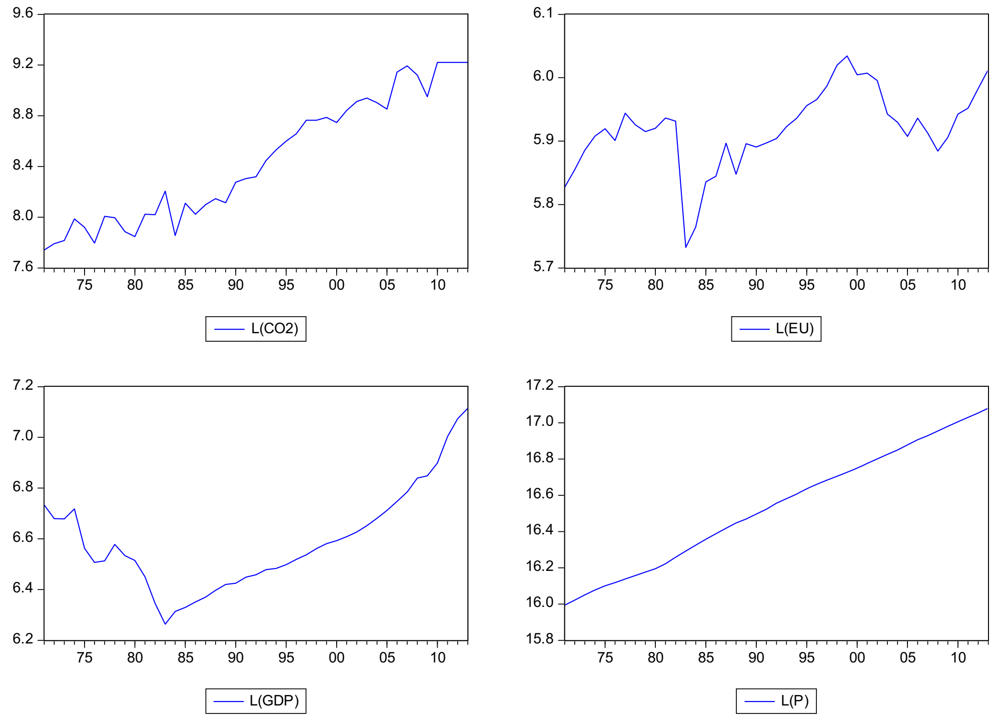
where LCO_2 is the dependent variable; LEU, LGDP, and *LP* are the explanatory variables in year *t*; Δ is the difference operator; ECT_{t-1} is the error correction term resulting from the long-run co-integration relationship; θs, αs, and βs are the parameters to be estimated; p is the number of lags; and ε_ts are the serially independent error terms.

Unlike other econometric techniques that require all variables to be I(1) or I(0) and I(1), Pesaran and Shin (1998) revealed that co-integration among variables can have different number of lag terms and can be estimated as ARDL model with variables in co-integration without pre-requirement of variables to be either I(0) or I(1). Following the work of Adom and Bekoe (2012), Asumadu-Sarkodie and Owusu (2016f), and Ozturk and Acaravci (2011), ARDL model for this study can be expressed as

$$\Delta \mathrm{LCO}_{2t} = \alpha_0 + \delta_1 \mathrm{LCO}_{2t-1} + \delta_2 \mathrm{LEU}_{t-1} + \delta_3 \mathrm{LGDP}_{t-1} + \delta_4 \mathrm{LP}_{t-1} + \sum_{i=1}^{p} \beta_{1j} \Delta \mathrm{LCO}_{2t-i} + \sum_{i=0}^{p} \beta_{2j} \Delta \mathrm{LEU}_{t-i} + \sum_{i=0}^{p} \beta_{3j} \Delta \mathrm{LGDP}_{t-i} + \sum_{i=0}^{p} \beta_{4j} \Delta \mathrm{LP}_{t-i} + \varepsilon_t \quad (2)$$

where α is the intercept, p is the lag order, ε_t is the error term, and Δ is the first difference operator. The study employs the F tests in order to test the long-run equilibrium relationship between LCO_2, LEU, LGDP, and LP. The ARDL bound test functions under the null hypothesis of no co-integration between LCO_2, LEU, LGDP, and LP $[H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0]$, against the alternative hypothesis of co-integration between LCO_2, LEU, LGDP, and LP $[H_1: \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq 0]$.

Fig. 1 Trend of variables



According to Pesaran et al. (2001), if the computed *F* statistic is above the upper bound critical value, then the null hypothesis of no co-integration between LCO_2, LEU, LGDP, and LP is rejected. Otherwise, the null hypothesis of no co-integration is accepted if the *F* statistic lies below the critical values of the lower bound.

Descriptive analysis

This section outlines the descriptive statistical analysis of the variables before logarithmic transformation was applied in the study. Figure 1 shows the trend of the variables after logarithmic transformation was applied. It is evident that the trend of population increases periodically, trend of GDP follows that of CO_2 emissions, but trend fluctuations seem to occur in energy use. The descriptive statistical analyses of the variables are presented in Table 2. While CO_2, GDP, and P have a long-right tail (positive skewness), EU has a long-left tail (negative skewness). However, as EU and GDP show a leptokurtic distribution, CO_2 and P show a platkurtic distribution. Since energy use, CO_2, and GDP have been revealed to be collinear for research in several countries, the study tests for multicollinearity among variables of carbon dioxide emissions, energy use, GDP, and population using the variance inflation factor and the correlation matrix of coefficients of the regress model. Evidence from Table 2 shows that all the variance inflation factors are less than 4, an acceptable VIF in existing literature (Pan and Jackson 2008). In addition, the correlation matrix of coefficients of the regression model shows that energy use, GDP, and population are negatively correlated with carbon dioxide emissions, meaning that the variables are free from the

Table 2 Descriptive analysis

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	GT	Prob
CO_2	5,271.628	2,632.695	2,300	10,100	0.6043	1.9935	1.55	1.0000
EU	372.7371	22.8558	308.659	417.5492	−0.4335	3.6470	2.99	0.0690
GDP	743.907	161.6834	525	1,230	1.2884	4.4326	2.62	0.2790
P	16,100,000	5,208,591	8,830,000	26,200,000	0.3355	1.9040	1.66	1.0000
e (*V*)	EU	GDP	*P*	_cons	VIF	1/VIF		
EU	1				1.33	0.7502		
GDP	−0.0825	1			1.93	0.5190		
P	−0.3351	−0.6212	1		2.16	0.4639		
_cons	−0.9628	−0.1159	0.3297	1	Mean VIF	1.81		

Table 3 Augmented Dickey-Fuller, Kwiatkowski-Phillips-Schmidt-Shin, and break point unit root tests

	LCO_2		LEU		LGDP		LP	
ADF level	Test statistic	Prob	Test statistic	Prob	Test statistic	Prob	Test statistic	Prob
None	4.2668	1.0000	0.6647	0.9981	2.7531	0.8557	2.9442	0.9989
Intercept	0.8046	0.9929	−2.2617	0.9999	2.3620	0.1887	−0.0137	0.9518
Trend and intercept	−3.9020	0.0207	−2.5716	0.9359	−0.9793	0.2946	−2.6089	0.2786
ADF first difference								
None	−8.8488	0.0000	−6.5609	0.0047	−2.9042	0.0000	−7.2618	0.0000
Intercept	−6.9035	0.0000	−6.5366	0.0025	−4.1147	0.0000	−7.1700	0.0000
Trend and intercept	−7.0585	0.0000	−6.4486	0.0003	−5.5124	0.0000	−7.0861	0.0000
	Test statistic	Critical value	Test statistic	Critical value	Test statistic	Critical value	Test statistic	Critical value
KPSS level								
Intercept	0.8080	0.4630	0.4126	0.3470	0.5541	0.4630	0.8275	0.4630
Trend and intercept	0.1543	0.1460	0.0736	0.1190	0.1458	0.1190	0.1085	0.1190
KPSS first difference								
Intercept	0.1662	0.4630	0.0659	0.4630	0.3128	0.4630	0.0843	0.4630
Trend and intercept	0.1577	0.2160	0.0658	0.1190	0.0979	0.1190	0.0778	0.1460
	Test statistic	Prob	Test statistic	Prob	Test statistic	Prob	Test statistic	Prob
Break test level								
Intercept	−2.6332 (1990[a])	0.8573	−3.4529 (1983[a])	0.4126	−4.3449 (2005[a])	0.0663	−0.5341 (1983[a])	>0.99
Trend and intercept	−5.5306 (1994[a])	<0.01	−3.1072 (1992[a])	0.8773	−4.5393 (2005[a])	0.1186	−3.5438 (1990[a])	0.6659
Break test first difference								
Intercept	−10.6286 (2009[a])	<0.01	−6.9257 (1985[a])	<0.01	−7.3953 (2000[a])	<0.01	−5.0821 (1992[a])	<0.01
Trend and intercept	−10.5906 (2009[a])	<0.01	−6.9209 (1985[a])	<0.01	−7.3333 (1990[a])	<0.01	−5.4782 (1990[a])	<0.01

[a] Break date

problem of collinearity. The study further estimate outliers in the variables using the Grubbs' test. Evidence from Table 2 shows that the null hypothesis that all data values come from the same normal population cannot be rejected at 5 % significance level.

Unit root test

This subsection focuses on testing stationarity for Johansen's test of co-integration analysis. According to Mahadeva and Robinson (2004), executing unit root test is vital in minimizing spurious regression and it ensures that variables employed in the regression are stationary by differencing them and estimating the equation of interest through the stationary processes. The study employs the augmented Dickey-Fuller (ADF) (Dickey and Fuller 1979), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Vogelsang's break point unit root tests in order to have robust results. Table 3 presents the results of ADF, KPSS and break point unit root tests. At level, the null hypothesis of unit root cannot be rejected at 5 % significance level but is rejected at first difference. Evidence from Table 3 shows that the null hypothesis of stationarity in the KPSS results is rejected at level but cannot be rejected at first difference based on 5 % significance level. In the same way, since ADF and KPSS may fail to test stationarity in the presence of structural breaks, the study estimates the order of integration with break point unit root test taking into consideration the innovational outlier. Evidence from Table 3 shows that the null hypothesis of unit root in the break point results cannot be rejected at level. However, the study rejects the null hypothesis at first difference based on 5 % significance level. The ADF, KPSS, and break point unit root tests suggest that the variables are integrated at I(1), which satisfies the precondition of Johansen's method of co-integration.

Lag selection for vector error correction model

This subsection focuses on lag selection criteria, which is the first step for Johansen test of co-integration. Table 4 shows the vector autoregression (VAR) lag order selection criteria. VAR lag order selection criteria is used to select the optimal lag for the test of co-integration in the study. The sequential modified likelihood-ratio test statistic (LR), final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC), and Hannan-Quinn information criteria (HQ) select 1 as the optimal lag as indicated by "a" in Table 4.

Results and discussion

In this section, the proposed VECM and ARDL models are applied in Ghana for the 1971–2013 period.

Co-integration test and vector error correction model

This subsection focuses on the application of Johansen co-integration test (Johansen 1995) using max-eigenvalue and trace methods. The results for unrestricted co-integration rank tests are presented in Table 5. Using co-integration test specifications, information criteria such as AIC, LogL, and SC select linear intercept and trend for trace and max-eigenvalue tests. Trace and max-eigenvalue tests indicate 2 co-integrating equation at the 5 % significance level, which rejects the null hypothesis of no co-integration between LCO_2 , LEU, LGDP, and LP.

Table 6 shows the long-run and short-run multivariate causalities of the error correction model. Results from Table 6 show that the error correction term [L1._ce1 = −0.86] is negative and significant at 5 % level, which shows evidence of long-run equilibrium relationship running from LEU, LGDP, and LP to LCO_2. In addition, there is evidence of short-run equilibrium relationship running LEU to LCO_2, LGDP to LCO_2, and LP to LCO_2, which is statistically significant at 5 % significance level.

Johansen co-integration reveals the existence of causality among variables but fails to indicate the direction of the causal relationship. It is realistic to ascertain the causal relationships between LCO_2, LEU, LGDP, and LP using the Granger causality test (Granger 1988). Granger causality tests based on VECM are presented in Table 7. The null hypotheses that LCO_2 does not Granger cause LEU, LCO_2 does not Granger cause LGDP, LCO_2 does not Granger cause LP, LEU does not Granger cause LGDP, LGDP does not Granger cause LEU, and LP does not Granger cause LEU are rejected at 5 % significance level. In other words, there is a bidirectional causality running from LEU to LGDP and a unidirectional causality running from LCO_2 to LEU, LCO_2 to LGDP, LCO_2 to LP, and LP to LEU. Evidence from the joint Granger-causality shows a unidirectional causality running from LCO_2 to a joint of LEU, LGDP, and LP; LEU to a joint of LCO_2, LGDP, and LP; and LGDP to a joint of LCO_2, LEU, and LP, respectively.

Table 4 Lag selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	57.6064	NA	0.0000	−2.7303	−2.6037	−2.6845
1	185.216	229.6977[a]	0.0000[a]	−8.6608[a]	−8.1541[a]	−8.4776[a]
2	193.868	14.27541	0.0000	−8.6434	−7.7567	−8.3228
3	202.012	12.21658	0.0000	−8.6006	−7.3339	−8.1426

LogL log likelihood, *LR* sequential modified LR test statistic (each test at 5 % level), *FPE* final prediction error, *AIC* Akaike information criterion, *SC* Schwarz information criterion, *HQ* Hannan-Quinn information criterion

[a] Lag order selected by the criterion

Table 5 Johansen tests for co-integration

Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5 % critical value	Max statistic	5 % critical value
0	8	388.9696		73.9532	54.64	33.0924	30.33
1	15	405.5157	0.5452	40.8608	34.55	30.0175	23.78
2	20	420.5246	0.5107	10.8433	18.17	9.3637	16.87
3	23	425.2064	0.1998	1.4795	3.74	1.4795	3.74
4	24	425.9461	0.0346				

ARDL co-integration test and regression analysis

The study presents the ARDL regression model and bound test co-integration as proposed by Pesaran et al. (2001). Table 8 presents a summary of ARDL bound test co-integration. Bound F test is performed to establish a co-integration relationship between LCO_2, LEU, LGDP, and LP. Results from Table 8 show that the F statistic lies above the 10, 5, 2.5, and 1 % critical values of the upper bound, meaning that the null hypothesis of no co-integration relationship between LCO_2, LEU, LGDP, and LP is rejected at 10, 5, 2.5, and 1 % significant levels.

Per the existence of co-integration, the next step is to select an optimal model for the long-run equilibrium relationship estimation using the Akaike information criterion. Table 9 presents a summary of the ARDL regression estimation. Results from Table 9 show that the error correction term [ECT(−1) = −0.90] is negative and significant at 5 % level, meaning that a long-run equilibrium relationship exists running from energy use, GDP, and population to carbon dioxide emissions.

Evidence from the long-run (LR) elasticity estimation in Table 9 shows that a 1 % increase in population in Ghana will increase carbon dioxide emissions by 1.72 %. Though not statistically significant, 1 % increase in GDP in Ghana will increase carbon dioxide emissions by 0.37 and a 1 % increase in energy use in Ghana will increase carbon dioxide emissions by 0.53 %.

The study performs a linear test of parameter estimates using the individual coefficient to analyze a joint effect of the independent variables (LEU, LGDP, and LP) on LCO_2. The joint linear test in Table 9 shows evidence of short-run (SR) equilibrium relationship running from energy use to carbon dioxide emissions and GDP to carbon dioxide emissions. The empirical evidence shows that the energy use in Ghana contributes more to carbon dioxide emissions than GDP in the short run. According to Asumadu-Sarkodie and Owusu

Table 6 Long-run and short-run multivariate causalities of the error correction model

		Coef.	Std. Err.	z	$P>z$
Long run					
D_LCO_2	L1._ce1	−0.8648	0.1506	−5.74	0.0000
	L1._ce2	0.7123	0.2710	2.63	0.0090
	_trend	0.0000	0.0012	0.03	0.9740
	_cons	−0.0399	0.0317	−1.26	0.2080
D_LEU	L1._ce1	−0.1201	0.0629	−1.91	0.0560
	L1._ce2	−0.1984	0.1132	−1.75	0.0800
	_trend	−0.0003	0.0005	−0.61	0.5410
	_cons	−0.0050	0.0132	−0.38	0.7070
D_LGDP	L1._ce1	−0.0033	0.0265	−0.13	0.9000
	L1._ce2	−0.1014	0.0477	−2.12	0.0340
	_trend	0.0009	0.0002	4.22	0.0000
	_cons	−0.0178	0.0056	−3.18	0.0010
D_LP	L1._ce1	−0.0004	0.0065	−0.06	0.9540
	L1._ce2	−0.0356	0.0117	−3.05	0.0020
	_trend	−0.0001	0.0001	−0.99	0.3230
	_cons	0.0263	0.0014	19.24	0.0000
Short run					
D_LEU	F (2, 28)	8.99		Prob > F	0.0010
D_LGDP	F (3, 28)	8.88		Prob > F	0.0003
D_LP	F (2, 28)	28.30		Prob > F	0.0000

Table 7 Pairwise Granger causality test

Equation	Excluded	Chi^2	df	Prob > chi^2
LCO_2	LEU	9.5918	1	0.0020*
LCO_2	LGDP	7.7412	1	0.0050*
LCO_2	LP	36.7160	1	0.0000*
LCO_2	*ALL*	*39.9980*	*3*	*0.0000**
LEU	LCO_2	2.4261	1	0.1190
LEU	LGDP	4.4454	1	0.0350*
LEU	LP	2.7529	1	0.0970
LEU	*ALL*	*6.6853*	*3*	*0.0830*
LGDP	LCO_2	0.0236	1	0.8780
LGDP	LEU	4.3730	1	0.0370*
LGDP	LP	1.6618	1	0.1970
LGDP	*ALL*	*28.6290*	*3*	*0.0000**
LP	LCO_2	0.3362	1	0.5620
LP	LEU	7.3292	1	0.0070*
LP	LGDP	1.6803	1	0.1950
LP	*ALL*	*15.7260*	*3*	*0.0010**

The Italic text inside indicates the joint significance rather than individual significance

*Rejected at 5 % significance level

Table 8 ARDL bound test

Test statistic	Value	k^a
F statistic	13.966	3
Critical value bounds		
Significance	I0 bound	I1 bound
10 %	2.72	3.77
5 %	3.23	4.35
2.5 %	3.69	4.89
1 %	4.29	5.61

[a] Number of non-deterministic regressors in long-run relationship

(2016a) as at December 2013, 1245 MW of the total 2631 dependable capacity for power generation in Ghana came from thermal generation with only 1.9 MW coming from renewable sources. Nevertheless, the recent energy crisis in Ghana as a result of a change in weather patterns leading to low inflows for hydro-power generation has increased Ghana's dependence on thermal power generation (natural gas and diesel), leading to the increasing rate of carbon dioxide emissions. Moreover, 60 % of Ghana's energy use comes from biomass consumption in the form of charcoal and firewood (Asumadu-Sarkodie and Owusu 2016a), which overexploitation of the forest increases the rate of carbon dioxide emissions.

Diagnostic tests for VECM and ARDL models

This subsection presents the diagnostic tests for VECM and ARDL models. Table 10 presents a diagnostic test of VECM.

VEC residual normality was tested using Jarque-Bera test based on the null hypothesis that residuals are normally distributed. Results from the test show that the null hypothesis cannot be rejected at 5 % significance level, meaning that the residuals are normally distributed. VEC residual serial correlation was tested using Lagrange multiplier test based on null hypothesis that no serial correlation exists at lag order h. Results from the test show that the null hypothesis cannot be rejected at 5 % significance level, meaning that no serial correlation exists.

Table 9 ARDL regression

	$D.LCO_2$	Coef.	Std. Err.	t	$P>\|t\|$
ECT					
	LCO_2				
	L1.	−0.9008	0.1400	−6.44	0.0000
LRE					
	LEU	0.5297	0.3524	1.50	0.1440
	LGDP	0.3701	0.2868	1.29	0.2070
	LP	1.7185	0.1375	12.50	0.0000
SR					
	LEU				
	D1.	−0.5690	0.4076	−1.40	0.1740
	LD.	1.0398	0.3726	2.79	0.0090
	LGDP				
	D1.	−2.0607	0.8845	−2.33	0.0270
	LD.	−0.8636	0.7859	−1.10	0.2810
	L2D.	−3.8898	0.7771	−5.01	0.0000
	LP				
	D1.	−6.3658	4.0762	−1.56	0.1300
	_cons	−21.6028	3.1607	−6.83	0.0000
Joint SR					
D_LEU	F (2, 28)	8.99		Prob > F	0.0010
D_LGDP	F (3, 28)	8.88		Prob > F	0.0003
D_LP	F (1, 28)	2.44		Prob > F	0.1296
Source	SS	df	MS	number of obs	39
Model	0.4571	10	0.0457	F (10, 28)	9.35
Residual	0.1369	28	0.0049	Prob > F	0.0000
Total	0.5940	38	0.0156	R^2	0.7695
Adjusted R^2	0.6872				
Root MSE	0.0699				

Table 10 Diagnostics of VECM

Lagrange multiplier			
Lag	Chi^2	df	Prob > chi^2
1	18.4943	16	0.2958
2	23.3558	16	0.1046
3	11.7021	16	0.7642
4	13.5685	16	0.6308
Jarque-Bera			
Equation	Chi^2	df	Prob > chi^2
D_CO2	0.2420	2	0.8862
D_EU	0.4670	2	0.7918
D_GDP	3.5800	2	0.1670
D_P	2.6090	2	0.2713
ALL	6.8980	8	0.5477

Table 11 presents a diagnostic test of the ARDL model. In the same way, ARDL was subjected to several diagnostic tests. For the ARDL diagnostics, the study employs LM test for autoregressive conditional heteroskedasticity (ARCH), Breusch-Pagan/Cook-Weisberg test for heteroskedasticity, Breusch-Godfrey LM test for autocorrelation, and Ramsey RESET test using powers of the fitted values of D.LCO_2. Evidence from Table 11 shows that the null hypothesis of no ARCH effects by the ARCH test cannot be rejected at 5 % significance level, meaning that there is no ARCH effects. The null hypothesis of no serial correlation by the Breusch-Godfrey LM test cannot be rejected at 5 % significance level, meaning that no serial correlation exists at lag order h. The null hypothesis of constant variance by the Breusch-Pagan/Cook-Weisberg test cannot be rejected at 5 % significance level, meaning that the residuals of the ARDL model have a constant variance. In addition, the null hypothesis of no omitted variables in the model by the Ramsey RESET test cannot be rejected at 5 % significance level, meaning that no variables are omitted in the ARDL model.

Table 11 Diagnostics of the ARDL model

LM test for autoregressive conditional heteroskedasticity (ARCH)			
	Value	df	Probability
Chi-square	1.317	1	0.2511
Ramsey RESET test			
	Value	df	Probability
F statistic	1.75	(3, 25)	0.1833
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity			
	Value	df	Probability
Chi-square	0.20	1	0.6514
Breusch-Godfrey LM test for autocorrelation			
	Value	df	Probability
Chi-square	2.089	1	0.1484

Table 12 Results of variance decomposition of GDP

Cholesky ordering LCO_2 LEU LGDP LP					
Variance decomposition of LCO_2					
Period	S.E.	LCO_2	LEU	LGDP	LP
1	0.0922	100	0	0	0
2	0.1070	76.2813	19.7806	0.4867	3.4514
3	0.1113	71.7013	20.3032	4.7920	3.2035
4	0.1128	70.0203	20.2644	6.4860	3.2293
5	0.1135	69.1092	19.9882	7.7071	3.1954
6	0.1141	68.5088	20.0391	8.2281	3.2239
7	0.1148	67.8098	20.2680	8.3744	3.5478
8	0.1156	66.8621	20.6017	8.3563	4.1799
9	0.1166	65.7156	20.9863	8.2477	5.0504
10	0.1178	64.4289	21.4023	8.0941	6.0748
Variance decomposition of LEU					
Period	S.E.	LCO_2	LEU	LGDP	LP
1	0.0365	0.0347	99.9653	0	0
2	0.0488	0.8670	82.6442	10.5159	5.9728
3	0.0550	0.6908	70.7104	15.0638	13.5350
4	0.0577	0.6524	65.9821	16.2774	17.0882
5	0.0588	0.8226	63.9488	16.7884	18.4402
6	0.0593	1.0366	63.1480	17.0007	18.8147
7	0.0595	1.1922	62.7643	17.1583	18.8852
8	0.0597	1.2867	62.5413	17.2923	18.8797
9	0.0597	1.3396	62.3989	17.4041	18.8574
10	0.0598	1.3704	62.3051	17.4914	18.8331
Variance decomposition of LGDP					
Period	S.E.	LCO_2	LEU	LGDP	LP
1	0.0387	2.2879	3.0013	94.7108	0
2	0.0568	4.1717	1.4720	91.9029	2.4534
3	0.0684	4.3143	2.5324	90.0286	3.1247
4	0.0772	5.1038	5.5322	86.5218	2.8423
5	0.0838	5.8542	8.5909	83.1390	2.4159
6	0.0892	6.3533	11.4428	79.9249	2.2791
7	0.0939	6.6025	14.0206	76.9382	2.4387
8	0.0981	6.6622	16.3612	74.1753	2.8013
9	0.1019	6.6099	18.5034	71.5934	3.2933
10	0.1053	6.4960	20.4570	69.1696	3.8774
Variance decomposition of LP					
Period	S.E.	LCO_2	LEU	LGDP	LP
1	0.0036	0.7514	4.0170	7.4484	87.7831
2	0.0067	0.2455	6.2326	9.7474	83.7745
3	0.0096	0.7461	8.5426	10.8572	79.8541
4	0.0124	1.3742	10.7891	11.7210	76.1157
5	0.0151	1.9349	12.4120	12.6330	73.0201
6	0.0177	2.3869	13.4903	13.5175	70.6053
7	0.0202	2.7549	14.1442	14.3676	68.7333
8	0.0226	3.0672	14.5010	15.1754	67.2565
9	0.0249	3.3402	14.6576	15.9437	66.0585
10	0.0270	3.5841	14.6778	16.6791	65.0589

Variance decomposition

This section focuses on the response of variables to each other in one standard deviation innovations. Results from the co-integrating relation of VECM and ARDL models show a nearly similar trend regarding the nature of co-integration that exists between LCO_2, LEU, LGDP, and LP. However, the impulse response function that traces the effect of a shock from one endogenous variable on the other variables is uncertain in both VECM and ARDL models. It is therefore necessary to analyze the variance decomposition to trace these shocks. The variance decomposition provides information about the relative importance of each random innovation in affecting the variables in the VAR.

Table 12 reports the result of the variance decomposition of LCO_2, LEU, LGDP, and LP within a 10-period horizon. Evidence from Table 12 shows that 21 % of future shocks in LCO_2 are due to fluctuations in LEU, 8 % of future shocks in LCO_2 are due to fluctuations in LGDP, and 6 % of future shocks in LCO_2 are due to fluctuations in LP.

Moreover, evidence from Table 12 shows that 19 % of future shocks in LEU are due to fluctuations in LP, 17 % of future shocks in LEU are due to fluctuations in LGDP, and 1 % of future shocks in LEU is due to fluctuations in LCO_2.

In addition, evidence from Table 12 shows that 20 % of future shocks in LGDP are due to fluctuations in LEU, 6 % of future shocks in LGDP are due to fluctuations in LCO_2, and 4 % of future shocks in LGDP are due to fluctuations in LP.

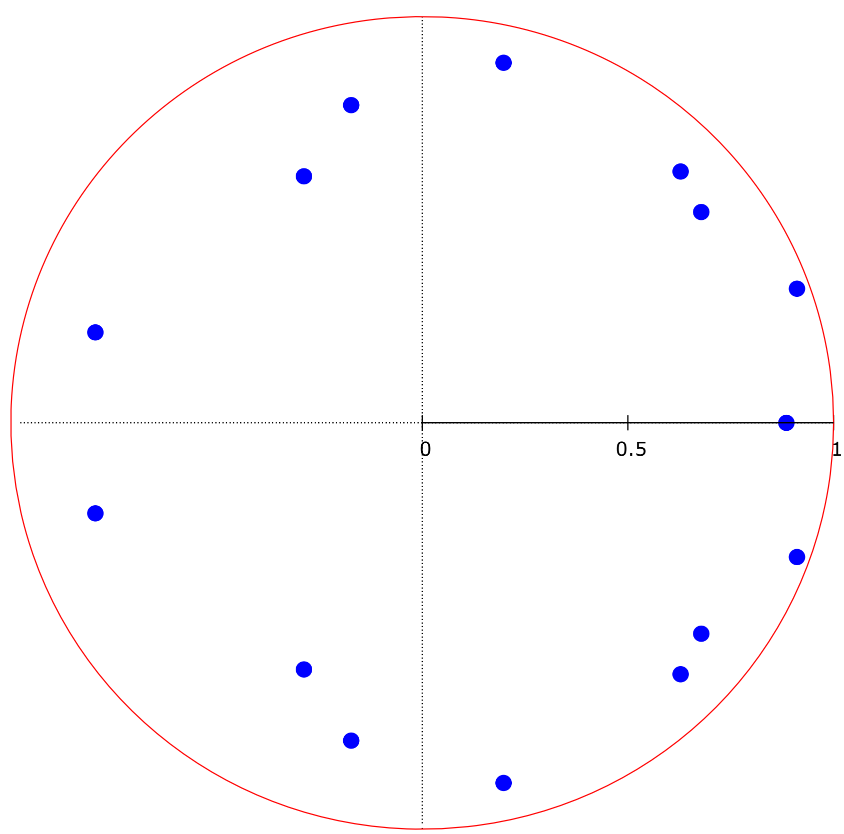
Evidence from Table 12 shows that 17 % of future shocks in LP are due to fluctuations in LGDP, 15 % of future shocks in LP are due to fluctuations in LEU, and 4 % of future shocks in LP are due to fluctuations in LCO_2.

Robustness of VECM and ARDL models

Figure 2 shows the inverse root of characteristic polynomial. The root characteristic polynomial is used to check the stability of the VEC model. VEC specification imposes no unit roots outside the unit circle (the eigenvalue of the respective matrix is less than 1); therefore, the VEC model meets the VAR stability conditions.

Figure 3 shows the CUSUM and CUSUM of square tests for the parameter instability from the ARDL model. The CUSUM and CUSUM of square tests are used to ascertain the parameter instability of the equation employed in the ARDL model. Since the plots in CUSUM and CUSUM of square tests lie within the 5 % significance level, the parameter of the equation is stable enough to estimate the long-run and short-run causalities in the ARDL model.

Fig. 2 VAR inverse roots of characteristic polynomial



Conclusion

In this study, the relationship between carbon dioxide emissions, energy use, GDP, and population growth in Ghana was investigated from 1971 to 2013 by comparing VECM and ARDL. Prior to testing for Granger causality based on VECM, the study tested for unit roots and Johansen's method of co-integration. In addition, the study performed a variance decomposition analysis using Cholesky technique, diagnostic, and stability tests.

Evidence from the VECM and ARDL models shows that carbon dioxide emissions, energy use, GDP, and population growth are co-integrated. There was evidence of bidirectional causality running from energy use to GDP and a unidirectional causality running from carbon dioxide emissions to energy use, carbon dioxide emissions to GDP, carbon dioxide emissions to population, and population to energy use. Evidence from the joint Granger-causality shows a unidirectional causality running from carbon dioxide emissions to a joint of energy use, GDP, and population; energy use to a joint of carbon dioxide emissions, GDP, and population; and GDP to a joint of carbon dioxide emissions, energy use, and population, respectively.

Evidence from the long-run elasticities shows that a 1 % increase in population in Ghana will increase carbon dioxide emissions by 1.72 %. Though not statistically significant, 1 % increase in GDP in Ghana will increase carbon dioxide emissions by 0.37 and a 1 % increase in energy use in Ghana will increase carbon dioxide emissions by 0.53 %. In addition, there was evidence of SR equilibrium relationship running from energy use to carbon dioxide emissions and GDP to carbon dioxide emissions.

The ARDL bound test results yield evidence of a long-run relationship between carbon dioxide emissions and energy use, GDP, and population in Ghana. Evidence from the variance decomposition shows that 21 % of future shocks in

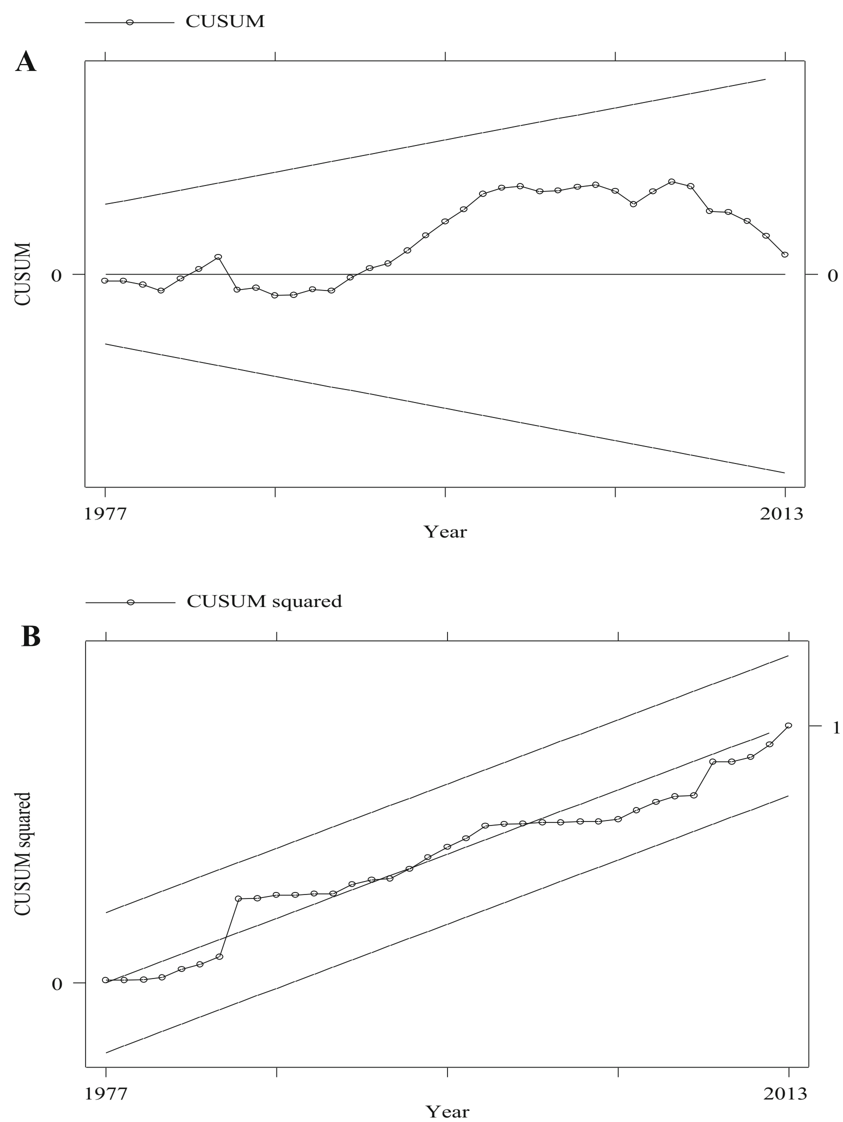


Fig. 3 Stability test of ARDL model using **a** CUSUM and **b** CUSUM of squares

carbon dioxide emissions are due to fluctuations in energy use, 8 % of future shocks in carbon dioxide emissions are due to fluctuations in GDP, and 6 % of future shocks in carbon dioxide emissions are due to fluctuations in population. Nineteen percent of future shocks in energy use are due to fluctuations in population, 17 % of future shocks in energy-use are due to fluctuations in GDP, and 1 % of future shocks in energy use is due to fluctuations in carbon dioxide emissions. In addition, 20 % of future shocks in GDP are due to fluctuations in energy use, 6 % of future shocks in GDP are due to fluctuations in carbon dioxide emissions, and 4 % of future shocks in GDP are due to fluctuations in population. Seventeen percent of future shocks in population are due to fluctuations in GDP, 15 % of future shocks in population are due to fluctuations in energy use, and 4 % of future shocks in population are due to fluctuations in carbon dioxide emissions.

The results from the variance decomposition have policy implications. It is noteworthy that energy use in Ghana affects carbon dioxide emissions in the long run. In this way, addition of renewable energy and clean energy technologies into Ghana's energy mix can help mitigate climate change and its impact in the future. In addition, future energy use in Ghana depends on GDP; therefore, efforts by Government towards boosting the economic growth in Ghana are worthwhile. Evidence from the study shows that future growth in GDP will likely depend on the access to energy in Ghana. Therefore, a progressive effort towards increasing the accessibility and supply of energy to meet the growing energy demand in Ghana will boost productivity leading to economic growth.

Based on the results of the study, the following policy recommendations are made:

- Since, energy-use Granger causes CO_2 emissions, the Government of Ghana should increase the share of renewable energy in Ghana's energy mix.
- Improving energy efficiency by facilitating access to clean energy and introducing energy management options in the national grid would help reduce the impact of CO_2 emissions.
- As an income effect is the most important factor contributing to increasing CO_2 emissions, the Government of Ghana should promote development-oriented policies that create jobs for the people, supporting entrepreneurship, creativity, and innovation, and provide the environment that supports small- and medium-scale enterprises.
- Providing financial services like subsidies, loan, and grants for energy efficiency measures and renewable energy systems.

Finally, creating awareness on climate change mitigation, impact, adaptation, and early warning signs through the integration of climate change measures into the national policy, planning, and strategies would help reduce climate change and its impacts, thereby fulfilling the thirteenth goal of sustainable development.

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