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

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Received: 21 December 2015 / Accepted: 21 March 2016
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Abstract In this study, the relationship between carbon dioxide emissions, GDP, energy use, and population growth in Ghana was investigated spanning from 1971 to 2013 by comparing a vector error correction model (VECM) and autoregressive and distributed lag (ARDL). Prior to testing for Granger causality based on VECM, we tested for unit roots and Johansen’s multivariate co-integration. We also performed a variance decomposition analysis using Cholesky technique and comparing it with other studies. 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.

Responsible editor: Philippe Garrigues

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Keywords	Variance decomposition · Carbon dioxide emissions · Ghana · Multivariate co-integration · ARDL bound test · Econometrics	36 37 38
JEL classification	Q43	39
Abbreviations		40
Chi ²	Chi square	43
Parms	Parameter	43
df	Difference	46
Prob	Probability	48
_ce	Co-integrated equation	50
Coef.	Coefficient	53
_cons	Constant	54
Std. Err.	Standard error	56
L1._ce	Error correction term	58
Acronyms		60
VECM	Vector error correction model	63
ECT	Error correction term	63
SR	Short run	66
LRE	Long-run elasticities	68
LL	Log likelihood	70
LR	Sequential likelihood ratio	73
AIC	Akaike information criterion	74
KPSS	Kwiatkowski-Phillips-Schmidt-Shin	76
SC	Schwarz information criterion	78
HQ	Hannan-Quinn information criteria	80
VIF	Variance inflation factor	83
LCUs	Local currency units	84
P	Population	86
GT	Grubbs’ test	88

Introduction

Access to energy is one of the many ways of achieving higher levels of economic productivity in every technological and advancing country. 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), DMM, 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 Herreras 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; Caraianni et al. 2015; Fuinhas and Marques 2012; Ohler and Feters 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 CO₂ 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 CO₂ 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 CO₂ emissions. They found a bidirectional relationship between CO₂ emissions and EI. Similarly, Hatzigeorgiou et al. (2008) employed a decomposition technique to investigate the factors affecting CO₂ emissions. Their findings show that energy intensity is the main factor responsible for the decrease in CO₂ emissions while income effect contributes to increasing CO₂ 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 (UNFCCC) 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 using Stata[®] 14 software. A time series dataset from 1971 to 2013 was employed from the World Bank database (World Bank 2015). Three study variables were used in the study which include CO₂—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 LCO₂, LEU, LGDP, and LP represent the logarithmic transformation of carbon dioxide emissions, energy use, gross domestic product, and population. 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

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

where LCOE is the dependent variable; LEU, LGDP, and P 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; θ s, α s, and β s are the parameters to be estimated; p is the number of lags; and ε_t s 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

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

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 LCO₂, LEU, LGDP, and LP. The ARDL bound test

functions under the null hypothesis of no co-integration between LCO₂, LEU, LGDP, and LP [$H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$], against the alternative hypothesis of co-integration between LCO₂, LEU, LGDP, and LP [$H_1: \delta_1 \neq \delta_2 \neq \delta_3 \neq \delta_4 \neq 0$].

Fig. 1 Trend of variables

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

261 Descriptive analysis

262 This section outlines the descriptive statistical analysis of the
263 variables used in the study. Figure 1 shows the trend of the
264 variables before logarithmic transformation was applied. It is
265 evident that the trend of population increases periodically,
266 trend of GDP follows that of CO_2 emissions, but trend fluctu-
267 ations seem to occur in energy use. The descriptive statistical
268 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 platykurtic
distribution. Since energy use, CO_2 , and GDP have been re-
vealed 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 correlation matrix of coeffi-
cients 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
corrected with carbon dioxide emissions, meaning that the
variables are free from the problem of collinearity. The study
further estimate outliers in the variables using the Grubbs' test.

t2.1 **Table 2** Descriptive analysis

t2.2	Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	GT	Prob
t2.3	CO_2	5,271.628	2,632.695	2,300	10,100	0.6043	1.9935	1.55	1.0000
t2.4	EU	372.7371	22.85575	308.659	417.5492	-0.4335	3.6470	2.99	0.0690
t2.5	GDP	743.907	161.6834	525	1,230	1.2884	4.4326	2.62	0.2790
t2.6	P	16,100,000	5,208,591	8,830,000	26,200,000	0.3355	1.9040	1.66	1.0000
t2.7	$e(V)$	EU	GDP	P	_cons	VIF	1/VIF		
t2.8	EU	1				1.33	0.7502		
t2.9	GDP	-0.0825	1			1.93	0.5190		
t2.10	P	-0.3351	-0.6212	1		2.16	0.4639		
t2.11	_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

t3.1	ADF level	LCO ₂		LEU		LGDP		LP	
		Test statistic	Prob	Test statistic	Prob	Test statistic	Prob	Test statistic	Prob
t3.2	None	4.2668	1.0000	0.6647	0.9981	2.7531	0.8557	2.9442	0.9989
t3.3	Intercept	0.8046	0.9929	-2.2617	0.9999	2.3620	0.1887	-0.0137	0.9518
t3.4	Trend and intercept	-3.9020	0.0207	-2.5716	0.9359	-0.9793	0.2946	-2.6089	0.2786
t3.5	ADF first difference								
t3.6	None	-8.8488	0.0000	-6.5609	0.0047	-2.9042	0.0000	-7.2618	0.0000
t3.7	Intercept	-6.9035	0.0000	-6.5366	0.0025	-4.1147	0.0000	-7.1700	0.0000
t3.8	Trend and intercept	-7.0585	0.0000	-6.4486	0.0003	-5.5124	0.0000	-7.0861	0.0000
t3.9	KPSS level								
t3.10	Intercept	0.8080	0.4630	0.4126	0.3470	0.5541	0.4630	0.8275	0.4630
t3.11	Trend and intercept	0.1543	0.1460	0.0736	0.1190	0.1458	0.1190	0.1085	0.1190
t3.12	KPSS first difference								
t3.13	Intercept	0.1662	0.4630	0.0659	0.4630	0.3128	0.4630	0.0843	0.4630
t3.14	Trend and intercept	0.1577	0.2160	0.0658	0.1190	0.0979	0.1190	0.0778	0.1460
t3.15	Break test level								
t3.16	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
t3.17	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
t3.18	KPSS first difference								
t3.19	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
t3.20	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

285 Evidence from Table 2 shows that the null hypothesis that all
286 data values come from the same normal population cannot be
287 rejected at 5 % significance level.

288 Unit root test

289 This subsection focuses on testing stationarity for Johansen's
290 test of co-integration analysis. According to Mahadeva and
291 Robinson (2004), executing unit root test is vital in minimiz-
292 ing spurious regression and it ensures that variables employed
293 in a regression are stationary by differencing them and esti-
294 mating the equation of interest through the stationary process-
295 es. We employ the augmented Dickey-Fuller (ADF) (Dickey
296 and Fuller 1979) unit root test in the study. Table 3 presents the
297 results of ADF unit root test. At level, we cannot reject the null
298 hypothesis based on 5 % significance level. We further
299 complement the ADF unit root test with Kwiatkowski-
300 Phillips-Schmidt-Shin (KPSS) and Vogelsang's break
301 point unit root tests in order to have robust results.
302 Evidence from Table 3 shows that the null hypothesis
303 of stationarity in the KPSS results is rejected at level
304 but cannot be rejected at first difference based on 5 %
305 significance level. In the same way, since ADF and
306 KPSS may fail to test stationarity in the presence of
307 structural breaks, the study estimates the order of inte-
308 gration with break point unit root test taking into con-
309 sideration the innovational outlier. Evidence from
310 Table 3 shows that the null hypothesis of unit root in
311 the break point results cannot be rejected at level.
312 However, the study rejects the null hypothesis at first differ-
313 ence based on 5 % significance level. The ADF, KPSS, and
314 break point unit root tests suggest that the variables are inte-
315 grated at $I(1)$, which satisfies the pre-condition of Johansen's
316 method of co-integration.

317 Lag selection for vector error correction model

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

328 Results and discussion

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

Co-integration test and vector error correction model

332 This subsection focuses on the application of Johansen co-
333 integration test (Johansen 1995) using max-eigenvalue and
334 trace methods. The results for unrestricted co-
335 integration rank tests are presented in Table 5. Using
336 co-integration test specifications, information criteria such as
337 AIC, LogL, and SC select linear intercept and trend for
338 trace test and max-eigenvalue test. Trace test and max-
339 eigenvalue test indicate 1 co-integrating equation at the
340 5 % significance level, which rejects the null hypothesis
341 of no co-integration.

342 Table 6 shows the long-run and short-run multivariate cau-
343 salities of the error correction model. Results from Table 6
344 show that the error correction term [$L1_ce1 = -0.86$] is neg-
345 ative and significant at 5 % level, which shows evidence of
346 long-run equilibrium relationship running from LEU, LGDP,
347 and LP to LCO_2 . In addition, there is evidence of short-run
348 equilibrium relationship running LEU to LCO_2 , LGDP to
349 LCO_2 , and LP to LCO_2 , which is statistically significant at
350 5 % significance level.

351 Johansen co-integration reveals the existence of causality
352 among variables but fails to indicate the direction of the causal
353 relationship. It is realistic to ascertain the causal relationships
354 between LCO_2 , LEU, LGDP, and LP using the Granger cau-
355 sality test (Granger 1988). Granger causality tests based on
356 VECM are presented in Table 7. The null hypotheses that
357 LCO_2 does not Granger cause LEU, LCO_2 does not
358 Granger cause LGDP, LCO_2 does not Granger cause
359 LP, LEU does not Granger cause LGDP, LGDP does
360 not Granger cause LEU, and LP does not Granger cause
361 LEU are rejected at 5 % significance level. In other
362 words, there is a bidirectional causality running from
363 LEU to LGDP and a unidirectional causality running
364 from LCO_2 to LEU, LCO_2 to LGDP, LCO_2 to LP, and LP to
365 LEU. Evidence from the joint Granger-causality shows a uni-
366 directional causality running from LCO_2 to a joint of LEU,
367 LGDP, and LP; LEU to a joint of LCO_2 , LGDP, and LP; and
368 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	-2.73032	-2.603654	-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

t5.1 **Table 5** Johansen tests
t5.2 for co-integration

	Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5 % critical value	Max statistic	5 % critical value
t5.3	0	8	388.96955		73.9532	54.64	33.0924	30.33
t5.4	1	15	405.51574	0.54521	40.8608	34.55	30.0175	23.78
t5.5	2	20	420.52449	0.51066	10.8433*	18.17	9.3637	16.87
t5.6	3	23	425.20636	0.19984	1.4795	3.74	1.4795	3.74
t5.7	4	24	425.94613	0.03461				

369 **ARDL co-integration test and regression analysis**

370 The study presents the ARDL regression model and bound
371 test co-integration as proposed by Pesaran et al. (2001).
372 Table 8 presents a summary of ARDL bound test co-integration.
373 Bound *F* test is performed to establish a co-integration
374 relationship between LCO₂, LEU, LGDP, and LP. Results
375 from Table 8 show that the *F* statistic lies above the 10, 5,
376 2.5, and 1 % critical values of the upper bound, meaning that
377 the null hypothesis of no co-integration relationship between
378 LCO₂, LEU, LGDP, and LP is rejected at 10, 5, 2.5, and 1 %
379 significant levels.

380 Per the existence of co-integration, the next step is to select
381 an optimal model for the long-run equilibrium relationship estimation
382 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 LCO₂. 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

t6.1 **Table 6** Long-run and short-run multivariate causalities of the error
t6.2 correction model

t6.2			Coef.	Std. Err.	<i>z</i>	<i>P</i> > <i>z</i>
t6.3	Long run					
t6.4	Long run					
t6.5	D_LCO ₂	L1._ce1	−0.8648	0.1506	−5.74	0.0000
t6.6		L1._ce2	0.7123	0.2710	2.63	0.0090
t6.7		_trend	0.0000	0.0012	0.03	0.9740
t6.8		_cons	−0.0399	0.0317	−1.26	0.2080
t6.9	D_LEU	L1._ce1	−0.1201	0.0629	−1.91	0.0560
t6.10		L1._ce2	−0.1984	0.1132	−1.75	0.0800
t6.11		_trend	−0.0003	0.0005	−0.61	0.5410
t6.12		_cons	−0.0050	0.0132	−0.38	0.7070
t6.13	D_LGDP	L1._ce1	−0.0033	0.0265	−0.13	0.9000
t6.14		L1._ce2	−0.1014	0.0477	−2.12	0.0340
t6.15		_trend	0.0009	0.0002	4.22	0.0000
t6.16		_cons	−0.0178	0.0056	−3.18	0.0010
t6.17	D_LP	L1._ce1	−0.0004	0.0065	−0.06	0.9540
t6.18		L1._ce2	−0.0356	0.0117	−3.05	0.0020
t6.19		_trend	−0.0001	0.0001	−0.99	0.3230
t6.20		_cons	0.0263	0.0014	19.24	0.0000
t6.21	Short run					
t6.22	D_LEU	<i>F</i> (2, 28)	8.99		Prob > <i>F</i>	0.0010
t6.23	D_LGDP	<i>F</i> (3, 28)	8.88		Prob > <i>F</i>	0.0003
t6.24	D_LP	<i>F</i> (2, 28)	28.30		Prob > <i>F</i>	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*

*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

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 over-exploitation 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 null hypothesis; residuals are multivariate normal. Results from the test show that the null hypothesis cannot be rejected at 5 % significance level, meaning that residuals are multivariate normally. VEC residual serial correlation was tested using Lagrange multiplier test based on null hypothesis, no serial correlation 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.

(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

Table 9 ARDL regression

	D.CO ₂	Coef.	Std. Err.	t	$P > t $
ECT					
CO ₂					
L1.	−0.9008	0.1400	−6.44	0.0000	
LRE					
EU	0.5297	0.3524	1.50	0.1440	
GDP	0.3701	0.2868	1.29	0.2070	
P	1.7185	0.1375	12.50	0.0000	
SR					
EU					
D1.	−0.5690	0.4076	−1.40	0.1740	
LD.	1.0398	0.3726	2.79	0.0090	
GDP					
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	
P					
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

t10.2	Lagrange multiplier			
t10.3	Lag	Chi ²	df	Prob> chi ²
t10.4	1	18.4943	16	0.2958
t10.5	2	23.3558	16	0.1046
t10.6	3	11.7021	16	0.7642
t10.7	4	13.5685	16	0.6308
t10.8	Jarque-Bera			
t10.9	Equation	Chi ²	df	Prob> chi ²
t10.10	D_CO2	0.2420	2	0.8862
t10.11	D_EU	0.4670	2	0.7918
t10.12	D_GDP	3.5800	2	0.1670
t10.13	D_P	2.6090	2	0.2713
t10.14	ALL	6.8980	8	0.5477

Table 11 presents a diagnostic test of 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.LCO₂. 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 are 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 there are residuals of the ARDL model 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.

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

449 Variance decomposition

450 This section focuses on the response of variables to
 451 each other in one standard deviation innovations.
 452 Results from the co-integrating relation of VECM and
 453 ARDL models show a nearly similar trend regarding the
 454 nature of co-integration that exists between LCO₂, LEU,
 455 LGDP, and LP. However, the impulse response function
 456 that traces the effect of a shock from one endogenous
 457 variable on the other variables is uncertain in both
 458 VECM and ARDL models. It is therefore necessary to
 459 analyze the variance decomposition to trace these shocks. The
 460 variance decomposition provides information about the rela-
 461 tive importance of each random innovation in affecting the
 462 variables in the VAR.

463 Table 12 reports the result of the variance decomposition of
 464 LCO₂, LEU, LGDP, and LP within a 10-period horizon.
 465 Evidence from Table 12 shows that 21 % of future
 466 shocks in LCO₂ are due to fluctuations in LEU, 8 %
 467 of future shocks in LCO₂ are due to fluctuations in
 468 LGDP, and 6 % of future shocks in LCO₂ are due to
 469 fluctuations in LP.

470 Moreover, evidence from Table 12 shows that 19 % of
 471 future shocks in LEU are due to fluctuations in LP, 17 % of
 472 future shocks in LEU are due to fluctuations in LGDP, and
 473 1 % of future shocks in LEU is due to fluctuations in LCO₂.

474 In addition, evidence from Table 12 shows that 20 % of
 475 future shocks in LGDP are due to fluctuations in LEU, 6 % of
 476 future shocks in LGDP are due to fluctuations in LCO₂, and
 477 4 % of future shocks in LGDP are due to fluctuations in LP.

478 Evidence from Table 12 shows that 17 % of future shocks
 479 in LP are due to fluctuations in LGDP, 15 % of future shocks
 480 in LP are due to fluctuations in LEU, and 4 % of future shocks
 481 in LP are due to fluctuations in LCO₂.

Robustness of VECM and ARDL models

482
 483 Figure 2 shows the inverse root of characteristic polynomial.
 484 The root characteristic polynomial is used to check the stabil-
 485 ity of the VEC model. VEC specification imposes no unit
 486 roots outside the unit circle (the eigenvalue of the respective
 487 matrix is less than 1); therefore, the VEC model meets the
 488 VAR stability conditions.

489 Figure 3 shows the CUSUM and CUSUM of square tests
 490 for the parameter instability from the ARDL model. The
 491 CUSUM and CUSUM of square tests are used to ascer-
 492 tain the parameter instability of the equation employed
 493 in the ARDL model. Since the plots in CUSUM and
 494 CUSUM of square tests lie within the 5 % significance
 495 level, the parameter of the equation is stable enough to
 496 estimate the long-run and short-run causalities in the
 497 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 CO₂ 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 CO₂ emissions.
- As an income effect is the most important factor contributing to increasing CO₂ 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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