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The Effects of Gross Domestic Product and Energy Consumption on Carbon Dioxide Emission in Uganda (1986-2018)

Jacob Otim[1], Geoffrey Mutumba[1]*, Susan Watundu[2], Geoffrey Mubiinzi[3], Milly Kaddu[1,3]

[1]Department of Economics and Statistics, Kyambogo University, Uganda, [2]Department of Management Science, Makerere University Business School, Uganda, [3]Department of Economics, Uganda Martyrs University, Nkozi, Uganda.
*Email: gmutumba@kyu.ac.ug

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ABSTRACT

This study examines the effects of energy consumption and per capita gross domestic product on carbon dioxide emission which is a precursor for global warming due to its large scale impact on the environment. The effect of per capita gross domestic product and per capita energy consumption on carbon emission per capita in Uganda is not clearly known. This study fills the empirical gap for Uganda for 1986-2018. The study used Vector Error Correction techniques and the results suggest evidence of a long-run relationship between the variables at a 5% significance level using the Johansen cointegration test. The estimated elasticity of carbon dioxide emission per capita with respect to gross domestic product per capita is 1.856. The results for the existence and direction of Granger causality show a unidirectional causality running from gross domestic product per capita to carbon dioxide emission per capita and the environmental Kuznets curve hypothesis is supported. In addition, there is no causal link between energy consumption per capita and gross domestic product per capita, which supports the growth neutrality hypothesis. The overall results indicate that gross domestic product per capita has a positive effect on carbon dioxide emission in Uganda while energy consumption does not Granger cause carbon dioxide emission.

Keywords: CO_2 emission, energy consumption, GDP per capita, Johansen cointegration test, Granger causality, VECM
JEL Classifications: K32, P18, Q43, Q48, Q54

1. INTRODUCTION

Global warming has attracted considerable debate in the area of environment in the last three decades (Held and Rogers 2018). This has been attributed to the risk of change in climate on human beings and the ecosystem. Due to large-scale impact of human activities, most countries of the United Nations have agreed to keep the global warming below 2°C by cutting down Greenhouse Gases (GHGs) emission mainly due to CO_2. The commitment ratified through the signatures of the Kyoto Protocol in 1997 (Protocol, 1997). This was followed by the Paris Agreement with the main aim of addressing the global response to the threat of climate change (Horowitz, 2016).

Carbon emission is the release of carbon to the atmosphere. The emission is composed of GHGs which are the main contributors to climate change. GHGs are often calculated as carbon equivalent. The Kyoto protocol spelled out six main GHG pollutants which have significant impact on the environment namely; CO_2, CH_4 (Methane), N_2O (Nitrous Oxide), HFCs (hydrofluorocarbons), PFCs (perfluorocarbons) and SF_6 (sulfur hexafluoride). CO_2 is considered to be the main contributor to global warming (Zhang and Da, 2015). The summit on sustainable development held in 2002 in Johannesburg, South Africa highlighted the detrimental impact of energy consumption on the environment despite its key role in economic growth and development (Sghari and Hammami, 2016).

In Uganda, CO_2 emission from hydrocarbon combustion and industrial use contribute roughly to 0.099% of the global carbon stock. Even though Uganda contributes less to the potentially catastrophic accumulation of man-made carbon footprints, the country is susceptible to the influence of climate change. Uganda's carbon stock is among the lowest in the world and is estimated at 1.39 tons of carbon equivalent less than the world average of 7.99 tons of carbon emission equivalent per capita (GOU, 2015). However, the contribution of carbon emissions to the growth trajectory of Uganda is not clearly known (Markandya et al., 2015). The Uganda's vision 2040 may be severely hampered by climate factors in the absence of adaptation actions (GOU, 2020) due to overreliance on traditional biomass as the main source of energy (Bamwesigye et al., 2020). Therefore, the achievement of Sustainable Development Goal (SDG) 7 (affordable clean energy) geared towards ensuring access to affordable, reliable and sustainable modern energy for all and SDG 13 (climate action) may be hampered. Actions to combat climate change and its impacts on the environment would all be practically impossible unless serious policy measures are put in place (Walters, 2021).

In this paper, we examine the effects of energy consumption per capita and per capita GDP on CO_2 emission per capita, in Uganda using the Johansen cointegration testing approach and vector error correction model (VECM) based on Granger causality for Uganda over 1986-2018 period. The major contribution of this paper is to provide the theoretical understanding of the effect of GDP and energy consumption on the environment in a multivariate framework using a vector error correction model. The rest of the paper is organized as follows. The next section presents the literature review. The third section shows the methods. The fourth section reports the empirical results and discussion. The final section is the conclusion of the study.

2. LITERATURE REVIEW

The link between carbon emission, energy consumption and economic growth has been widely analyzed and is a center of controversy and debate since the 1950s (Kuznets, 1955). Climate and energy are intrinsically linked. The quality of our environment, by and large, is determined the way we consume energy. As a result, examining the productive use of energy is key to the sustainable development goals 11 (develop sustainable cities and communities) and 13 (climate change). The awareness of the change in climate and its implication on planet earth makes it vital to examine the causal effect of energy consumption on development.

Energy consumption is key in the development process since it is a main driver for sustainable development (Ma, 2019). The rise in energy consumption is expected to lead to the growth in GDP in real terms through a transmission mechanism that cascades to CO_2 emission increase, which is an important factor in global warming and eventual climate change. Studying nexus among these global variables is pivotal. There are numerous stock pollutants that lead to climate change but CO_2 is a dominant gas of all GHGs (Sadik-Zada and Loewenstein, 2020). Investigating a causal link between carbon emission, energy consumption and economic growth has become a landmark of recent studies since energy consumption is the best vehicle to achieve sustainable development (Akadiri, 2019). Several studies have used a multivariate framework to examine the causal link between CO_2 emission, energy consumption, and economic growth, they find mixed results.

Alam (2011) uses a Johansen test and autoregressive distributed lag to explain a long-run relationship between electricity consumption, energy consumption, CO_2 emission, and GDP in Bangladesh. His results show a one-way causality running from energy consumption to economic development both in the short-run and the long-run. Additional results show a bidirectional causality between CO_2 emission and energy consumption and also electricity consumption and economic development. In Chang's (2010) study, different energy sources- crude oil, natural gas, electricity and coal are used to examine the relationship between CO_2 emission, energy consumption, and GDP in China. The results show that more CO_2 emission is a caused by energy consumption and GDP growth. Ang (2007) employs a multivariate error correction model to investigate the causal link between energy consumption, CO_2 emission and output in France. The results show energy consumption to increase emissions, while the study by Halicioglu (2009) shows that there is bidirectional causality between output and CO_2 emission both in the short-run and long-run for Turkey.

A couple of studies have been conducted in sub-Saharan Africa (SSA) Menyah and Wolde-Rufael's (2010) study, show causality between economic development, energy consumption, and pollutant emission in South Africa and there exist long-run relationships between the variables. The result also indicates that there is one-way causality running from both energy consumption and carbon emission to economic development. Adom et al. (2012) find a bidirectional relationship between CO_2 emission and economic growth in Morocco and one-way causality running from economic growth to CO_2 emission in Senegal. A study by Appiah (2018) on the multivariate Granger causality between energy consumption, economic growth and CO_2 emission in Ghana from 1960-2015 using Toda-Yamamoto and Granger causality test shows a feedback Granger causality between energy consumption and CO_2 emission. Further still, a unidirectional Granger causality from energy consumption to economic growth was detected.

Studies in Uganda's context, include Senkantsi and Okot (2016) on electricity consumption- and GDP for Uganda from 1982-2013 using ARDL bound test and the Granger causality framework. Their study found a unidirectional causal flow from economic growth to electricity consumption. Mawejje and Mawejje (2016) also conducted a similar study using vector error correction techniques and Granger causality test, where they found a unidirectional causal link running from electricity consumption to GDP. Appiah et al. (2019) studied the causal link between industrialization, energy intensity, and GDP and carbon oxide emission using data from Uganda from 1990 to 2014. The existence of unidirectional causality comes from energy intensity to CO_2 and from GDP to CO_2. This implies that the increase in energy intensity leads to more environmental pollution. A similar study that investigates the effect of energy on CO_2 emission in Uganda is by Appiah et al. (2019). They use energy intensity as a predictor for CO_2 emission in Uganda yet its applications in real world policy making is troublesome. Due to the fact that the GDP of the individual economies are converted to a common currency using the purchasing power parity or the market exchange rates (Samuelsson, 2014), energy intensity becomes a poor predictor of CO_2 emission. The weakness in Appiah et al. (2019) paper gives a justification for our paper to make a theoretical contribution and use energy consumption per capita as a better predictor for CO_2 emission in Uganda.

3. METHODS

3.1. Research Design

A correlational research design and quantitative approach for time series analysis were adopted. All the data from the selected variables are continuous in nature over time and statistical methods of measurement are used (Beard et al., 2020). The study covered a period of 33 years from 1986 to 2018. This period has been selected because there has been a stable government under one leadership without any serious interruption from war or takeover of government as always common in developing countries.

3.2. Expected Signs of the Variables

The expected signs, symbols, measurements, and data sources used in the model are presented in Table 1. The data used for this paper obtained from the World Bank Development indicators.

3.3. Model Specifications

Following the empirical literature in economics, we have observed that energy is a significant factor of CO_2 emission. According to the EKC hypothesis CO_2 emission and output have a nonlinear quadratic relationship (Dinda 2004). At a steady state, the cointegrating relationship between carbon emissions, energy and output can be specified as follows:

$$c_t = \alpha + \theta ec_t + \gamma gdp_t + \varepsilon_t \tag{1}$$

Where C_t=ln(CO_{2t}/L_t) is per capita CO_2 emission, ec_t=ln(EC_t/L_t) is per capita energy consumption, gdp_t=ln(GDP_t/L_t) is per capita GDP and ε_t is the residuals. L_t is the total population over time. Equation one is expressed in the natural logarithmic form to reduce the effect of heteroskedasticity and to obtain the growth rate of the relevant variables by differencing their natural logarithmic form. The expected sign in equation 1 is such that $\theta>0$ because high energy consumption is expected to increase CO_2 emission. The parameters θ, and γ are long-run elasticities of CO_2 emission per capita with respect per capita energy use, and per capita GDP respectively.

3.4. Unit Root Tests

The stationarity was tested using the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) developed by Phillips and Perron (1988). Dickey and Fuller (1981) examine the unit root in each time series with the following hypothesis:

H_o: θ=0, when the time series has unit root

H_1: θ<0, when the time series has no unit root

Following the ordinary least square (OLS) assumption, ADF is expressed as:

$$\Delta y_t = \psi + \beta_t + \theta y_{t-1} + \sum_{i-1}^{p} \delta_i \Delta y_{t-i} + u_t \tag{2}$$

Where t is a deterministic trend, ψ and β are the constants, p is the lag order selection based Schwartz Bayesian Criterion (SBC). If the calculated value in the absolute term, is more than the t-statistic, we reject the H_0 (θ=0), if H_0 is rejected it implies the series is stationary and is an I(0) process. When H_0 is rejected at the first difference, the series is I(1). Similarly, when the series becomes stationary at the second difference, the series exhibits an I(2) process. The PP test is used to correct for any serial correlation and heteroskedasticity in the error u_t since it is more robust than Dickey-Fuller.

3.5. Cointegration Test

We applied the Johansen cointegration test by Johansen and Juselius (1990). It is used to check for existence long-run cointegrating equation(s) between or among variables of the I(1) series. The cointegration is performed in levels but not in first difference. But since the variables are in natural logarithmic form, the log transformed variables are used to interrogate the long-run relationship. The multivariate cointegration model of Johansen and Juselius is expressed as:

$$\Delta y_t = \psi + \pi y_{t-1} + \sum_{i-1}^{P-1} \Gamma_i \Delta y_{t-1} + u_t \tag{3}$$

Where, ϖ and Γ_i are coefficient matrices, Δ is the difference operator and P is the lag order selected based on SBC. Johansen and Juselius cointegration uses two likelihood ratio test-the trace and max eigenvalue tests and they are computed as follows:

$$T(r) = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i) \tag{4}$$

$$\lambda_{\max}\left(r, r+1\right) = -T \ln\left(1-\hat{\lambda}_{r+1}\right) \tag{5}$$

Where, $\hat{\lambda}_i$ is the expected eigenvalue of the characteristic roots and T is the sample size. In λ_{trac} test, the H_1 investigates the number

Table 1: Variable description and expected signs

Variables	Symbol	Measure	Expected Sign	Data source
Per capital CO_2 emission	C_t	CO2 emission in Kiloton	N/A	World bank: World development indicators
Per capita GDP	GDP_t	GDP constant 2010 US$	+	World bank: World development indicators
Per capita Energy consumption	EC_t	Energy consumption measured in Terra Joules	+	World bank: Sustainable energy for all.

of cointegrating vector r against H_1 of n cointegrating vector. Whereas, for λ_{max} test, H_0 investigates the number of cointegrating vectors r against H_1 of r+1 cointegrating vector. When using Johansen and Juselius cointegration test, where there is one or more cointegrating vectors, there is evidence of long-run equilibrium between or among variables. To establish the relationship we set the null hypothesis as follows:
H_0: No cointegrating equation(s)

The decision criteria is based on 5% level of significance. We reject the null if the value of λ_{trac} and λ_{max} is greater than 5% critical value. Otherwise, we fail to reject the null.

3.5. Vector Error Correction Model (VECM)

VECM is a system of vector of two or more variables that are exogenous. If the variables are non-stationary but I(1) time series and they are cointegrated, we can run VECM to examine both short-run and long-run dynamics of the series. The VECM for all the endogenous variables appears as follows:

$$\Delta c_t = \delta + \sum_{i=1}^{k-1} \alpha_i \Delta c_{t-i} + \sum_{j-1}^{k-1} \beta_j \Delta ec_{t-j} + \sum_{m=1}^{k-1} \mu_m \Delta gdp_{t-m} + \lambda_1 ECT_{t-1}. + u_{1t}. \tag{6}$$

$$\Delta ec_t = \phi + \sum_{i=1}^{k-1} \alpha_i \Delta c_{t-i} + \sum_{j-1}^{k-1} \beta_j \Delta ec_{t-j} + \sum_{m=1}^{k-1} \mu_m \Delta gdp_{t-m} + .\lambda_2 ECT_{t-1}. + u_{21t} \tag{7}$$

$$\Delta gdp_t = \vartheta + \sum_{i=1}^{k-1} \alpha_i \Delta c_{t-i} + \sum_{j-1}^{k-1} \beta_j \Delta ec_{t-j} + \sum_{m=1}^{k-1} \mu_m \Delta gdp_{t-m} + \lambda_3 ECT_{t-1} + u_{3t} \tag{8}$$

Where $k-1$ the lag length is reduced by 1 and α_i, β_j, μ_m are the short-run coefficients of the model's adjustment long-run equilibrium. λ_i is the coefficient of ECT and is the speed of the adjustment parameter towards long-run equilibrium. It has to be negative and statistically significant for it to maintain its economic interpretation. ECT_{t-1} = the term error correction relates to the fact that last year period deviation from long-run equilibrium (error) influences the short-run dynamics of the dependent variables. u_{it}= residuals (stochastic error term often called impulses or innovations or shocks. To find the long-term causality flowing from the dependent variable(s) to the dependent variable, the coefficient of the $ECT(\lambda)$ should be significant and is defined as:

$$ECT = \Delta c_t - \delta - \sum_{i=1}^{k-1} \alpha_i \Delta c_{t-1} - \sum_{j=1}^{k-1} \beta_j \Delta ec_{t-j} - \sum_{m=1}^{k-1} \mu_m \Delta gdp_{t-m} \tag{9}$$

3.6. Granger Causality Test

We used a two-steps procedure from Engle and Granger (1987) model to investigate the link between CO_2 emissions per capita, energy consumption per capita, and GDP per capita. In the first step, we estimate the long-run model in equation 6 in order to get the estimated residuals. The second step is to estimate error correction based on the Granger causality approach. The error correction based on causality tests allows the inclusion of the lagged error term derived from the cointegration equation (Ozturk and Acaravci 2010). We also validated our result using the pairwise Granger causality test.

4. RESULTS AND DISCUSSIONS

4.1. Unit Root Tests

Most variables may not exhibit -stationarity, therefore we test for unit root. The time series properties of the variables under investigation are tested using Augmented Dickey-Fuller (ADF) test developed by Dickey (1981) and Philips-Perron (PP) tests by Phillips and Perron (1988) at a constant intercept without a trend are applied. This is always done to avoid spurious results in the data generation process. Table 2 illustrates the results.

From Table 2 all variables are non-stationary in levels and they are all stationary at first difference i.e, I(1). Since all the variables are I(1) series, we proceed to test for the existence of the cointegration equation. To do this we determine the appropriate lag length.

4.2. Optimal Lag Length Structure

The key issue in time series analysis is the optimal lag selection process for a finite set of observations (Hamilton, 2020). The selection of a lag structure in VECM is an empirical question because both over-fitting and under-fitting of the model with lags result into insignificant coefficients and spurious outcomes. For the purpose of this study, we consider Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) and Hannan-Quinn information criterion (HQ) for the selection of the optimal lag structure. Table 3 shows the results; the optimal lag length selected by the criteria is one. This is appropriate because we are dealing with annual observations for 33 years.

4.3. Cointegration Test

The existence of long-run cointegration is tested using Johansen cointegration test developed by Johansen (1988). It was carried out to establish whether the series are linearly related. In such a situation if there are shocks in the short-run, which often affect the individual series, they can convergein the long-run. If the series are not integrated we only estimate Vector Auto Regressive (VAR) model. To use the Johansen cointegration test, our null hypothesis supports the existence of no cointegrating equation and the decision criteria is based at a 5% level of significance. We reject the null hypothesis if the value of the trace and max statistics is greater than 5% critical value. Otherwise we fail to reject the null hypothesis. Table 4 depicts the Johansen unrestricted integrated rank test. We reject the null hypothesis of no cointegrating equation since the value of Trace statistic (λ_{trace}) and Max-Eigen (λ_{max}) value are above the critical value at 5%. We conclude that there are

Table 2: ADF and PP unit root tests

	ADF test				PP test			
	Level		1st difference		Level		1st difference	
Variables	Test statistics	Prob.	Test statistics	Prob.	Adj. t-stat	Prob.	Adj. t-stat	Prob.
C_t	0.625201	0.9883	−4.904261	0.0004***	0.595226	0.9874	−4.895838	0.0004***
ec_t	−2.023753	0.2757	−5.528474	0.0001***	−2.021908	0.2764	−5.528490	0.0001***
gdp_t	−0.969973	0.7518	−4.534485	0.0011***	−0.880853	0.7813	−4.561942	0.0010***

*** indicates statistical significance at 1%

Table 3: Optimal lag selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	55.52782	NA	6.77e-06	−3.388892	−3.250119	−3.343655
1	177.0059	211.6070*	4.80e−09*	−10.64554*	−10.09045*	−10.46460*
2	184.5813	11.72953	5.36e−09	−10.55363	−9.582219	−10.23697

*indicates lag order selected by the criterion, 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

Table 4: Johansen Unrestricted Cointegration Rank Test (Maximum Eigenvalue and Trace)

Hypothesized No. of CE (s)	Eigenvalue	Trace			Max-Eigen		
		Statistic	Critical Value at 5%	Prob.	Statistic	Critical Value at 5%	Prob.**
None *	0.386379	29.84717	29.79707	0.0493	15.13972	21.13162	0.2792
At most 1	0.291161	14.70745	15.49471	0.0655	10.66792	14.26460	0.1717
At most 2*	0.122174	4.039530	3.841466	0.0444	4.039530	3.841466	0.0444

Trace test indicates 1 cointegrating equation (s) at the 0.05 level, * denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) *P* values

long-run cointegration equation. This implies that the series are related and can be combined in a linear fashion and in case there is a shock in the short-run, which may affect the movement in the individual series they would converge in the long-run. Therefore, we can proceed a head to estimate the long-run equation in the Vector Error Correction (VEC) Model framework, because there is at least one cointegrating equation confirmed by the analysis of both Trace and Max-Eigen statistics. The normalise Johansen cointegration results from our estimation is expressed in Table 5. The figures in the parentheses are standard errors. Thus the Johansen long-run cointegration equation is expressed as follows:

$$c_t = -18.613 + 0.526\, ec_t + 1.856\, gdp_t \tag{10}$$

The result in equation 10 indicates that economic growth measured in terms of real GDP per capita is positively and statistically is associated with CO_2 emission. While energy consumption is positively corrected with CO_2 emission but it is not statistically significant. Specifically, a 1% increase in GDP per capita tends to increase CO_2 emission by about 1.856%, ceteris paribus. We conclude that the null hypothesis of no cointegration is rejected against its alternative of cointegrating relationship in the model. The positive link between CO_2 emission and GDP per capita makes rational economic sense, since the growth in GDP per capita is associated with the increase in the economic activities through consumption of goods and services which are likely to have negative effect of the environment. However, there is a lot of debate on this area in terms of causality between economic growth and CO_2 emission with no consensuses reach yet among the scholars as shown in the literature section.

4.4. Granger Causality and Short-run Dynamics

This paper also explores the direction of causality between the variables by using error-correction based Granger causality

Table 5: Long-run equilibrium

Variables	coefficient	Standard errors	t-statistic
C_t	1.000000		
ec_t	−0.525794	0.55246	−0.95175
gdp_t	−1.853266	0.16542	−11.2034***
Constant	18.61247		
Error correction term	−0.292670	0.08426	−3.47344***

*** indicates statistical significance at 1%

models which are weak (short-run) Granger causality and long-run causality. The results for models in Tables 6-8 can be summarised as follows:

(i) There is no causality between CO_2 emission per capita and energy consumption.
(ii) A unidirectional relationship running from GDP per capita to CO_2 emissions per capita and supports EKC hypothesis in the short-run.
(iii) There is no causality running from energy consumption per capita to GDP per capita.
(iv) There is no causality from GDP per capita to energy consumption per capita.
(v) Long-run relationship exists for CO_2 emission per capita equation and GDP per capita Granger cause CO_2 emission per capita.

The findings of positive relationship between economic growth and carbon emissions are in line with Appiah et al. (2019) in Uganda's context. Sekantsi and Okot (2016) and Mawejje and Mawejje, (2016) but did not test the causality between CO_2 emissions and economic growth. The generally, the results support energy growth neutrality hypothesis. Energy consumption does not pay a pivotal role in economic growth and economic growth does not impact on energy consumption. In addition, the result also support EKC hypothesis where economic growth leads to environmental degradation in the short-run. Uganda should take care on its energy

Table 6: Estimated coefficients

Error Correction:	Δc_t	Δec_t	Δgdp_t
CointEq1	−0.292670 [−3.47344]***	−0.035658 [−0.68657]	0.005443 [0.22625]
$\Delta c_t(-1)$	0.129217 [0.75817]	0.018054 [0.17186]	0.047877 [0.98390]
$\Delta ec_t(-1)$	−0.262820 [−0.82787]	−0.042364 [−0.21650]	0.104407 [1.15187]
$\Delta gdp_t(-1)$	−0.881842 [−1.31081]	−0.442069 [−1.06608]	0.135236 [0.70407]
Constant	0.058032 [2.46469]	0.003028 [0.20866]	0.025616 [3.81040]
R^2	0.331001	0.050923	0.129214
Adj. R^2	0.228078	−0.095089	−0.004753

*** indicates statistical significance at 1%

Table 7: Granger Causality test results

Variables	Short-run (or weak) Granger causality			Long-run granger causality
	Δc_t	Δec_t	Δgdp_t	λ_i, i=1,2,3,
$\Delta c_t(-1)$	…………	0.02954 (0.8635)	0.96805 (0.3252)	−0.29267 (0.0018)***
$\Delta ec_t(-1)$	0.68536 (0.4077)	………..	1.32681 (0.2494)	0.18749 (0.4984)
$\Delta gdp_t(-1)$	1.71821 (0.3083)	1.13652 (0.2864)	……….	−0.01009 (0.8228)

*** indicates statistical significance at 1% .The null hypothesis is that there is no causal relationship between variables. Values in the parentheses are *P* values for Wald tests with distribution. Δ is the first difference operator

Table 8: Pairwise granger causality tests

Null hypothesis:	F-statistic	P-value	Decision
ec_t does not Granger Cause c_t	2.12796	0.1554	Fail to reject the null hypothesis
c_t does not Granger Cause ec_t	0.07516	0.7859	Fail to reject the null hypothesis
gdp_t does not Granger Cause c_t	7.36712	0.0111**	Reject the null hypothesis
c_t does not Granger Cause gdp_t	3.34088	0.0779	Fail to reject the null hypothesis
gdp_t does not Granger Cause ec_t	0.34235	0.5630	Fail to reject the null hypothesis
ec_t does not Granger Cause gdp_t	0.38798	0.5382	Fail to reject the null hypothesis

*** indicates statistical significance at 1%

polices, the absence of causality between energy consumption and economic growth should not bring complacency because we see economic growth contributing to the environmental degradation in terms of increased CO_2 emission per capita. We expect when Uganda starts to extract the oil in 2022 (Wolf and Potluri, 2018) the consumption of fossil fuels will increased, which is likely to have an adverse effect on the environment. The government expect to refine 150,000bbl daily and generates US$ 1billions in profits yearly through import substitution industrialization and export earnings (Wolf and Potluri, 2018). If we are to go by these figures, we expect growth in GDP per capita and energy consumption of fossil fuels, which may affect the environment adversely unless strong policy action are put in place to mitigate the possibility of environmental degradation.

4.5. VECM Estimation Diagnostics

The estimated error correction term (ECT) is negative (−0.29267) and statistically significant at 1% confidence level (Tables 6 and 7). ECT indicates that any deviation from the long-run equilibrium between variables is corrected by about 29.27% for each period to return to the long-run equilibrium. In addition, figure 1 presents the plot of recursive estimate for Cumulative Sum (CUSUM) and Cumulative Sum Square (CUSUMSQ) of recursive residuals illustrated in figure 1. The coefficients were generated from VECM coefficients. The results indicate the absence of any instability of coefficients because the plots of CUSUM and CUSUMSQ statistics fall inside the critical band of the 5% confidence interval parameter stability. After estimating the VECM we tested for the robustness of the model through checking for serial correlation,

Table 9: VECM Post estimation test

VEC residual serial correlation LM tests		Residual normality tests		VEC residual heteroskedasticity tests	
LM Stat	Prob.	Jarque-Bera	Prob.	Chi-sq	Prob.
11.75350	0.2276	2.721445	0.25475	40.35525	0.7755

Table 10: Variance Decomposition of c_t

Period	S.E.	c_t	ec_t	gdp_t
1	0.072954	100.0000	0.000000	0.000000
2	0.093225	99.21564	0.327769	0.456591
3	0.102775	99.11120	0.297937	0.590868
4	0.110923	96.13280	1.456243	2.410956
5	0.119320	90.63697	3.958921	5.404113
6	0.128017	83.97681	7.144363	8.878828
7	0.137032	77.05142	10.52745	12.42112
8	0.146279	70.44342	13.80077	15.75581
9	0.155610	64.45631	16.79723	18.74646
10	0.164897	59.18318	19.45627	21.36055

residual normality, heteroskedasticity and model stability. Table 9 illustrates the results. We did not detect presence of serial correlation, and heteroskedasticity and the data is normality distributed. We can conclude that our model is pretty robust.

4.6. Variance Decomposition

Variance decomposition in multivariate analysis used in economic forecasting (Lutkepohl, 2010). Tables 10-12 illustrate our result. Each row represents the percentage of the forecast error variance

Figure 1: Plot of cusum and cusumsq recursive residuals

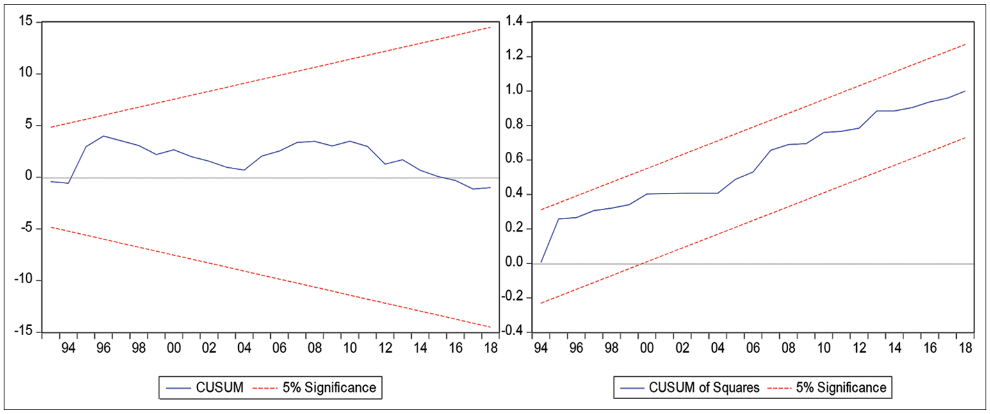

Table 11: Variance Decomposition of ec_t

Period	S.E.	c_t	ec_t	gdp_t
1	0.044967	0.671658	99.32834	0.000000
2	0.062794	0.381364	98.38387	1.234766
3	0.076261	0.650727	97.81901	1.530259
4	0.088252	0.859977	97.70996	1.430061
5	0.099174	0.995514	97.70586	1.298622
6	0.109195	1.109107	97.70500	1.185889
7	0.118496	1.209148	97.70150	1.089355
8	0.127215	1.295287	97.69797	1.006740
9	0.135443	1.369108	97.69441	0.936483
10	0.143247	1.432719	97.69057	0.876707

Table 12: Variance decomposition of gdp_t

Period	S.E.	c_t	ec_t	gdp_t
1	0.020829	20.20908	0.414469	79.37645
2	0.033550	27.24880	3.421960	69.32924
3	0.042056	29.14400	4.257522	66.59848
4	0.048961	29.03441	4.722091	66.24350
5	0.055195	28.41374	5.180753	66.40551
6	0.060931	27.74243	5.614048	66.64352
7	0.066245	27.11078	5.994692	66.89453
8	0.071213	26.53698	6.324101	67.13892
9	0.075894	26.02628	6.609572	67.36415
10	0.080331	25.57655	6.857346	67.56610

Cholesky Ordering c_t, ec_t, gdp_t

by the all the variables under investigation. We made a forecast of 10 year period. We divide our forecast in the short-run, mid-term and long-run. Table 10 shows that in the short-run 100% of the forecast error variance is explained by CO_2 emission per capita itself. The contribution from energy consumption per capita, and GDP per capita to CO_2 emission per capita are strongly exogenous implying that they have very weak influence in predicting CO_2 emission per capita in the short-run. In the mid-term period, 90.6% CO_2 emission per capita is explained by its standard innovation shock. This further still show that the weak influence of energy consumption per capita and GDP per capita is explained by CO_2 emission per capita in Uganda. In the long-run, we see the influence of CO_2 emission per capita on itself dwindling the further we move to the future. It implies that energy consumption and economic growth will start to have a strong endogenous influence on the carbon emission in Uganda. Table 11 shows that in the short-run 99.32% of the forecast error variance is explained by energy consumption itself and the contribution from GDP per capita and carbon emission per capita throughout the period of 10 years are very weak at less than 5%. In Table 12 we see only carbon emission per capita having fairly strong endogenous influence on GDP per capita while energy consumption is having weakly endogenous effect on GDP per capita. The forecast error variance reflect the Granger causality test results.

5. CONCLUSIONS

This paper examines the long-run and causal links between emissions CO_2, energy consumption, and economic growth in Uganda using VECM and Johansen cointegration test for long-run relationship and Granger causality models for 1986-2018 period. Empirical results suggest an evidence of a long-run relationship between variables at 5% levels of significance in Uganda. The estimated elasticity of CO_2 emission per capita with respect to GDP capita is 1.856. The main results for the existence and direction of Granger causality are as follows:

(i) The interesting finding is that energy consumption does not Granger cause CO_2 emission per capita, although the main cause of CO_2 emission in literature is energy consumption. Uganda can still continue to engage in oil exploration and start oil extraction to boost its economic growth without causing much damage to the environment at least in the short-run.
(ii) There is a unidirectional causality flowing from GDP per capita to CO_2 emissions per capita. The result does support the Environmental Kuznets Curve hypothesis, implying that economic growth leads to environmental pollution through CO_2 emissions.
(iii) There is no causal link between energy consumption per capita and GDP per capita. The result support growth neutrality hypothesis. The government of Uganda can pursue policies that promote energy consumption and economic growth such us increasing the level of industrialisation. To take care of environment green energy growth policy can be adopted for sustainable growth and development in the long-run.
(iv) Long-run causality exists only for CO_2 emission per capita equation.

The main result of this study indicates that GDP is key determinant of CO_2 emissions in the long-run. As the growth in an economy is reflected through the increase in GDP at both nominal and real terms. This is because the growth in GDP is characterised by the growth in a number of economic activities besides energy consumption. A country like Uganda is predominantly agrarian and peasantry in nature. Therefore, the growth in its GDP is facilitated by unregulated economic practices. Therefore policies that are pro-growth may certainly conflict with policies that promote reduction in CO_2 emission. The growth in GDP as the country strive to attain a middle income status is a precursor for future emission in Uganda. Thus, whereas growth in GDP is necessary for the welfare of the people, it should be sustainable for the posterity. The goals for economic growth and sustainable development are all important. Therefore, green growth strategy is likely to be the future of Uganda's economy, if the country is to strike a balance between the two. The impact on energy consumption on the CO_2 emission was found to be insignificant. This result suggests that there are other causal factors responsible CO_2 emission. We used 33 years observations which may affect the predictive ability of our model. When more data are available in future, this study can be repeated to take care of the long-run time variation.

However, the study did not consider the effect of population growth on the economic growth which could have been control variable to bite the influence of endogeneity in the model. Therefore, further research should investigate the impact of population activities on the environment as key factors for CO_2 emission. Even though energy consumption is not the cause of CO_2 emission in Uganda, we expect the long-run sustained economic growth to make energy consumption to be a key driver that will propel future emission like what is happening in China, where there is a huge utilisation of fossil fuels in construction and manufacturing sectors (Jiang et al., 2019; Yang et al., 2020; Zhu and Shan, 2020). The long-run scaled effect of economic growth and energy consumption on the environment can be mitigated by creating public awareness on the importance of green investments, supporting and adopting the clean use of energy technologies such as solar, hydro, geothermal and wind.

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