

Economic Growth, CO₂ Emission and the Environmental Kuznets Hypothesis in Kenya; an Ardl Bounds Test Approach to Cointegration

Samuel Otieno John

*Moi University Kenya, School of Agriculture and Natural Resources
Correspondent Author: Samuel Otieno John*

ABSTRACT

This study investigated the relationship between CO₂ emission, energy consumption, population growth, urban population growth, trade openness, gross domestic product and industrial activities in Kenya over the period 1970-2017. Autoregressive distributor lag approach to cointegration was used. The objective of the study was to investigate the relationship between Economic growth, CO₂ emission and whether the Environmental Kuznets Hypothesis holds in Kenya. The study was based on secondary time series data which was obtained from the World Development Index (WDI) World Bank database. The study used descriptive and inferential statistics in the data analysis. The results proved that the Environmental Kuznets Hypothesis does not hold in Kenya, and therefore policy makers have to look for cleaner ways to develop the country rather than following the environmentally degrading patterns in which the developed countries followed in the process of developing.

KEY WORDS: Economic Growth, Environmental Kuznets, Ardl Bounds, Cointegration

Date of Submission: 17-01-2020

Date of Acceptance: 05-02-2020

I. INTRODUCTION

Global warming due to climate change has been a source of major concern worldwide over the recent years. CO₂ is the major contributor to global warming as it contributes the largest portion of Green House Gases (GHGs), it makes up 70% of GHGs to be precise. CO₂ emission has grown dramatically over the past century due to human activities especially the consumption of fossil fuels, the main power source of electricity generation, manufacturing activities, transport and consumption of goods and services that are directly linked with economic growth. So there is a systematic relationship between economic growth and environmental quality, the relationship known as the Environmental Kuznets Curve (EKC), by analogy with the income-inequality relationship postulated by Kuznets. The EKC is named after Simon Kuznets, (1955) who hypothesized that as a country develops, economic inequality increases first and then decreases after reaching a certain average income. The EKC hypothesis in 1991 stated an inverted U shape relation between various indicators of environmental quality and per capita income (Alam, 2013). There is much evidence available in the literature that is in favor of the EKC. However this inverted U shaped curve has been rejected for an N shaped curve which indicates that pollution increases as a country grows then decreases as the level of growth is reached to its threshold level, then rises again as the economy grows further (King'ori, 2011).

According to Zhang and Cheng, (2009), GDP growth causes energy consumption while energy consumption causes CO₂ emission. In Kenya production of energy from primary sources, natural gas, solid fuels, and combustible renewable and primary electricity has continuously been on the rise over the recent years. Rapid production of energy occurs as a result of the ever increasing demand for energy due to the increase in total population and rapid economic growth of the country, the Kenyan population increases at a rate of 2.6% annually (World Bank, 2015). Kenya experienced rapid economic growth with Gross Domestic Product (GDP) expanding by 5.6% in 2010 after suppressed growth of 1.5% and 2.6% in 2008 and 2009 (Republic of Kenya, 2011). Over this period, most sectors in the economy experienced increased productivity. The agricultural sector reported a 6.3% real growth rate compared to the contractions of 4.1% in 2008 and 2.6% in 2009 and the manufacturing sector grew by 4.4% compared to the marginal growth of 2.6% in 2009. The agricultural and forestry sectors continued to be the key contributors to GDP with their contributions being unparalleled by other sectors.

In 2010, the two sectors contributed 21.5% of the GDP a decline from 24.4% contribution in 2009. The manufacturing and wholesale and retail trade sectors remained the second highest contributors to the GDP. The manufacturing sector contributed 10% and 9.9% of the GDP in 2010 and 2009 respectively (Republic of Kenya,

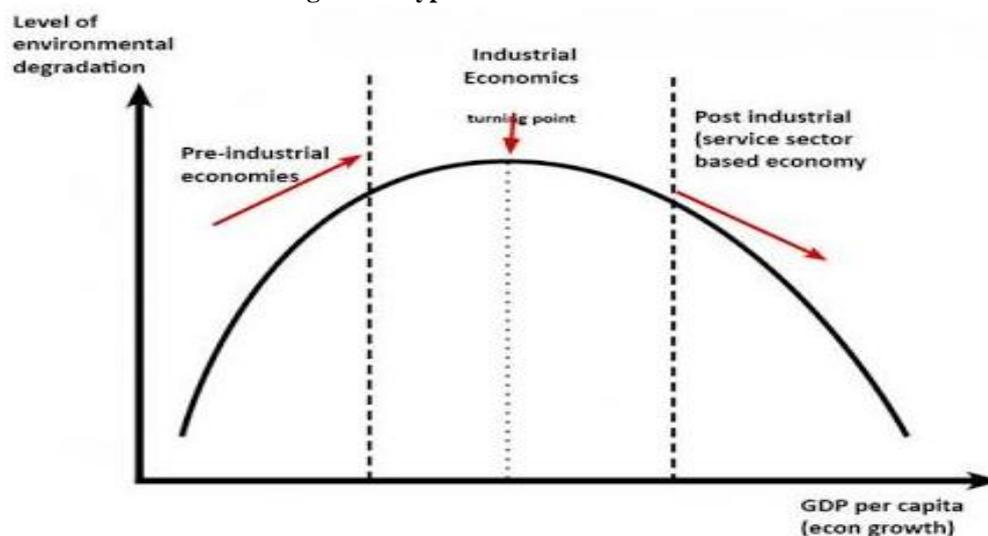
2011). Over the same period however, environmental degradation became more severe. Forest plantation stock decreased from 112.7 thousand hectares in 2009 to 111.8 thousand hectares in 2010. In addition, natural resource mining also increased from 1,399 thousand tons in 2009 to 1,497 thousand tons in 2010 (Republic of Kenya 2011). The 21st session of the United Nations Climate Change Conference, COP 21 was held in Paris, France in 2015. A major outcome of the Conference was the consensus to limit global warming to less than 2°C, several countries undertook different initiatives to achieve this and Kenya is one of them the government implemented energy proposals targeting developing renewable energy and restoration of forests in Kenya. Total installed electricity capacity increased by 6.3 per cent to 2,333.6 MW in 2015, while total electricity generation expanded by 4.1 per cent to 9,514.6 GWh during the same period. Demand for electricity increased from 7,415.4 million KWh in 2014 to 7,826.4 million KWh in 2015 (KNBS, 2016). The high demand for electricity attributed to the increased investments in the country and the increase in population with government implementing the last mile electricity program to bring more homesteads on the grid.

Macro economists have shown that energy steers economic growth. Most sources of energy in Kenya are based on fossil fuels. Combustion of these fossil fuels leads to production of harmful gases like CO₂. This gas is the leading culprit when it comes to global warming and climate change. The effects of climate change are adverse ranging from increase the cost on achievement of development and alleviation of poverty, increase in diseases, reduced agricultural production, poverty, flooding, drought and increased insecurity due to fighting for scarce resources which are an additional burden to African countries (Muhammad, Solarin, & Ozturk, 2016). The CO₂ emissions have been rising gradually over the years. The increase may be attributed to the accelerated growth of sectors such as construction which expanded by 13.6% in the year 2015 and manufacturing and transport which demand higher energy supply (KNBS, 2016).

Little information is available in the country on the determination of the relationship between CO₂ emission and economic growth. This study aims to reduce environmental effects of economic growth and other factors since there are no market prices to use as guides, economists interested in pollution must begin by looking at scientific evidence (Romer, 2012). In the case of global warming, for example, a reasonable point estimate is that in the absence of major intervention, the average temperature will rise by 3⁰ centigrade over the century, with various effects on climate (Nordhaus, 2008). Economists can help estimate the welfare consequences of these changes. This study provides additional literature on the subject, provide new insights on variables yet to be studied and provide policy implications to guide in reducing the effects of environmental degradation.

II. THEORETICAL FRAMEWORK

Figure 1: Hypothetical Kuznets Curve



Source: EKC in India, (1940)

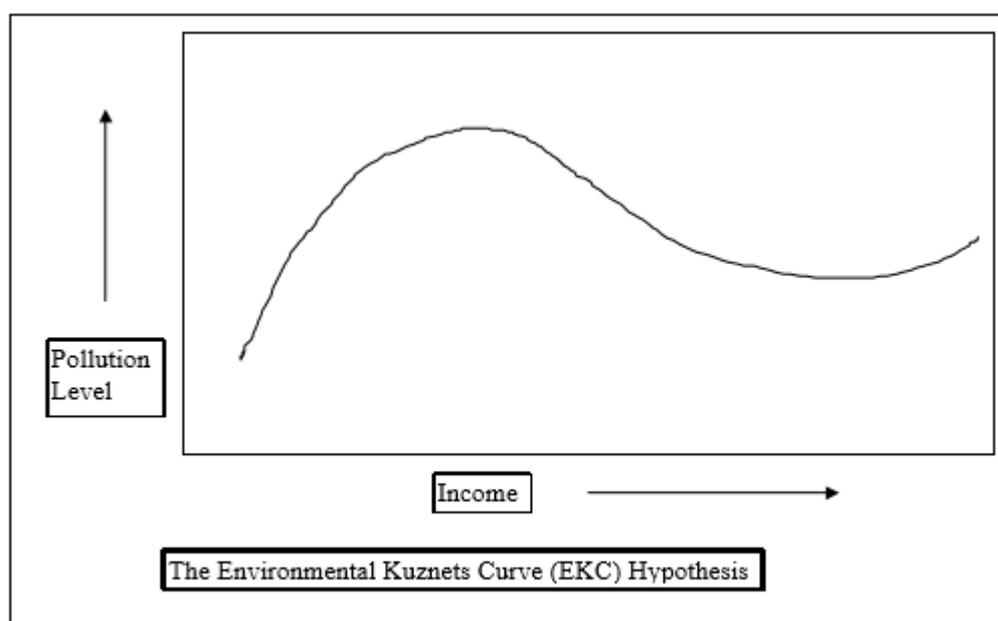
The Environmental Kuznets curve (EKC) analysis is an econometric methodology that assumes that environmental quality or pollutant emissions are correlated with economic growth, specifically per capita gross domestic product (GDP). Regression analysis has in some cases found an “inverted U-shaped” relationship between the variables. This has been interpreted to mean that pollution increases with national industrial and income growth, but once a specific income “turning point” is reached, environmental quality begins to improve

as incomes grow further (Shafik and Bandyopadhyay, 1992; World Bank, 1992; Grossman and Krueger, 1993; Selden and Song, 1994). Economist Simon Kuznets originally identified a similar historic relationship between income distribution and income growth in the 1940's which is known as the "Kuznets curve" (KC), and this antecedent is the source of the environmental, EKC hypothesis.

Based on economic theory, two dominant explanations have been put forth to explain the relationship. The first is that Kuznets behavior is an income effect and results because the environment is a luxury good. Early in the economic development process individuals are unwilling to trade consumption for investment in environmental protection; as a result environmental quality declines. Once individuals reach a given level of consumption, known in the EKC literature as the "income turning point", they begin to demand increasing investments in an improved environment. Thus after the turning point, environmental quality indicators begin to demonstrate decreases in pollution and environmental degradation.

The other common explanation is that the EKC is another expression of the "stages of economic growth" economies pass through as they make a transition from agriculturally based to industrial and then post-industrial service based economies. The transition from agricultural to industrial economies results in increasing environmental degradation as mass production and consumption grow in the economy. The transition from industrial to service based economy is assumed to result in decreasing degradation due to the lower impact of service industries. A slightly modified view is the idea that economies pass through technological life cycles, moving from smokestack technology to high technology, Moomaw and Unruh, (1997). The EKC curve of a pollutant can be linear, quadratic, cubic or logarithmic. In the case of a quadratic function, per capita emission of a pollutant exhibit an inverted U shaped relationship with the per capita income. In the cubic case an N shaped relationship between CO₂ emissions and income per capita can result (EKC-India, 2012). An N shaped curve indicates that pollution increases as a country grows then decreases as the level of growth reaches its peak, and then begins increasing as economy grows further.

Figure 2: N-Shaped Kuznets Curve



Source: Moomaw and Unruh (1997)

Eunho Choi *et al.*, (2010) find N-shaped curve describing the relationship between pollution and GDP in case of China. Though it is not a fine N-shaped curve but the curve hints to follow such relationship in the long run. Miah *et al.*, (2010) show that EKC for CO₂ in Bangladesh follows a monotonous straight line in most cases. Agras and Chapman (1999) and Perrings and Ansuategi (2000) do not find inverted U-shaped EKC for carbon dioxide emissions rather increase with the increase in income. Moomaw and Unruh, (1997) also do not find EKC relationship for 16 countries for the period (1950-92). Maddison and Rehdanz (2008) find strong evidence for bidirectional causal relationship between per capita GDP and per capita CO₂ emissions except for Asia. In case of Asia, there is no evidence of CO₂ per capita caused by GDP per capita.

III. METHODOLOGY

Research Design

The study assumes a causal relationship between CO₂ emissions and determining variables based on current literature. This informs the adoption of an explanatory design since it provides a framework of determining the underlying relationship, confirming and refuting and cause and effect relationship between the determinants (Salkind, 2010).

Data Sources

This study employs the annual time series data covering the period 1970 to 2017. In this study the data for CO₂ emissions (measured in metric tons per capita) per capita Energy Consumption and Industrial Activities, GDP and demographics that is population growth, urban population growth, per capita GDP and per capita GDP squared and the data for financial and economic influencers that is trade openness was obtained from the World Development Indicators (World Bank).

Data Analysis

The study employed descriptive and inferential statistics in its analysis. STATA software of data analysis was used to estimate descriptive statistic and all regression analyses. The software was also used to carry out test statistics, determination of the short run and the long run relationship between the variables and diagnostic tests. The augmented Dickey-Fuller test was used to determine stationarity. The ARDL model was utilized to estimate the long-run and short-run relationships among study variables.

Model Specification

The study assumed a positive relationship between CO₂ and the determinants of CO₂ as evidenced from the available literature. The study closely followed the methodology applied by (Shahbaz *et al.*, 2012) and (Ahmed *et al.*, 2012) but makes relevant modifications in order to fit the Kenyan situation. To estimate EKC for Kenya, the study captured more variables such as population growth, urban population growth and inflation as they appeared relevant on CO₂ emission in Kenya. The relation is specified as follows

$$CO2_t = f(ENC_t + GDP_t + GDP^2_t + TR_t + IN_t + PG_t + UPG_t) \dots\dots\dots Eqn 1$$

The linear model is converted into log-linear specification as it provides more appropriate and efficient results as compared to the simple linear functional form of the model (Shahbaz, *et al* 2012). The equation is re-written as follows:

$$\ln CO2_t = \beta_0 + \beta_1 \ln ENC_t + \beta_2 \ln GDP_t + \beta_3 \ln GDP^2_t + \beta_4 \ln TR_t + \beta_5 \ln IN_t + \beta_6 \ln PG_t + \beta_7 \ln UPG_t + \varepsilon_t \dots\dots\dots Eqn 2$$

Where CO_{2t} is the Carbon (IV) Oxide emission, per capita ENC_t is energy consumption, GDP_t is real Gross Domestic Product per capita, GDP²_t is real GDP squared per capita, TR_t is trade openness, IN_t is industrial activities, PG_t is population growth and UPG_t is urban population growth. In this study we will use the Auto Regressive Distributor Lag (ARDL) model by Pesaran, *et al.*, (2001). It is preferred as it is more efficient in small samples and avoids the problem of endogeneity and helps to estimate the coefficients in the long run. In order to examine the longrun relationship between the variables through ARDL bound approach to cointegration. The equation of the model is as follows:

$$\begin{aligned} \Delta \ln CO2_t = & \beta_0 + \sum_{k=1}^n \beta_{1k} \Delta \ln CO2_{t-k} + \sum_{k=1}^n \beta_{2k} \Delta \ln ENC_{t-k} + \sum_{k=1}^n \beta_{3k} \Delta \ln GDP_{t-k} \\ & + \sum_{k=1}^n \beta_{4k} \Delta \ln GDP^2_{t-k} + \sum_{k=1}^n \beta_{5k} \Delta \ln TR_{t-k} + \sum_{k=1}^n \beta_{6k} \Delta \ln IN_{t-k} + \sum_{k=1}^n \beta_{7k} \Delta \ln PG_{t-k} \\ & + \sum_{k=1}^n \beta_{8k} \Delta \ln UPG_{t-k} + \lambda_1 \ln CO2_{t-1} + \lambda_2 \ln ENC_{t-2} + \lambda_3 \ln GDP_{t-1} \dots\dots\dots Eqn 3 \\ & + \lambda_4 \ln GDP^2_{t-1} + \lambda_5 \ln TR_{t-1} + \lambda_6 \ln IN_{t-1} + \lambda_7 \ln PG_{t-1} + \lambda_8 \ln UPG_{t-1} + \varepsilon_t \end{aligned}$$

The time domain analysis is the approach based on autocorrelation functions to make inference from an observed time series to make inference from an observed time series to estimate the model.

The autocorrelation function (ACF) is an extremely important tool to describe the properties of a stationary stochastic process it may be summarized compactly in the *spectral density function*. It is defined as

$$F_Y(\lambda) = (2\pi)^{-1} \sum_{j=-\infty}^{\infty} \gamma_j e^{-i\lambda_j} = (2\pi)^{-1} \left(\gamma_0 + 2 \sum_{j=1}^{\infty} \gamma_j \cos(\lambda_j) \right) \dots\dots\dots \text{Eqn 4}$$

Where $i = \sqrt{-1}$ is the imaginary unit, $\lambda \in [-\pi, \pi]$, is the frequency and γ_j are the autocovariances of Y_t . The model that was estimated was as follows;

$$\hat{F}_Y(\lambda) = (2\pi)^{-1} \left(w_0 \hat{\gamma}_0 + 2 \sum_{j=1}^{M_T} W_j \hat{\gamma}_j \cos(\lambda_j) \right) \dots\dots\dots \text{Eqn 5}$$

Where the weights $w_j (j = 1, 2, \dots, M_T)$ represent the so-called *spectral window* and MT is the *truncation point*. The Bartlett window was used: $w_j = 1 - j/M_T$ (Bartlett (1950). Choosing all $w_j = 1$ and $M_T = T - 1$ results in the periodogram. This was obtained by setting the window size to 1 Greene, (2007).

Sometimes it is useful to investigate the direct relationship between two variables. Crossplots offer an intuitive graphical tool to look at co-movements between two different variables. It may also be helpful to compare the plot with a simple OLS regression line, as well as with a nonparametric estimate.

A stationary series is that which has a constant mean and variance for each given period of time and “the value of the covariance between the two time periods depends on the distance or lag between the two time periods not on the time at which the covariance is calculated” (Gujarati, 2003). If a series is non stationary, it must be differenced d times before it becomes stationary. It is then said to be in order of d and written as $I(d)$ where d is the order of integration that is the number of unit roots. Stationary tests should be done on all the variables before estimating the parameters. There are several tests for stationarity. This study will make use of the Augmented Dickey-Fuller test. According to Gujarati (2003) the Dickey Fuller and the Augmented Dickey Fuller tests are the most frequently used tests for stationarity.

If the hypothesis of interest is $\alpha(1) = 0$. To test this null hypothesis against the alternative of stationarity of the process, it is useful to reparameterize the model. Subtracting $yt-1$ on both sides and rearranging terms results in a regression:

$$\Delta Y_t = \phi Y_{t-1} + \sum_{j=1}^{p-1} \alpha_j^* \Delta Y_{t-j} + v_t \dots\dots\dots \text{Eqn 6}$$

In this model we wish to test the pair of hypotheses $H_0 : \phi = 0$ versus $H_1 : \phi < 0$ $H_1 : \phi < 0$. The so-called *augmented Dickey-Fuller (ADF) test* statistic is based on the t -statistic of the coefficient ϕ from on OLS estimation of (2.15) [Fuller (1976) and Dickey & Fuller (1979)]. It does not have an asymptotic standard normal distribution, but it has a nonstandard limiting distribution. Critical values have been obtained by simulation, and they are available, for instance, in Fuller (1976) and Davidson & MacKinnon (1993).

This is a cointegration method developed by *Pesaran et al., (2001)* to test for the presence of long run relationships between the variables. This procedure is a relatively new method. It is superior over the existing methods with many advantages over classical cointegration tests. First it is used irrespective of whether the series is of $I(0)$ or $I(1)$. Secondly, unrestricted error correction model UECM can be derived from the ARDL bounds testing through a simple linear transformation. This model has both short and long run dynamics. Thirdly, the empirical results usually show that the approach is superior and provides consistent results for small samples.

Diagnostic Testing

In the package VARs functions for diagnostic testing are arch test, normality test, serial test and stability. The former three functions return a list object with class attribute VAR check for which plot and print method exist. The plots one for each equation include a residual plot, an empirical distribution plot and the ACF and PACF of the residuals and their squares. The plot method offers additional arguments for adjusting its appearance.

The implemented tests for Heteroscedasticity are the univariate and multivariate ARCH test (Engle 1982; Hamilton, 1994; Lütkepohl, 2005).

For testing the lack of serial correlation in the residuals of a VAR_p, a Portmanteau test and the Breusch-Godfrey LM test was implemented in the function serial test. For both tests small sample modifications will be calculated, whereby the modification for the LM test has been introduced by Edgerton and Shukur, (1999). The Portmanteau statistic is defined as:

$$Q_h = T \sum_{j=1}^h tr(\hat{C}'_j \hat{C}_0^{-1} \hat{C}_j \hat{C}_0^{-1}) \dots \dots \dots \text{Eqn 7}$$

with $\hat{C}_i = \frac{1}{T} \sum_{t=i+1}^T \hat{\mu}_t \hat{\mu}'_{t-i}$. The test statistic has an approximate $\chi^2(K^2h - n^*)$ distribution, and n^* is the number of coefficients excluding deterministic terms of a VAR_p - model. The limiting distribution is only valid for h tending to infinity at a suitable rate with growing sample size. Hence, the trade-off is between a decent approximation to the χ^2 distribution and a loss in power of the test, when h is chosen too large. The small sample adjustment of the test statistic is given as:

$$Q_{hh}^* = T^2 \sum_{j=1}^h \frac{1}{T-j} tr(\hat{C}'_j \hat{C}_0^{-1} \hat{C}_j \hat{C}_0^{-1}) \dots \dots \dots \text{Eqn 8}$$

Lomnicki, (1961) and Jarque and Bera, (1987) have proposed a test for non-normality based on the skewness and kurtosis of a distribution. The test Jarque-Bera test was used to check the pair of hypotheses; $H_0 : E(v_t^s)^3 = 0$ and $E(v_t^s)^4 = 3$ versus $H_1 : E(v_t^s)^3 \neq 0$ or $E(v_t^s)^4 \neq 3$ The test statistic used was as follows;

$$JB = \frac{T}{6} \left[T^{-1} \sum_{t=1}^T (\hat{v}_t^s)^3 \right]^2 + \frac{T}{24} \left[T^{-1} \sum_{t=1}^T (\hat{v}_t^s)^4 - 3 \right]^2 \dots \dots \dots \text{Eqn 9}$$

This statistic has an asymptotic $\chi^2(2)$ distribution if the null hypothesis is correct (Jarque and Bera (1987)).

The Breusch-Godfrey Lagrangian

Multiplier statistic is based upon the following auxiliary regressions (Breusch 1978; Godfrey 1978):

$$\hat{\epsilon}_t = A_1 Y_{t-1} + \dots + A_p Y_{t-p} + CD_t + B_1 \hat{\epsilon}_{t-1} + \dots + B_h \hat{\epsilon}_{t-h} + \mu_t \dots \dots \dots \text{Eqn 10}$$

The null hypothesis is: $H_0 : B_1 = B_2 = \dots = B_h = 0$ and correspondingly the alternative hypothesis is of the form $H_1 : \exists B_i \neq 0$ for $i = 1, 2, \dots, h$. The test statistic is defined as:

$$LM_h = T(K - tr(\sum_R^{-1} \sum_e^{-1})) \dots \dots \dots \text{Eqn 11}$$

Where \sum_R^{-1} and \sum_e^{-1} assign the residual covariance matrix of the restricted and unrestricted model, respectively. The test statistic LM_h is distributed as $\chi^2(hK^2)$.

In this study the residual autocorrelations (ACs) $\tilde{\rho}_{v,h} = \tilde{\gamma}_{v,h} / \tilde{\gamma}_{v,0}$ (ACs) $\tilde{\gamma}_{v,h} = \sum_{t=h+1}^T (v_t - \bar{v})(v_{t-h} - \bar{v})$ were obtained from the following statistic;

$$\tilde{\gamma}_h = \frac{1}{T} \sum_{t=h+1}^T (v_t - \bar{v})(v_{t-h} - \bar{v}) \dots \dots \dots \text{Eqn 12}$$

In the above model $\bar{v} = T^{-1} \sum_{t=1}^T v_t$ is the sample mean. The partial autocorrelation (PAC) between v_t and v_{t-h} is the conditional autocorrelation given by; $v_{t-1}, \dots, v_{t-h+1}$. The corresponding sample quantity \hat{a}_h was obtained by use OLS estimator of the coefficient α_h in an autoregressive model of the form

$\hat{v}_t = v + \alpha_1 \hat{v}_{t-1} + \dots + \alpha_h \hat{v}_{t-h} + error_t$. In this study, OLS estimates were obtained for each h with sample size $T - h$.

All models with 0 to n lagged differences is estimated. The lag length which minimizes the respective information criterion is presented. The sample length is the same for all different lag lengths and is determined by the maximum order. In other words, the number of values set aside as pre-sample values is determined by the maximum lag order.

The information criteria was computed for VAR models in the levels of the variables using LS estimation on the following model set up?

$$Y_t = D_t A_1 Y_{t-1} + \dots + A_n Y_{t-n} + v_t \dots \dots \dots \text{Eqn 13}$$

Here D_t denotes deterministic terms which are also estimated. Before considering an artificial data set, one topic should be touched on first, namely the empirical determination of an appropriate lag order. As in the univariate AR (p)-models, the lag length can be determined by information criteria such as those of Akaike [1981], Hannan and Quinn [1979], Quinn [1980], or Schwarz [1978], or by the final prediction error (see Lütkepohl [2006] for a detailed exposition of these criteria). These measures are defined as:

Akaike Information Criteria

$$AIC(n) = LogDet\left(\sum_v \tilde{}(n)\right) + \left[\frac{2}{T} nK^2\right] \dots \dots \dots \text{Eqn 14}$$

Hannan and Quinn Information Criteria

$$HQ(n) = LogDet\left(\sum_v \tilde{}(n)\right) + \frac{2LogLogT}{T} nK^2 \dots \dots \dots \text{Eqn 15}$$

Schwarz Bayesian Information Criteria

$$SBIC(n) = LogDet\left(\sum_v \tilde{}(n)\right) + \frac{LogT}{T} nK^2 \dots \dots \dots \text{Eqn 16}$$

Final Prediction Information Criteria

$$FPE(n) = \left(\frac{T + n^*}{T - n^*}\right)^K Det\left(\sum_v \tilde{}(n)\right) \dots \dots \dots \text{Eqn 17}$$

The Granger causality test was used to test for causality between the variable.

IV. EMPIRICAL RESULTS

Augmented Dickey Fuller Tests

GDP per capita and GDP per capita square were stationary at levels. Trade openness, Energy consumption, Industrial activities, Population growth and urban population growth were stationary at 1st difference.

Table 1: Descriptive statistics

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Ln_CO2	58	.2850702	.0476731	.1918291	.3861901
Ln_GDP	58	22.7189	1.289706	20.48914	24.97929
Ln_GDP2	58	45.43779	2.579413	40.97829	49.95858
Ln_TR	58	4.049069	.1334394	3.635722	4.311784
Ln_PG	58	1.151392	.1302323	.9403687	1.339682
Ln_IN	58	2.124202	1.143419	-3.399621	3.956011
Ln_UPG	58	2.73389	.3697106	1.996332	3.26021
Ln_ENC	58	-1.979993	.2845384	-2.321768	-1.434645

The above table shows the mean and standard deviations of the data.

Table 2: Correlation Matrix

Correlation matrix (Pearson):

Variable	Ln_CO2	Ln_GDP	Ln_GDP^2	Ln_TR	Ln_PG	Ln_IN	Ln_UPG	Ln_ENC
Ln_CO2	1	-0.0928	-0.0928	0.1761	0.0771	0.0184	-0.1605	0.0878
Ln_GDP	-0.0928	1	1.0000	-0.5616	-0.6049	0.1489	0.9790	0.8410
Ln_GDP^2	-0.0928	1.0000	1	-0.5616	-0.6049	0.1489	0.9790	0.8410
Ln_TR	0.1761	-0.5616	-0.5616	1	0.4241	-0.1392	-0.4953	-0.4299
Ln_PG	0.0771	-0.6049	-0.6049	0.4241	1	-0.0182	-0.5344	-0.7514
Ln_IN	0.0184	0.1489	0.1489	-0.1392	-0.0182	1	0.1250	0.1369
Ln_UPG	-0.1605	0.9790	0.9790	-0.4953	-0.5344	0.1250	1	0.7639
Ln_ENC	0.0878	0.8410	0.8410	-0.4299	-0.7514	0.1369	0.7639	1

Values in bold are different from 0 with a significance level alpha=0.05

Source: Research data, (2018)

The values that are closer to one or -1 indicate strong linear relationship while those further away denote weak relationship between variables. The matrix indicates high and significant correlation between most variables.

Table 3: Cointegration.

Pesaran, Shin, and Smith (2001) bounds test

H0: no level relationship
Case 3

F = 7.345
t = -5.279

Finite sample (5 variables, 56 observations, 8 short-run coefficients)

Kripfganz and Schneider (2018) critical values and approximate p-values

	10%		5%		1%		p-value	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F	2.355	3.638	2.810	4.242	3.860	5.623	0.000	0.001
t	-2.491	-3.792	-2.836	-4.196	-3.526	-4.996	0.000	0.005

do not reject H0 if

both F and t are closer to zero than critical values for I(0) variables
(if p-values > desired level for I(0) variables)

reject H0 if

both F and t are more extreme than critical values for I(1) variables
(if p-values < desired level for I(1) variables)

Source: Research data, (2018)

The critical values for I(0) variables are closer to zero than both F and t, hence fail to reject the null hypothesis. Therefore the variables are cointegrated and the ARDL and Error Correction Models are appropriate.

Diagnostic tests

Table 4: DURBIN WATSON

Durbin's alternative test for autocorrelation

lags (p)	chi2	df	Prob > chi2
1	0.170	1	0.6802

H0: no serial correlation

Source: Research data, (2018)

From the autocorrelation table above, we fail to reject the null hypothesis at 5% significance level; therefore there is no serial correlation.

Table 5: ARCH-LM

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags (p)	chi2	df	Prob > chi2
1	0.101	1	0.7510
2	1.378	2	0.5021
3	2.374	3	0.4985

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Source: Research data, (2018)

The table above shows results for tests of ARCH(1), ARCH(2) and ARCH(3) effects, respectively. At the 5% significance level, all three tests fail to reject the null hypothesis that the errors are not autoregressive conditional heteroskedastic.

Table 6: Breusch-Godfrey

Breusch-Godfrey LM test for autocorrelation

lags (p)	chi2	df	Prob > chi2
1	0.223	1	0.6369

H0: no serial correlation

Source: Research data, (2018)

At the 5% significance level, Breusch-Godfrey LM test for autocorrelation fails to reject the null hypothesis of no serial correlation

Table 7: ARDL Output.

ARDL(1,0,0,2,0,2,0) regression

Sample: 1964 - 2017 Number of obs = 54
 R-squared = 0.5884
 Adj R-squared = 0.4806
 Log likelihood = 131.11767 Root MSE = 0.0242

D.Ln_CO2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

ADJ						
Ln_CO2						
L1.	-.6085682	.0947506	-6.42	0.000	-.7997826	-.4173538

LR						
Ln_GDP	.1460092	.043598	3.35	0.002	.0580249	.2339934
Ln_TR	.1000964	.0640658	1.56	0.126	-.0291936	.2293863
Ln_PG	.0659653	.1058997	0.62	0.537	-.1477489	.2796795
Ln_IN	-.0030233	.0050731	-0.60	0.554	-.0132613	.0072146
Ln_UPG	-.3745876	.1347337	-2.78	0.008	-.6464912	-.102684
Ln_ENC	-.092751	.0742532	-1.25	0.219	-.2426	.0570981

SR						
Ln_PG						
D1.	2.991081	1.99946	1.50	0.142	-1.043992	7.026155
LD.	-4.021504	1.996901	-2.01	0.050	-8.051413	.008405
Ln_UPG						
D1.	.0990566	.8457849	0.12	0.907	-1.607806	1.805919
LD.	2.546208	.8950286	2.84	0.007	.739967	4.352449
_cons	-1.685761	.5314612	-3.17	0.003	-2.758293	-.613229

Source: Research data, (2018)

GDP per capita is significant in the long run and it has a positive effect on CO₂ emission, a percentage change in GDP per capita leads to a 0.435 increase in CO₂ emission. Urban population growth is significant both in the short run and in the long run, in the short run it has a positive impact on CO₂ emission while in the long run the impact is negative that is it leads to reduction of CO₂ emissions in the long run thus it is good for environmental sustainability.

V. CONCLUSION AND POLICY IMPLICATIONS

The empirical tests reveal that a uni-directional causal relationship between per capita carbon dioxide and per capita GDP and its squared and cubic transformations was observed implying that changes in income causes changes in environmental degradation and not vice versa. The derived ARDL reveals that there exists a strong cointegrating relationship amongst the variables. The short run coefficient of per capita GDP is 0.146. In addition, an N-shaped curve between income and the environment is observed which differs from the inverted U-shaped curve proposed by the EKC hypothesis. The results also indicate that the share of trade openness and industrial activities and energy consumption variables are insignificant, implying that changing them does not significantly cause a change in CO₂ emission. From the study findings, the following policies on reduction of CO₂ emission are implied. Economic growth is significantly associated with increased environmental degradation both in the long run. The finding of an inverted N-shape curve implies that at very high income levels, the scale of economic activity becomes significantly large such that its negative impact on the environment cannot be counterbalanced by the positive impact of the composition and technology effects. Therefore, any beneficial effect that economic growth may have on the environment is transitory.

The finding of an inverted N-shaped relationship also suggests that Kenya cannot out-grow its environmental problems by simply emphasizing economic growth. There is need for special attention to the environment. This suggests that in order to realize sustainable development, environmental policies should be pursued alongside developmental policies.

Some of the core environmental policies that should be adopted are those that address; the need for intensified environmental preservation, adoption of clean production methods, reforms to improve the signals received by economic agents and provision of the right incentives for protecting the resilience of ecological systems and the adoption of ecologically friendly means of economic growth.

Environmental degradation and economic growth relationship shows unidirectional causality running from income to pollutant emissions growth in the long-run. It is important for the government to formulate emission reduction policies and increase investment on abatement since this will be beneficial towards attaining economic development. The recent political changes towards enhanced democratization is expected to have beneficial effects on the environment through effective policies and institutions which should significantly reduce environmental degradation at low income levels while at the same time speeding up improvements at higher income levels, thereby reducing the environmental cost of growth. This would also lead to implementation and adherence to environmental regulations. In addition greater democratic rights are expected to positively influence the demand and lobbying for better environmental policies.

This study concentrated on the environment and economic growth relationship in Kenya. Even though the study has achieved its objectives we cannot claim to have addressed all aspects of this topic. Other researchers can explore the following areas to extend the frontiers of knowledge in this topic: Undertake sector specific studies to determine the presence and impact of technical innovations in subsector activities. The benefit of this in terms of policy prescriptions is that one can be able to propose sectoral policies that address the issues associated with CO₂ emission in the Sub Saharan Africa and in the developing countries globally. Even though CO₂ emissions are significant contributors to greenhouse gases and thus to environmental degradation, the relationship with other causes of environmental degradation and economic growth may vary. Therefore there's need to investigate the nature of the relationship between economic growth and other environmental variables such as gaseous emissions and water pollutants.

REFERENCES

- [1]. Coondoo, D., Dinda, S., (2008). The carbon dioxide emission and income: A temporal analysis of cross-country distributional patterns. *Ecological Economics* 65, 375–385
- [2]. Dinda, S., Coondoo, D., (2006). Income and emission: A panel data-based cointegration analysis. *Ecological Economics* 57, 167–181.
- [3]. Engle, R.F., and Granger, C.W.J. (1987). Co-integration and error-correction: representation, estimation and testing. *Econometrica*, 55, 255-276.
- [4]. Grossman, G., Krueger, A., (1991). Environmental impacts of a North American free trade agreement. National Bureau of Economics Research Working Paper, no. 3194, NBER, Cambridge.
- [5]. Grossman, G., Krueger, A., (1995). Economic environment and the economic growth. *Quarterly Journal of Economics* 110, 353–377.
- [6]. Horvath, R.J., (1997). Energy Consumption and The Environmental Kuznets Curve debate. Department of Geography. University of Sydney, Australia. Mimeo.
- [7]. Jalil, A., Mahmud, S.F., (2009). Environment Kuznets curve for CO₂ emissions: A Cointegration analysis for china. *Energy Policy* 37, 5167– 5172.
- [8]. Shahbaz, M.S., (2011), Environmental Kuznets Curve and the Role of Energy Consumption in Pakistan. MPRA papers No. 34929 online link. <http://mpa.ub.uni-muenchen.de/34929/11>
- [9]. Khalid Ahmed and Wei Long / *Procedia Economics and Finance* 1 (2012) 4 – 13
- [10]. Narayan, P.K., Narayan, S., Prasad, A., (2008). A structural VAR analysis of electricity consumption and real GDP: Evidence from the G7 countries. *Energy Policy* 36, 2765–2769.
- [11]. Ozturk, I., Acaravci, A. CO₂ emissions, energy consumption and economic growth in Turkey. *Renewable and Sustainable Energy Reviews* (2010); 14: 3220-3225.
- [12]. *Economic Survey of Pakistan*, (2009).
- [13]. Panayotou, T., (1993). Empirical Tests and Policy Analysis of Environmental Degradation at Different Stages of Economic Development. Working Paper WP238, Technology and Employment Programme, International Labour Office, Geneva.
- [14]. Panayotou, T., (1997). Demystifying the environmental Kuznets curve: turning a black box into a policy tool. *Environment and Development Economics* 2 (4), 465–484.

- [15]. Shafik, N., Bandyopadhyay, S., (1992). Economic Growth and Environmental Quality: Time Series and Cross-Country Evidence. Background Paper for the World Development Report. The World Bank, Washington, DC.
- [16]. Stern, D.I., (1993). Energy and economic growth in the USA. A multivariate approach. *Energy Economics* 15, 137–150.
- [17]. Stern, D.I., 2000. Suri, V., Chapman, D., (1998). Economic growth, trade and the environment: Implications for the environmental Kuznets curve. *Ecological Economics* 25, 195–208.
- [18]. World Bank World Development Indicators (WDI), (2016)

Samuel Otieno John. "Economic Growth, Co₂ Emission and the Environmental Kuznets Hypothesis in Kenya; an Ardl Bounds Test Approach to Cointegration." *IOSR Journal of Humanities and Social Science (IOSR-JHSS)*, 25(2), 2020, pp. 41-52.