Energy Use, Economic Growth, and Carbon Dioxide Nexus in Ethiopia: An Auto Regressive Distributed Lag-Bound Test of Co-Integration Analysis

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Abstract

Understanding energy, economic growth, and carbon dioxide nexus in Ethiopia help to develop and refine contemporary policies and strategies. This study is used the Auto-Regressive Distributed Lag model to test and analyze data. The finding shows unidirectional and negative causality from the square of per capita gross domestic product to carbon dioxide emission in the short run, while the relationship between carbon dioxide emission and energy use is bidirectional and positive in the long run. Besides, energy use and the per capita gross domestic product bidirectionally related to each other in the short run. Thus, we found that energy is an engine to enhance economic growth and to reduce carbon dioxide emissions. So, it is pivotal to give an emphasis to the untouched energy sources.

Keywords: Trends; relationship; causality; CUSUM; carbon dioxide emission forecast

JEL Classification: O44, P18, Q43, Q56

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1. Introduction

Many developing countries have the ambition to meet a higher level of economic growth within the challenges of energy supply and climate change. Carbon dioxide induced climate change is an innate concern for the economic growth of these countries. It is one of the Greenhouse Gases (GHG) accountable for global warming (Houghton, 2004; IEA, 2019; Miller and Spoolman, 2009). According to the International Energy Agency (IEA), the global CO_2 emissions are contributed 30 percent of the surface temperature (IEA, 2019), which is increasing over time. For instance, in the1970s and 2012 CO_2 emissions were 24.3 and 46.4 gigatons, respectively (Janssens-Maenhout et al., 2017). The trend shows an increment of 2.3 percent per year from 2004 to 2014, with no significant growth between 2014 to 2016, and enhanced again by 1.2 percent in 2017 (UNEP, 2018). The global CO_2 emission has been increasing (Janssens-Maenhout et al., 2017; Olivier et al., 2017; Olivier et al., 2013) while showing variation between countries (Janssens-Maenhout et al., 2017) and between cities within the national boundary (Han et al., 2018; Wang and Feng, 2018).

The implications of economic activities for CO_2 emission are profound. Practically the effect of economic activities on CO_2 emission is observed during the economic lockdown following the Covid-19 pandemic in 2020. During this specific period, CO_2 emission has reduced by 7% owing to the fall in the energy demand (IEA, 2020). This phenomenon implies that the effect of economic activities on CO_2 emission is substantial. However, the level of emission varies from one nation to another based on their economic activity. For instance, economic growth contribute to CO_2 emission for lower-middle-income countries such as India (Boutabba, 2014), Ghana (Aboagye, 2017), and Pakistan (Ahmed and Long, 2012; Javid and Sharif, 2016; Shahbaz, Hooi, and Shahbaz, 2012). The same goes true for higher-income countries like Kuwait (Salahuddin, Alam, Ozturk, and Sohag, 2018), Saudi Arabia (Saad and Belloumi, 2017), and Qatar (Charfeddine, 2017). Moreover, economic growth also contribute to CO_2 emission for the upper-middle-income countries like China (Zhang and Xu, 2017) and Malaysia (Saboori et al., 2012).

Moreover, some empirical evidence shows that economic growth suppresses CO_2 emission for the case of BRICS (Brazil, Russia, India, China, and South Africa) economies (Haseeb et al., 2019), for China (Rauf et al., 2018), Sub-Saharan Africa (Inglesi-lotz and Dogan, 2018), for selected South Asian countries such as Nepal, Sir-Lanka, and Pakistan (Ahmed et al., 2017), and for 26 high income and 52 emerging OECD countries (Özokcu and Özdemir, 2017). However, CO_2 emission in Africa grows fast (Nathaniel and Iheonu, 2019) with an average rate of 3.2 percent per year from 2000 to 2005 (Canadell et al., 2009), while its average GHG emission increased from 2.9 to 3.1 percent per year between 1994 to 2014 (Tongwane and Moeletsi, 2018). Specifically, agricultural activities in the North African countries cause CO_2 emission (Jebil and Youssef, 2017).

Ethiopia is said to have one of the fastest-growing economies in the world over the last decade (FocusEconomics, 2020; IMF, 2020). The average GDP growth during the Derg regime (1974-1991) was declined by 1 percent while after government change in 1991 (Shiferaw, 2017), the average real GDP grew by 1.3 and 10.9 percent from 1992 to 2003 and 2004 to 2014, respectively (World Bank, 2016) while it shows a 9 percent increment in 2018/19 (IMF, 2020). Hence, to achieve the target of becoming a middle-income country by 2025 (FDRE, 2011), Ethiopia has planned a Climate Resilient Green Economy (CRGE) strategy to sustain economic growth and fighting climate change (FDRE, 2011). Ethiopia also ratifies the Intended Nationally Determined Contribution (INDC) to reduce GHG emission by 2030 (Gota, et al., 2016). Despite the fact that the conventional growth path is expected to increase CO_2 emission (FDRE, 2011), Ethiopia like other countries whose economies are emerging are unable to achieve the green growth strategy due to lack of technology, energy inefficiency, and poor management (OECD, 2012).

The pace at which the Ethiopian economy is growing coupled with the increasing energy consumption (Oqubay, 2015) which might cause CO_2 emission unless it is properly managed and regulated (Danyo et al., 2017). Besides, 100 % of the rural households and 68% of the urban population in Ethiopia uses energy from firewood and charcoal (Beyene et al., 2018) which favors CO_2 emission (Asumadu-Sarkodie and Owusu, 2017). Hence, population expansion is likely to increase energy use and CO_2 emission (Ahmed and Long, 2012; Ahmed et al., 2017b; Ara et al., 2015). So, it is better to assess whether the ever-increasing population exacerbate CO_2 emission in Ethiopia or not.

In addition, agriculture, the backbone of the Ethiopian economy, shares 70 percent (EPMES, 2017) to 80 percent (EEA, 2017) of the total employment. Accordingly, the agricultural land in Ethiopia shows some increment for the last four decades following population expansion and domestic and foreign direct investments (CSA, 2014, 2018; Keeley et al., 2014; Rahmato, 2011). According to the Ethiopian Economics Association (EEA), cultivated agricultural land was increased by 1.3 percent in 2016/17 as compared to 2013/14 while it accounted for

26.2 percent of the GDP for the specific year (EEA, 2017). However, its share of the GDP declines over time (Ferede and Kebede, 2015; Geda, 2001). Hence, it is healthier to search for the contribution of agricultural land expansion to CO_2 emission particularly for emerging agrarian economies like Ethiopia.

From the discussions above, it is noted that there is a significant difference in the theoretical and empirical gaps with regard to the relationship between CO_2 emission, economic growth, and energy use. Hence, it is difficult to conclude the finding in one country significantly represents the other unless addressed by empirical evidence. Even though there are few findings related to this study in Ethiopia (Adem, et al., 2020; Hundie, 2018; Mahrous, 2017; Wolde, 2015) their findings regards to the EKC is not consistent. For instance, the findings by Adem, et al. (2020) and Hundie (2018) support the existence of the EKC while Mahrous (2017) presents the otherwise. Furthermore, Wolde (2015) misinterpreted EKC, yet the displayed result of GDP and its square value is against the hypothesis. In these regards, this study tries to fill the literature gap of the applicability of the EKC theory in Ethiopia. Thus, the necessity of this study is timely and incontestable. Specifically, it intends to show the trend of CO_2 emission, energy use, and GDP, its causality and relationships considering the structural changes related to government change and environmental policy.

This study is expected to contribute its part to the motive of climate change adaptation and GHG mitigation campaign. So, the pattern of energy use and economic growth towards carbon dioxide emission expected to back governors on development plans. The outcome contributes towards the short- and long-term plans of energy use and economic growth which likely to gear the development path towards climate-smart resource use, technological adaptation, and pollution mitigation practices.

This study is organized and presented in five sections. Following the introduction section, the methodology includes the analytical framework, data type and source, and model selection strategy. The result section explains the descriptive statistics, unit root, lag length, and bound test of co-integration. In addition, trends and relationships, co-integration and long-run estimates, post-model estimation, and the robustness of the ARDL model is presented. The discussion section elaborates the result in relation to previous empirical findings. The last section, conclusion and policy implication, summarizes major findings and forwards policy recommendations.

2. Methodology

This section contains the discussions on analytical framework, data types and sources, model selection strategy, results, unit root and lag length, co-integration and long run estimates, co-integration and long run estimates and other related issues.

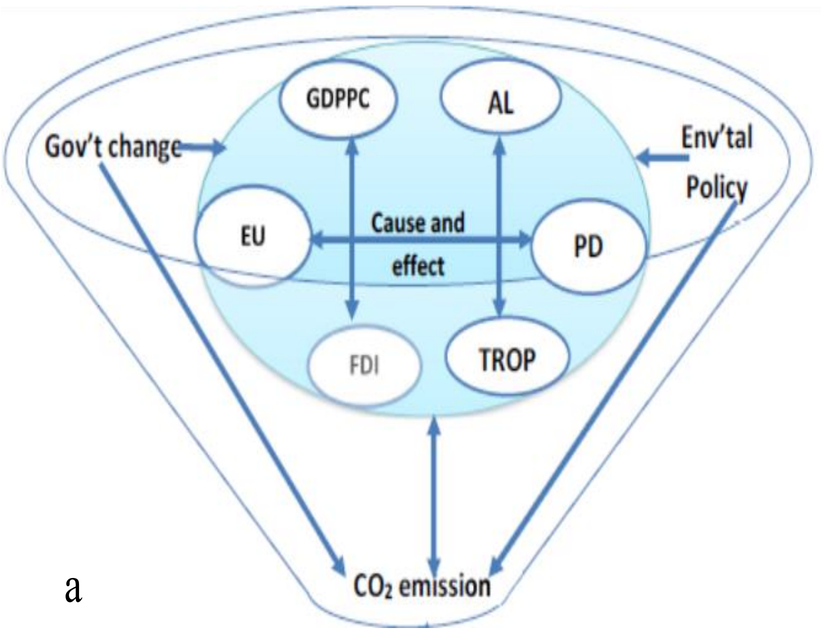
2.1 Analytical Framework

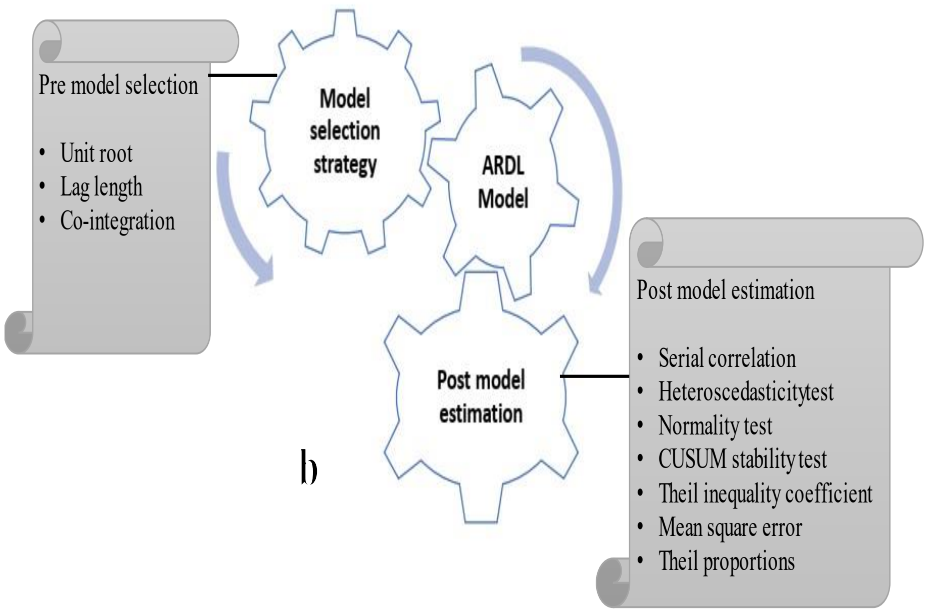
Figure 1 shows the analytical framework based on the objectives of the study. It encompasses all the stages that needs to be followed in order to address the nexus of energy use, carbon dioxide emission, and economic growth. As it is shown in Figure 1(a), all variables are expected to have either unidirectional, bi-directional or neutral relationship to one another, However, all or some of the variables can cause CO_2 emissions directly or indirectly. In turn, CO_2 emission might have an effect on other variables. At the same time exogenous variables such as government change and environmental policy are likely to have an effect on CO_2 emission and other variables.

Figure 1 (b) shows pre and post econometric model selection strategies. Nonetheless, the model selection strategy is the drive to choose the particular model based on unit root test, lag length selection criterion, and co-integration test. Accordingly, the ARDL model is proposed to this study. Again, the ARDL result would be worthless without the post model estimation. So, the post-model estimation tests such as Breusch-Godfrey LM test, Auto-Regressive Conditional Heteroscedasticity, and the Jarque-Bera normality are used to assure the absence of spurious regression, the existence of constant variance, and normal distribution of the residuals, respectively. Moreover, the cumulative sum (CUSUM) test is also used to prove the stability of the model in the long run.

Moreover, the robustness of the ARDL model is compared with other models such as Least Square (LS), Fully Modified Ordinary Least Squares (FMOLS), and Auto-Regressive Conditional Heteroscedasticity (ARCH) models. In this regard, the Theil inequality coefficient, the mean square error, and the Theil proportions such as the bias, variance, and covariance are considered.

Figure 1: Analytical framework, (a) the relationship between variables, (b) pre and post model selection strategy.





Source: Own computation, 2021

2.2 Data Types and Sources

To achieve the goals, data are used from the official web sites of World Development Indicators (WDI), United Nations Conference on Trade and Development (UNCTAD), and the national documents for the period of 1971 to 2014. The time period is restricted to 2014 because the energy use data were not released until this study is launched. Four variables, CO_2 emissions, Energy Use (EU), Population density (PD), and Agricultural land (AL) are accessed from the WDI, while Gross Domestic Product Per Capita (GDPPC) and Foreign Direct Investment (FDI) are retrieved from UNCTAD. Trade Openness (TROP) is own calculation using GDP from WDI and export and import data from UNCTAD. The values of net export and GDP are in the US dollar at the current price in millions. Then TROP is computed by the ratio of net export (export - import) to the GDP. The last two variables, Environmental policy (EP) and Government change (GC), are obtained from the ratified Ethiopian proclamations and official documents, respectively (Table 1). All continuous data are transformed to the natural logarithmic form before conducting descriptive and econometric analyses.

CO_2 emission is measured in kiloton that includes carbon dioxide produced during consumption of solid, liquid, and gas fuels. Energy use expressed in terms of the per capita per $1000 GDP measured in a kilogram of oil equivalent. It refers to the use of primary energy before transformation to other end-use fuels. Agricultural land is expressed in terms of land under temporary crops, pasture, kitchen gardens, and fallows. Population density is a midyear population divided by land area in square kilometers. Trade openness is continuous data measured in percent. Gross domestic product per capita is the annual per capita GDP at current and constant prices measured in USD. FDI is presented by the inward flow of Foreign Direct Investment measured in US Dollars at current prices in millions. The remaining variables, EP and GC are dummies that take the value of zero before the event years and one after the event. Hence, before the enforcement of EP in 1997, it is zero, while it takes one for the rest of the study periods. Similarly, GC is represented before and after the ruling party, EPRDF. For the years before 1991 it takes the value of zero, otherwise one for the rest of the study years.

Table 1: Description of variables and data sources

Variable name	Code	Unit	Nature of data	Source
Carbon Dioxide Emission	CO_2	Kilo ton	Continuous	WDI*
Energy Use	*EU*	Kg of oil equivalent per capita	Continuous	WDI
Population Density	*PD*	People per sq. km of land area	Continuous	WDI
Agricultural Land	*AL*	Square. Kilo meter	Continuous	WDI
Trade Openness	*TROP*	Percent	Continuous	UNCTAD, WDI
Gross Domestic Product Per Capita	*GDPPC*	Current and constant (2010) prices in USD	Continuous	UNCTAD*
Foreign Direct Investment	*FDI*	Inward USD at current prices in millions	Continuous	UNCTAD
Environmental Policy	*EP*	Categorical	Dummy	Official document
Government Change	*GC*	Categorical	Dummy	Official document

*https://data.worldbank.org/country/ethiopia

** https://unctadstat.unctad.org/wds/TableViewer/downloadPrompt.aspx

2.3 Model Selection Strategy

To analyze the nexus of CO_2 emission, economic growth, and energy use, the first step is specifying the econometric model before justifying the standard model (Wooldridge, 2000). Selecting the fitted model among VEC, VAR, and ARDL depends on the unit roots and cointegration results. The VEC model would be applicable when all variables are stationary at I (1) and at least one co-integration equation. Similarly, if all variables are I(0) the model would be VAR, otherwise, ARDL is appropriate in any level of variable integration.

Even though there is no perfect and unique econometric model, ARDL has an advantage over other models. First, it is best for small sample size and its computational convenience (Pesaran and Shin, 1997). Second, it is more applicable irrespective of the order of variable integration; either level, 1st difference, or mixed (Pesaran and Shin, 1997; Rauf et al., 2018). Third, it can handle endogeneity problems (Sinha and Shahbaz, 2018). Lastly, it permits dummy variables to be used in the model (Leal, Marques, & Fuinhas, 2018). ARDL is popular and used by several scholars (Boutabba, 2014; Leal et al., 2018; Rauf et al., 2018; Salahuddin et al., 2018; Sinha and Shahbaz, 2018; Ssali et al., 2019). So, due to these reasons, the ARDL model is selected and the analyses are done by an EVIEW software of version 10.

2.3.1 Unit root test and lag length selection

Unit root, non-stationary, and random walk are synonymously used terms to represent time-variant mean and/or variance of a given time series data (Planas, 1997). For instance, if the macroeconomic variable *X* depends on the lagged time, it will face non-constant mean and variance. If the consecutive *X* variable is independent of the time t, it is somehow stationary (Gujarati, 2004). Equation (1), expresses the mathematical model of the unit root test for *X* variable. If $\rho = 1$, it becomes a random walk without drift, and it faces the unit root problem. If $|\rho| < 1$, then it is at stationary (Harris and Sollis, 2003), with zero mean and constant variance.

$$X = \rho X_{(t-1)} + U_t, \text{ where } -1 \leq \rho \leq 1 \quad \textbf{(1)}$$

When $X_{(t-1)}$ subtracted from both side of the Equation (1) become Equation (2).

$$X_{(t)} - X_{(t-1)} = \rho X_{(t-1)} - X_{(t-1)} + U_t \quad \textbf{(2)}$$

It can be rewritten as Equation (3)

$$\Delta X_{(t)} = \delta X_{(t-1)} + U_t \quad \textbf{(3)}$$

Where $\delta = \rho - 1$ and Δ is the 1st difference operator. It is important to note that if $\delta = 0$, then $\rho = 1$, that is a unit root, meaning the time series under consideration is non-stationary. Thus, the Equation (3) become,

$$\Delta X_{(t)} = X_{(t)} - X_{(t-1)} = U_t \quad \textbf{(4)}$$

Where, U_t is a white noise error term, if it is at stationary, the 1st differences of a random walk time series are stationary.

It is also better to estimate Equation (3) taking the 1st difference of $X_{(t)}$ and regress on $X_{(t-1)}$ and see whether the estimated slope coefficient (δ) is zero or not. If it is zero, $X_{(t)}$ is concluded as non-stationary, otherwise, if negative, $X_{(t)}$ is stationary (Gujarati, 2004). Hence, to check whether the time series contains a unit root or not, the Augmented Dickey-Fuller (ADF) test is used. Under the null hypotheses $\delta = 0$, the estimated value of the coefficient in Equation (3) follows the tau (τ) statistic. If the null hypothesis is rejected, the time series would be stationary. However, in case U_t is correlated, the Augmented Dickey-Fuller test is applied to include lagged difference terms so that the error term (ε) in Equation (5) is serially uncorrelated.

$$\Delta X_{(t)} = B_0 + + \Sigma^{m}{}_{i=1} B_i X_{(t-i)} + \varepsilon \qquad \textbf{(5)}$$

Two steps were followed to identify the optimum lag length based on the values of SIC. First, the VAR model was employed treating one variable as an endogenous and the remaining variables as exogenous, successively for all variables. Next, from the VAR estimate lag order selection criteria for each endogenous variable was computed by Likelihood Ratio (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SIC), and Hannan-Quinn information criterion (HQ). Thus, the lag order is selected by the criterion at 5 percent level.

2.3.2 Specification of auto regressive distributed lag

ARDL model shows short-run and long-run relationships among co-integrating variables. Though the variables are co-integrated in a different order, as discussed earlier the ARDL model best in any level of relationship (Pesaran and Shin, 1997). So, the ARDL model of automatic selection criteria was used to get the maximum lag length, which is generally expressed in Equation (6) (Wooldridge, 2000).

$$\Delta ln\ Y_{(t)} = B_{n0} + \Sigma^{p}{}_{i=1} B_{n(t-i)} ln\ Y_{(t-i)} + \Sigma^{p}{}_{i=1} \gamma_{n\,(t-i)}\ ln\ X_{n\,(t-i)} + U_{nt} \qquad \textbf{(6)}$$

Where Y is the dependent variable and X_n represents the nth variable other than the dependent (CO_2, *AL*, *EU*, *FDI*, *GDPPC*, *PD*, *TOP*, *GC*, and *EP*), i (i = 1 … P) is the lag length, and U is the error term of the nth variable (n = 1… 9). The detail ARDL model is expressed in the form of Equation 7-16.

$$\Delta ln\ CO_{2(t)} = \beta_{10} + \beta_{1(t-i)}\ \Delta ln\ CO_{2(t-i)} + \ldots + \beta_{1p}\ \Delta ln\ CO_{2(t-p)} + \Delta ln\ AL + \Delta ln\ EU + \Delta ln\ FDI + \Delta ln\ GDPPC + \Delta ln\ PD + \Delta ln\ TOP + \Delta ln\ GC + \Delta ln\ EP + V_{1t} \quad \textbf{(7)}$$

$$\Delta ln\ AL_t = \beta_{20} + \beta_{2(t-i)}\ \Delta ln\ AL_{(t-i)} + \ldots + \beta_{2p}\ \Delta ln\ AL_{t-p} + \Delta lnCO_2 + \Delta ln\ EU + \Delta ln\ FDI + \Delta ln\ GDPPC + \Delta ln\ PD + \Delta ln\ TOP + \Delta ln\ GC + \Delta ln\ EP + V_{2t} \quad \textbf{(8)}$$

$$\Delta ln\ EU_t = \beta_{30} + \beta_{31}\Delta ln\ EU_{t-1} + \ldots + \beta_{3p}\ \Delta ln\ EU_{t-p} + \Delta ln\ AL + \Delta ln\ CO_2 + \Delta ln\ FDI + \Delta ln\ GDPPC + \Delta ln\ PD + \Delta ln\ TOP + \Delta ln\ GC + \Delta ln\ EP + V_{3t} \quad \textbf{(9)}$$

$$\Delta ln\ FDI_t = \beta_{40} + \beta_{41}\ \Delta ln\ FDI_{t-1} + \ldots + \beta_{4p}\ \Delta ln\ FDI_{t-p} + \Delta ln\ AL + \Delta ln\ EU + \Delta ln\ CO_2 + \Delta ln\ GDPPC + \Delta ln\ PD + \Delta ln\ TOP + \Delta ln\ GC + \Delta ln\ EP + V_{4t} \quad \textbf{(10)}$$

$$\Delta ln\ GDPPC_t = \beta_{50} + \beta_{51}\ \Delta ln\ GDPPC_{t-1} + \ldots + \beta_{5p}\ \Delta ln\ GDPPC_{t-p} + \Delta ln\ AL + \Delta ln\ EU + \Delta ln\ FDI + \Delta ln\ CO_2 + \Delta ln\ PD + \Delta ln\ TOP + \Delta ln\ GC + \Delta ln\ EP + V_{5t} \quad \textbf{(11)}$$

$$\Delta ln\ PD_t = \beta_{60} + \beta_{61}\ \Delta ln\ PD_{t-1} + \ldots + \beta_{6p}\ \Delta ln\ PD_{t-p} + \Delta ln\ AL + \Delta ln\ EU + \Delta ln\ FDI + \Delta ln\ GDPPC + \Delta ln\ CO_2 + \Delta ln\ TOP + \Delta ln\ GC + \Delta ln\ EP + V_{6t} \quad \textbf{(12)}$$

$$\Delta ln\ TOP_t = \beta_{70} + \beta_{71}\ \Delta ln\ TOP_{t-1} + \ldots + \beta_{7p}\ \Delta ln\ TOP_{t-p} + \Delta ln\ AL + \Delta ln\ EU + \Delta ln\ FDI + \Delta ln\ GDPPC + \Delta ln\ PD + \Delta ln\ CO_2 + \Delta ln\ GC + \Delta ln\ EP + V_{7t} \quad \textbf{(13)}$$

$$\Delta ln\ GC_t = \beta_{80} + \beta_{81}\ \Delta ln\ GC_{t-1} + \ldots + \beta_{8p}\ \Delta ln\ GC_{t-p} + \Delta ln\ AL + \Delta ln\ EU + \Delta ln\ FDI + \Delta ln\ GDPPC + \Delta ln\ PD + \Delta ln\ TOP + \Delta ln\ CO_2 + \Delta ln\ EP + V_{8t} \quad \textbf{(14)}$$

$$\Delta ln\ EP_t = \beta_{90} + \beta_{91}\ \Delta ln\ EP_{t-1} + \ldots + \beta_{9p}\ \Delta ln\ EP_{t-p} + \Delta ln\ AL + \Delta ln\ EU + \Delta ln\ FDI + \Delta ln\ GDPPC + \Delta ln\ PD + \Delta ln\ TOP + \Delta ln\ GC + \Delta ln\ CO_2 + V_{9t} \quad \textbf{(15)}$$

where the explanatory variables are expressed in the form of their lag terms,

$\Delta ln\ CO_2 = \beta_{1(t-i)}\ \Delta ln\ CO_{2(t-i)} + \ldots + \beta_{1p}\ \Delta ln\ CO_{2(t-p)} + U_{1t}$

$\Delta ln\ AL = \beta_{2(t-i)}\ \Delta ln\ AL_{(t-i)} + \ldots + \beta_{2p}\ \Delta ln\ AL_{(t-p)} + U_{2t}$

$\Delta ln\ EU = \beta_{3(t-i)}\ \Delta ln\ EU_{(t-i)} + \ldots + \beta_{3p}\ \Delta ln\ EU_{(t-p)} + U_{3t}$

$\Delta ln\ FDI = \beta_{4(t-i)}\ \Delta ln\ FDI_{(t-i)} + \ldots + \beta_{4p}\ \Delta ln\ FDI_{(t-p)} + U_{4t}$

$\Delta ln\ GDPPC = \beta_{5(t-i)}\ \Delta ln\ GDPPC_{(t-i)} + \ldots + \beta_{5p}\ \Delta ln\ GDPPC_{(t-p)} + U_{5t}$

$\Delta ln\ PD = \beta_{6(t-i)}\ \Delta ln\ PD_{(t-i)} + \ldots + \beta_{6p}\ \Delta ln\ PD_{(t-p)} + U_{6t}$

$\Delta ln\ TOP = \beta_{7(t-i)}\ \Delta ln\ TOP_{(t-i)} + \ldots + \beta_{7p}\ \Delta ln\ TOP_{(t-p)} + U_{7t}$

$\Delta ln\ GC = \beta_{8(t-i)}\ \Delta ln\ GC_{(t-i)} + \ldots + \beta_{8p}\ \Delta ln\ GC_{(t-p)} + U_{8t}$

$\Delta ln\ EP = \beta_{9(t-i)}\ \Delta ln\ EP_{(t-i)} + \ldots + \beta_{9p}\ \Delta ln\ EP_{(t-p)} + U_{9t}$

Where *'t'* is the time length, U_n is the error term of the corresponding variable, *'p'* is the lags of itself and the other entire *n–1* variable and V_{it} is the error term for the corresponding ith dependent variables.

2.3.3 ARDL bound test of co-integration

The other important issue in a time series analysis is co-integration, the regression of a unit root time series data on another unit root time series, which may produce spurious regression (Gujarati, 2004). The bound test of cointegration was conducted by using the Pesaran et al. (2001) approaches to see whether the long-run relationship exists or not among variables. The estimation of the nine equations (Equation 7-15) are used to test for the existence of a long-run relationship among the variables. It applies the F-statistics of joint significance for the coefficients of the lagged variables, i.e.: H0: $B_{1i} = B_{2i} = B_{3i} = B_{4i} = B_{5i} = B_{6i} = B_{7i} = B_{8i} = B_{9i} = 0$ against the alternative one: H1: $B_{1i} \neq B_{2i} \neq B_{3i} \neq B_{4i} \neq B_{5i} \neq B_{6i} \neq B_{7i} \neq B_{8i} \neq B_{9i} \neq 0$. The F-statistic which is normalized on ln*CO2; F lnCO2 (lnCO2\ ln AL, ln EU, ln FDI, ln GDPPC, ln PD, ln TOP, ln GC, ln EP)* and detected by two sets of critical values, lower bound and upper bound, for the given level of significance. The lower bound, I(0), and the upper bound, I(1), were computed on the assumption that all variables included in the ARDL model integrated of order zero and order one, respectively. The null hypothesis of no cointegration is rejected when the value of the F-statistic exceeds the upper critical bounds value, while it is accepted if the F-statistic is lower than the lower bounds value. Furthermore, the existence of negative coefficient of the error correction equation was used to crosscheck the long-run relationship between variables (Gujarati, 2004).

3. Results

The discussion under this section includes description of variable characteristics, unit root and lag length, ARDL Bounds Test of co-integration, ARDL Bounds Test of co-integration, and other related concerns.

3.1 Description of Variable Characteristics

Table 2 summarizes the natural logarithmic form of variables such as; *ln* CO_2, *ln EU, ln PD, ln AL, ln TROP, ln GDPPC,* and *ln FDI*. The mean value of *ln* CO_2 is 8 units with the maximum and minimum values of 9 and 7, respectively. Similarly, *ln EU* and *ln GDPPC* have the mean value of 6 and 5 units, respectively.

The two dummy variables represent government change (before and after Ethiopian People's Revolutionary Democratic Front) and the implementation of environmental policy. The mean value of GC shows that an equal time period is used for the study period between the successive regimes. Likewise, the launch of EP represents 39 percent of the study period.

Table 2: Descriptive statistics of variables

Variables	*Mean*	*Median*	*Maximum*	*Minimum*	*Std. Dev.*	*Sum*
Ln CO	8.008953	7.976920	9.358650	6.955366	0.618404	352.3939
Ln A	12.98773	13.02244	13.29682	12.62715	0.295140	571.4600
E	0.386364	0.000000	1.000000	0.000000	0.492545	17.00000
G	0.500000	0.500000	1.000000	0.000000	0.505781	22.00000
Ln E	6.169095	6.164950	6.208217	6.153700	0.013217	271.4402
Ln FD	3.982060	3.340586	7.531043	2.002830	1.665972	175.2106
Ln GDPP	5.355824	5.338935	6.004096	4.962982	0.230594	235.6563
Ln PI	3.914372	3.914263	4.578485	3.279497	0.420025	172.2323
Ln TRO	3.009338	2.945105	3.730860	1.613219	0.479906	132.4109

Source: Own computation, 2021

3.2 Unit Root and Lag Length

Table 3 shows the unit root test and lag length choice criteria. The Schwarz Information Criterion (SIC) exhibits a unit root problem at level, but they are stationary at the 1st difference. The result shows the non-existence of the unit root problem at a one percent significant level. All variables also show the optimal lag length of one by the SIC criterion at a 5% level.

Table 3: The Augmented Dickey-Fuller unit root test and lag length selection

Variables	Stationary (t-statistics)		Lag length				
	level	1st difference	LR	FPE	AIC	SC	HQ
ln CO_2	0.701144	-7.017713***	1	1	1	1	1
ln AL	-1.196010	-6.336477***	1	1	1	1	1
EP	-0.766004	-6.480741***	1	1	1	1	1
GC	-0.976467	-6.480741***	1	1	1	1	1
ln EU	1.951301	-5.749762***	1	1	1	1	1
ln FDI	-0.508102	-6.107624***	1	3	3	1	1
ln GDPPC	1.491198	-4.228584***	1	2	2	2	2
ln $GDPPC^2$	1.801313	-4.029462***	2	2	2	2	2
ln PD	0.298150	-5.135759***	1	1	1	1	1
ln TROP	-1.546170	-7.742962***	1	1	1	1	1

Source: Own computation, 2021

Significance: ***p<0.01

3.3 ARDL Bounds Test of Co-integration

Table 4 shows eight co-integrating equations in both criteria, by the bound test and cointegration equation coefficients (ECT_{t-1}). Their F-statistic are significantly higher than the upper bound I (1) value at 1 percent p-level of significance. So, the null hypothesis of no long-run relationships among variables is rejected. Rather the result indicates co-integration among these variables. For instance, the F- statistics of *ln* CO_2 is 7.146 which is higher than the upper bound I (1) (3.68) and the cointegration equation coefficient is negative and significant (-0.913806) at 1% *p*-level. Likewise, the F- statistics of *ln EU* is 5.545 which is higher than the upper bound (3.68) and the cointegration equation coefficient is negative and significant (-0.945768) at 1% *p*-level. In addition, the F- statistics of *ln GDPPC* is 33.507 which is higher than the upper bound (3.68) and the cointegration equation coefficient is negative and significant (-0.104839) at 1% *p*-level.

Table 4: ARDL Bounds Test of co-integration

Variables	F-statistic	ECT_{t-1}	F-bounds test		
			Sig. Level	**I(0)**	**I(1)**
ln CO2	7.146293***	-0.913806***	10%	1.8	2.8
ln AL	9.367343***	-0.078139***	5%	2.04	2.08
EP	4.449788***	-0.515336***	2.5%	2.24	3.35
GC	10.47216***	0.123342***	1%	2.5	3.68
ln EU	5.545122***	-0.945768***			
ln FDI	4.444306***	-0.840623***			
ln GDPPC	33.50720***	-0.104839***			
ln $GDPPC^2$	33.63181***	-0.058573***			
ln PD	316.4737***	-0.015424***			
ln TROP	2.543887	-0.620605***			

Source: own computation, 2021

Significance: ***p<0.01

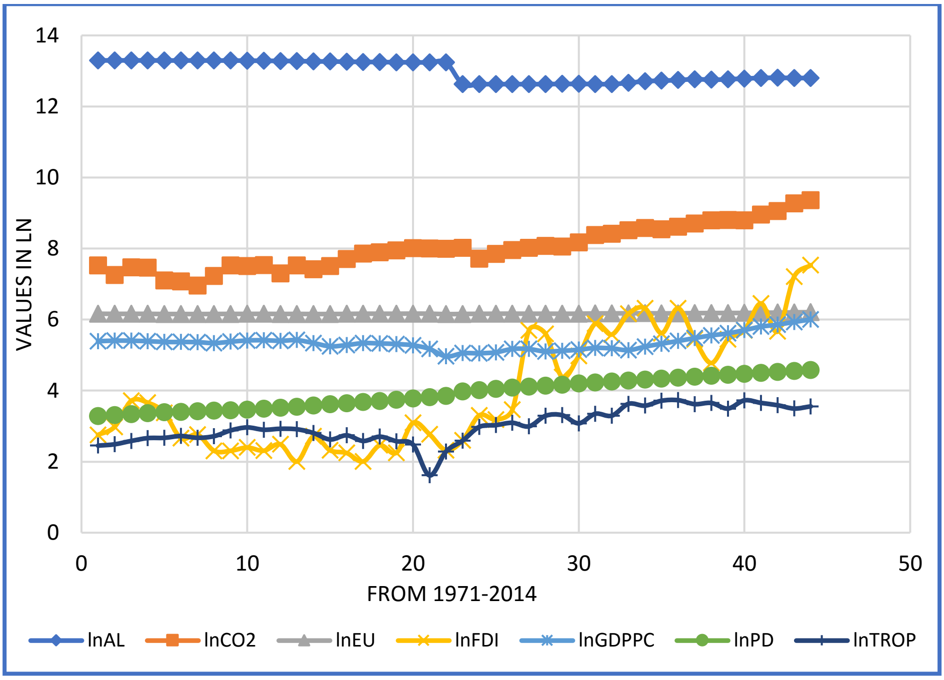
3.4 Trends and Relationships

Trends and relationships are discussed as follows.

3.4.1 Trends

Figure 2 shows trends of *ln* CO_2, *ln EU*, *ln GDPPC* and other variables from 1971 to 2014. Except for agricultural land and energy use, the trend of all other variables is unsustainable through time. For instance, *ln* CO_2 and *ln FDI* show more increment as compared to *ln GDPPC, ln PD,* and *ln TROP*. Following the government change in 1991, particularly, *ln* CO_2, *ln FDI*, and *ln TROP* have enhanced in contrast to the Derg Regime (1974-1991). Even though the *EP* being implemented since 1997, it might not show a declining trend in *ln* CO_2 after the implementation period. Besides, *ln AL* and *ln EU* seem constant for the specified period of time while *ln PD has* increased somehow in a similar fashion to *ln* CO_2. To this end, it is possible to guess the increasing trend of *ln* CO_2 is associated with *ln FDI*, *ln TROP*, and *ln PD* keeping other variables constant. It doesn't mean that *ln AL*, *ln EU*, and *ln GDPPC* has no correlation with *ln* CO_2 emission.

Figure 2: Trends of *ln CO_2, ln EU, ln GDPPC,* and other variables



Source: Own computation, 2021

3.4.2 Relationships

Table 5 reveals the relationship among *ln CO_2* emission *ln EU, ln GDPPC,* and other variables in terms of a correlation matrix. The result depicts *ln CO_2* has a strong relationship with all variables except *ln GDPPC*. Particularly, *ln CO_2* has a strong positive correlation with *ln EU, ln PD, ln FDI*, EP, *ln TROP*, and *ln GC*. Energy use has a strong relationship with *ln FDI, ln GDPPC, ln PD*, and *ln TROP*. Similarly, other variables also show some correlation between themselves. For instance, *ln AL* negatively correlated with *ln GC, ln PD, ln EP*, and *ln TROP*. In general, the aforementioned descriptive and trend results give some clue towards the nexus of *ln CO_2* emission, *ln EU*, and *ln GDPPC*. However, it needs an empirical evidence to conclude their relationship and causality.

Table 5: Correlation matrix

Variables	*LN AL*	*LN* CO_2	*EP*	*GC*	*LN EU*	*LN FDI*	*LN GDPPC*	*LN PD*	*LN TROP*
LN AL	1.000								
LN CO_2	-0.695	1.000							
EP	-0.722	0.834	1.000						
GC	-0.983	0.776	0.793	1.000					
LN EU	-0.536	0.920	0.776	0.659	1.000				
LN FDI	-0.745	0.837	0.889	0.820	0.835	1.000			
LN GDPPC	0.069	0.471	0.359	0.100	0.736	0.419	1.000		
LN PD	-0.858	0.942	0.859	0.909	0.822	0.850	0.292	1.000	
LN TROP	-0.706	0.721	0.846	0.790	0.719	0.806	0.425	0.785	1.000

Source: own computation, 2021

3.4.3 Causality

The discussion in the earlier subsection of the bound test of co-integration and the correlation matrix gives some clue on the relationship between variables. The F-statistics (Table 6) depicts the significance of the overall ARDL models at 1% *p*-level. As a result, *ln* CO_2 emission has a strong causal relationship with *ln EU*, *GC* and its lags, *ln PD* and its lags, lag of *ln TROP*. The *ln EU*, one-period lag of *GC*, and *ln PD* enhance *ln* CO_2 emission at 1% *p*-level of significance. In contrast, *GC* and its two-period lag, a one-period lag of *ln PD*, and a one-period lag of *ln TROP* significantly decline *ln* CO_2 emission.

Similarly, *ln EU* and its lag, *EP*, *GC* its lags, lags of *ln FDI*, *ln* $GDPPC^2$ its lags, *ln PD* and its lags, and lags of *ln TROP* significantly affect *ln GDPPC*. For instance, lag of *ln EU*, one-period lag of *EP*, *GC* and its two-period lag, *ln* $GDPPC^2$, one-period lag of *ln PD*, and lags of *ln TROP* have a positive effect while others' negatively affect *ln GDPPC*. Moreover, *ln*CO_2, *ln GDPPC*, lag of *ln* $GDPPC^2$, and lag of *ln PD* induce *ln EU* whereas the lag of *ln GDPPC*, *ln* $GDPPC^2$, *ln PD*, and a two-period lag of *ln TROP* retard *ln EU*. Generally, there is bidirectional causality between *ln*CO_2 emission and *ln EU as* well as between *ln EU* and *ln GDPPC*. Yet, the finding shows no relationship between *ln*CO_2 emission and *ln GDPPC*.

Table 6: ARDL model results

	ln CO_2		***ln GDPPC***		***ln EU***	
Selected Model:	***(1, 0, 2, 1, 0, 0, 0, 1, 2, 1)***		***(1, 0, 2, 2, 1, 1, 2, 1, 2, 2)***		***(1, 1, 0, 0, 0, 0, 0, 1, 1, 2)***	
Variable	***Coefficient***	***Std. Error***	***Coefficient***	***Std. Error***	***Coefficient***	***Std. Error***
Ln CO_2 (-1)	0.086	0.121	-	-	-	-
Ln CO_2			0.000	0.002	0.013	0.003***
Ln GDPPC (-1)	-	-	0.895	0.059***	-0.828	0.329**
Ln GDPPC	3.000	4.056	-	-	0.720	0.314**
Ln EU (-1)	-	-	0.326	0.089***	0.054	0.144
LNEU	29.621	5.664***	0.121	0.099	-	-
EP	0.063	0.076	0.002	0.002	0.000	0.002
EP (-1)	-	-	0.004	0.002**	-	-
EP (-2)	-	-	-0.002	0.001	-	-
GC	-4.354	1.166***	0.049	0.019**	0.000	0.011
GC (-1)	8.103	2.066***	-0.108	0.032***	-	-
GC (-2)	-2.757	0.814***	0.058	0.014***	-	-
Ln AL	-0.744	1.461	-0.035	0.018	0.000	0.017
Ln AL (-1)	2.818	1.861	0.035	0.026	-	-
Ln FDI	0.034	0.027	0.000	0.000	0.001	0.001
Ln FDI (-1)	-	-	-0.001	0.0005**	-	-
Ln FDI (-2)	-	-	-0.002	0.001***	-	-
Ln $GDPPC^2$	-0.284	0.380	0.094	0.001***	-0.066	0.029**

	ln CO_2		*ln GDPPC*		*ln EU*	
Selected Model:	***(1, 0, 2, 1, 0, 0, 0, 1, 2, 1)***		***(1, 0, 2, 2, 1, 1, 2, 1, 2, 2)***		***(1, 1, 0, 0, 0, 0, 0, 1, 1, 2)***	
Variable	***Coefficient***	***Std. Error***	***Coefficient***	***Std. Error***	***Coefficient***	***Std. Error***
Ln $GDPPC^2$(-1)	-0.072	0.038	-0.087	0.005***	0.079	0.032**
Ln PD	39.113	9.182***	-0.608	0.169***	-0.135	0.037***
Ln PD (-1)	-69.401	17.244***	1.224	0.316***	0.143	0.039***
Ln PD (-2)	31.117	8.446***	-0.636	0.151***	-	-
Ln TROP	0.025	0.076	-0.001	0.001	0.000	0.002
Ln TROP (-1)	-0.250	0.102**	0.007	0.001***	0.000	0.003
Ln TROP (-2)	-	-	0.007	0.002***	-0.006	0.003**
C	-211.606	41.384***	-2.359	0.833**	5.933	0.873***
R^2	0.992		0.999		0.989	
Adjusted R^2	0.986		0.999		0.984	
AIC	-2.113		-11.172		-9.608	
SC	-1.367		-10.179		-8.946	
HQ	-1.839		-10.808		-9.365	
DW	2.210		2.316		1.994	
F-statistic	172.897***		161961.2***		165.09***	

Source: Own computation, 2021

Significance: ***p<0.01, **p<0.05

3.5 Co-integration and Long Run Estimates

3.5.1 CO_2 emission

Table 7 shows the short-run co-integration form and the long-run estimates. The short-run coefficient of error correction term (ECT_{t-1}) expresses the speed of *ln* CO_2 emission adjustment in the long run. Both *GC*, *ln* $GDPPC^2$, and lag *ln PD* reduce *ln* CO_2 emission in the short run while lag in *GC* and *ln PD* increase *ln* CO_2 emission in the short run. Likewise, *ln AL*, *ln EU*, and *ln PD* increase *ln* CO_2 emission in the long run. The co-integration in Equation 16 links the short run *ln* CO_2 emission with its long run, which is corrected by the estimate of ECT_{t-1}. Hence, ECT_{t-1} represents the speed of adjustment for a one-period deviation on *ln* CO_2 emission to be at equilibrium in the long run. Accordingly, 91.4 percent of the error on *ln* CO_2 emission adjusts after one year to be equilibrium in the long run.

$$ECT_{t-1} = \ln CO2 - (0.0685*EP + 1.0859*GC + 2.2705*\ln AL + 32.4151*\ln EU + 0.0373*\ln FDI + 3.2832*\ln GDPPC - 0.3903*\ln GDPPC2 + 0.9074*\ln PD - 0.2460*\ln TROP - 231.5656) \quad \mathbf{(16)}$$

An increase in *ln* $GDPPC^2$ by one percent reduces *ln* CO_2 emission by 0.28 percent in the short run while it has no effect in the long run, keeping other variables constant, though. Similarly, *GC* reduces *ln* CO_2 emission by 4.35 units, whereas one period lag in *GC* increases *ln* CO_2 emission by 2.76 units in the short run. A one percent increase in agricultural land also increases *ln* CO_2 by 2.27 percent in the long run. Moreover, an increase in *ln PD* by one percent increases *ln* CO_2 by 39.11 and 0.91 percent in the short and long runs, respectively, while an increase in one period lag in *ln PD* by one percent decreases *ln* CO_2 emission by 31.12 in the short run. Besides, one percent increase in *ln EU* increases *ln* CO_2 by 32.42 percent in the long run.

Table 7: ARDL co-integrating and long run form (*ln* CO_2 as dependent variable): ARDL (1, 1, 0, 1, 0, 0, 0, 0, 0, 0)

Co-integrating Form			Long Run Coefficients		
Variable	**Coef.**	**Std. Err**	**Variable**	**Coef.**	**Std. Err**
D (*ln AL*)	-0.744	(0.865)	*ln AL*	2.2705	(1.0009) **
D (*GC*)	-4.354	(0.737) ***	*EP*	0.0685	(0.0825)
D (*GC*) (-1)	2.757	(0.554) ***	*GC*	1.0859	(0.6302)
D (*ln* $GDPPC^2$)	-0.284	(0.036) ***	ln EU	32.4151	(6.4174) ***
D (*ln PD*)	39.113	(5.839) ***	ln FDI	0.0373	(0.0283)
D (*ln PD*) (-1)	-31.117	(5.614) ***	*ln* $GDPPC^2$	-0.3903	(0.3910)
D (*ln TROP*)	0.025	(0.046)	*ln GDPPC*	3.2832	(4.3990)
ECT_{t-1}	-0.914	(0.087) ***	*ln PD*	0.9074	(0.2121) ***
			ln TROP	-0.2460	(0.1382)
			C	-231.5656	(45.3737) ***

Significance: ***p<0.01, **p<0.05
Source: Own computation, 2021

3.5.2 GDPPC

Table 8 presents the short run co-integration and the long run estimates of *ln GDPPC*. The co-integration equation (Equation 17) links the short-run *ln GDPPC* with its long-run by the coefficient of ECT_{t-1}. The ECT_{t-1} is the speed of adjustment for a one-period deviation in *ln GDPPC* to be at equilibrium in the long run. As represented in Table 11, its coefficient is negative and significant at one percent of *p*-levels. This implies that 11 percent of the error on *ln GDPPC* adjusts after one year to be equilibrium in the long run.

$$ECT_{t-1} = ln\ GDPPC - (4.2697*ln\ EU + 0.0035*ln\ CO2 + 0.0386*EP - 0.0053*GC - 0.0057*ln\ AL - 0.0260*ln\ FDI + 0.0693*ln\ GDPPC2 - 0.1896*ln\ PD + 0.1252*ln\ TROP - 22.4967) \quad \textbf{(17)}$$

Table 8 shows that change in *EP* and its lag, *GC*, *ln EU*, lag of *ln FDI*, *ln GDPPC2*, and lag of *ln PD* positively contribute to *ln GDPPC* increment in the short run, keeping other variables constant. In contrast, *ln AL*, lag *GC*, *ln PD*, and lag in *ln TROP* negatively affect *ln GDPPC* in the short run. An increase in *EP* and its lag, *ln EU*, lag of *ln FDI*, $ln\ GDPPC^2$, and lag of *ln PD* by 100 percent increase the *ln GDPPC* by 2, 2, 12, 2, 9, and 64 percent, respectively, in the short run. Whereas one percent increase in *ln AL*, *ln PD*, and lag in *ln TROP* reduce the *ln GDPPC* by 0.04, 0.61, and 0.01 percent, respectively, in the short-run.

Table 8: ARDL co-integrating and long run form (*ln GDPPC* as dependent variable): ARDL (1, 0, 0, 0, 0, 1, 0, 0, 0)

Co-integrating Form			Long Run Coefficients		
Variable	**Coef.**	**Std. Err**	**Variable**	**Coef.**	**Std. Err**
D (*ln AL*)	-0.035	(0.009) ***	*ln AL*	-0.006	(0.149)
D (*EP*)	0.002	(0.001) **	$ln\ CO_2$	0.003	(0.021)
D (*EP*) (-1)	0.002	(0.001) **	*EP*	0.039	(0.020)
D (*GC*)	0.049	(0.008) ***	*GC*	-0.005	(0.087)
D (*GC*) (-1)	-0.058	(0.006) ***	*ln EU*	4.270	(2.646)
D (*ln EU*)	0.121	(0.044) **	*ln FDI*	-0.026	(0.013)
D (*ln FDI*)	0.00002	(0.00001)	$ln\ GDPPC^2$	0.069	(0.012) ***
D (*ln FDI*) (-1)	0.002	(0.00002) ***	*ln PD*	-0.190	(0.102)
D ($ln\ GDPPC^2$)	0.094	(0.0002) ***	*ln TROP*	0.125	(0.062)
D (*ln PD*)	-0.608	(0.060) ***	C	-22.497	(15.394)
D (*ln PD*) (-1)	0.636	(0.061) ***			
D (*ln TROP*)	-0.001	(0.001)			
D (*ln TROP*) (-1)	-0.007	(0.001) ***			
ECT_{t-1}	-0.105	(0.004) ***			

Significance: ***p<0.01, **p<0.05

Source: own computation, 2021

3.5.3 Energy use

Table 9 shows the short run co-integration form and the long-run estimates of energy use. The co-integration equation (Equation 18) links the short-run *ln EU* with its long run by the coefficient of ECT_{t-1}. The ECT_{t-1} is the speed of adjustment for a one-period deviation in *ln EU to* be at equilibrium in the long run. This means *ln EU* has a long-run relationship with $ln\ CO_2$ and *ln TROP*. The coefficient of the ECT_{t-1} is negative and significant at one percent of *p*-levels. It implies that 95 percent of the error on *ln EU* adjusts after one year to be equilibrium in the long run.

$$EC = \ln EU - (-0.1139*\ln GDPPC + 0.0136*\ln CO2 + 0.0002*EP + 0.0004*GC + 0.0004*\ln AL + 0.0009*\ln FDI + 0.0133*\ln GDPPC2 + 0.0085*\ln PD - 0.0073*\ln TROP + 6.2734) \quad \mathbf{(18)}$$

As shown in Table 9, on the one hand, *ln GDPPC* and a lag of *ln TROP* enhance the *ln EU* while *ln* $GDPPC^2$, *ln PD* and *ln TROP* reduce the *ln EU* in the short run. Accordingly, an increase in *ln GDPPC* and one period lag in *ln TROP* by 100 percent increase *ln EU* by 72 and 0.6 percent, respectively, keeping other variables constant. Yet, a 100 percent increase in *ln* $GDPPC^2$, *ln PD* and *ln TROP* reduce the *ln EU* by 7, 13, and 0.01 percent. On the other hand, an increase in *ln* CO_2 emission by 100 percent enhances the *ln EU* by 1.4 percent while an increase in *ln TROP* by 100 percent declines the *ln EU* by 0.7 percent in the long run, keeping other variables constant.

Table 9: ARDL Co-integrating And Long Run Form (Energy use as dependent variable): ARDL (1, 1, 0, 0, 0, 0, 0, 0, 1, 0)

Co-integrating Form			Long Run Coefficients		
Variable	**Coef.**	**Std. Error**	**Variable**	**Coef.**	**Std. Error**
D (*ln GDPPC*)	0.720125	(0.127) ***	*ln AL*	0.0004	(0.018)
D (*ln* $GDPPC^2$)	-0.06634	(0.012) ***	*ln* CO_2	0.014	(0.003) ***
D (*ln PD*)	-0.13452	(0.018) ***	*ln FDI*	0.001	(0.001)
D (*ln TROP*)	-9.41E-05	(0.001)	*ln GDPPC*	-0.114	(0.104)
D (*ln TROP*) (-1)	0.006452	(0.002) ***	*ln PD*	0.008	(0.007)
ECT_{t-1}	-0.94577	(0.103) ***	*ln TROP*	-0.007	(0.003) **
			EP	0.0002	0.002
			GC	0.0003	(0.011)
			ln $GDPPC^2$	0.013	(0.009)
			C	6.273	(0.306) ***

Significance: ***$p<0.01$, **$p<0.05$

Source: Own computation, 2021

3.6 Post Model Estimation

The result in Table 10 shows serial correlation LM tests. The probability of *Obs.* R^2 is more than the 10% p-value; the null hypothesis of no serial correlation isn't rejected. So, there are no problems of spurious regression for the applied ARDL models. The variance of the residual is also checked by using the heteroscedasticity test of Auto-Regressive Conditional Heteroscedasticity (ARCH). The result in Table 11 implies that constant variance is existed, so there is no reason to reject the null hypothesis. Moreover, Table 12 also presents the Jarque-Bera normality test to strengthen the result of a normal distribution of the residual with zero mean and constant variance. As a result, since the p-value is above 10%, there is no evidence to reject the null hypothesis for the ln EU. Hence, this implies that the residual distribution is normal with zero mean and constant variance for ln EU.

Table 10: Breusch-Godfrey Serial Correlation LM Test

Dep. Var.	F-statistic	Prob.	Obs.R^2	Prob. Chi- Square
ln CO_2	0.359059	0.5549	0.645595	0.4217
ln GDPPC	0.850761	0.3692	2.001706	0.1571
ln EU	0.000351	0.9852	0.000590	0.9806

Table 11: Heteroscedasticity Test: ARCH

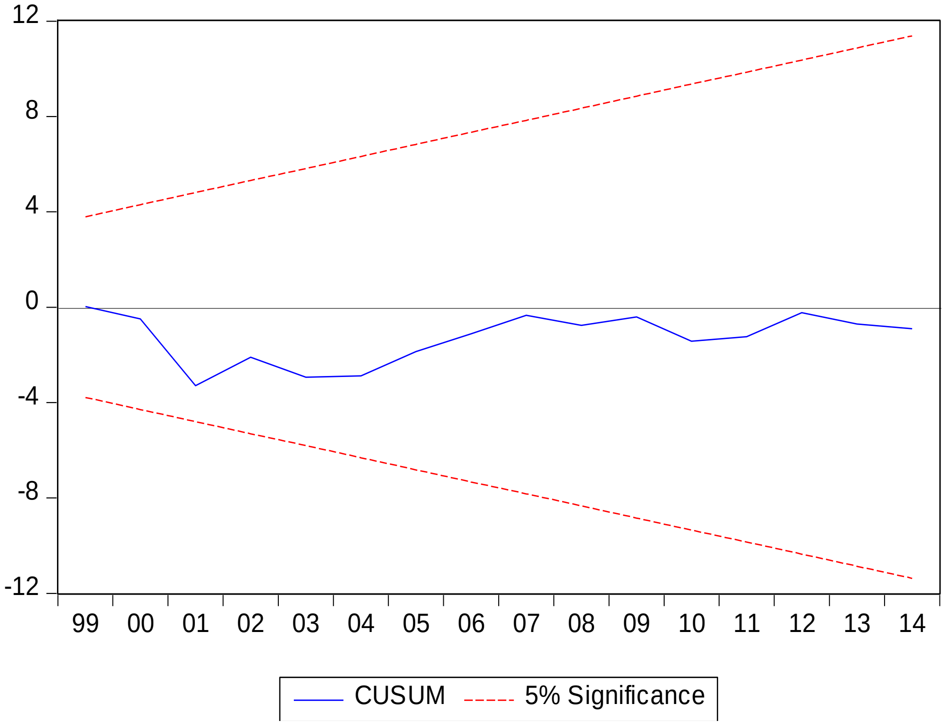
Dep. Var.	F-statistic	Prob.	Obs.R^2	Prob. Chi-Square
ln CO_2	0.427953	0.9622	9.769991	0.9130
ln GDPPC	0.415785	0.9756	14.57198	0.9093
ln EU	0.865353	0.6057	13.98585	0.5266

Table 12: Normality test

Dep. Var.	Jarque-Bera	Probability
ln CO_2	15.38712	0.000456
ln GDPPC	10.20646	0.006077
ln EU	1.396904	0.497355

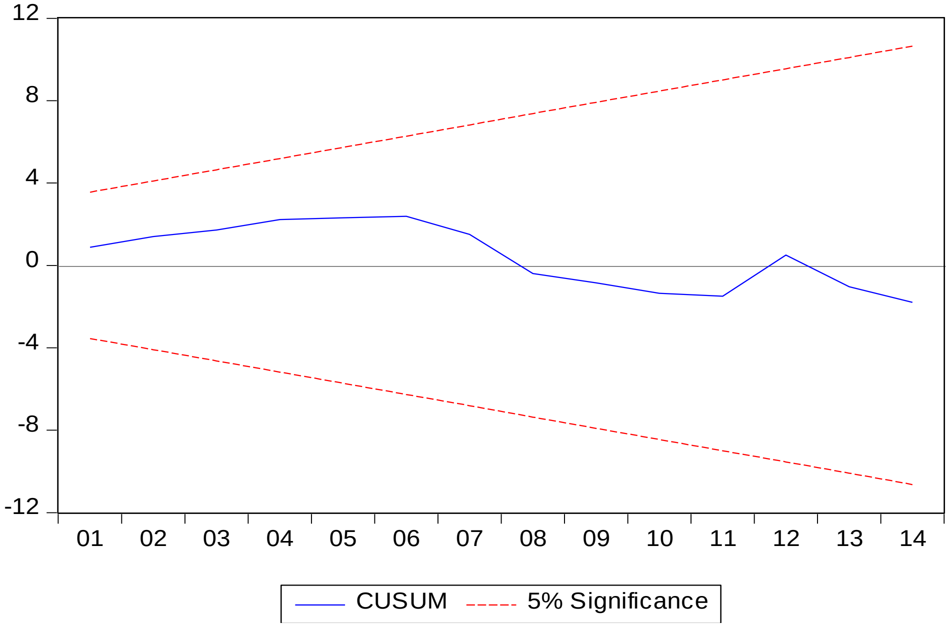
Furthermore, the CUSUM test is used to check the stability of the model. So, the stability tests for those co-integrated variables such as *ln* CO_2, *ln GDPPC*, and *ln EU* reveal that they are stable in the short and long runs. As depicted in Figure 3 (a-c), the stability lines lie between the boundaries (broken lines) at a 5% significance level. This means the coefficients are stable over the period of 1971-2014. Thus, the ARDL co-integration models are stable and consistent in the short run and long run.

Figure 3a: Stability of the models, *ln* CO_2



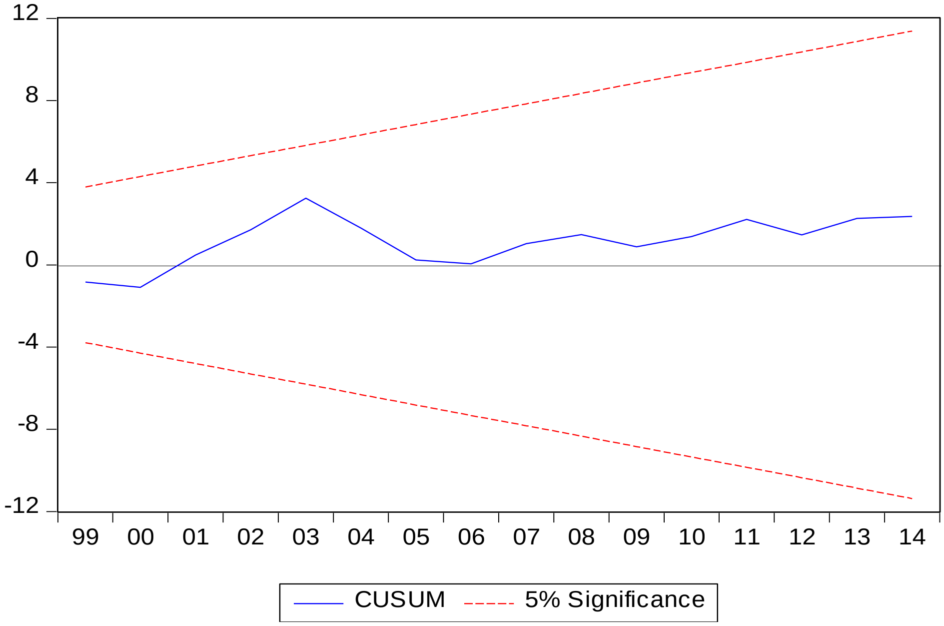
Source: Own computation, 2021

Figure 3b: Stability of the models, *ln GDPPC*



Source: Own computation, 2021

Figure 3c: Stability of the models, *ln EU*

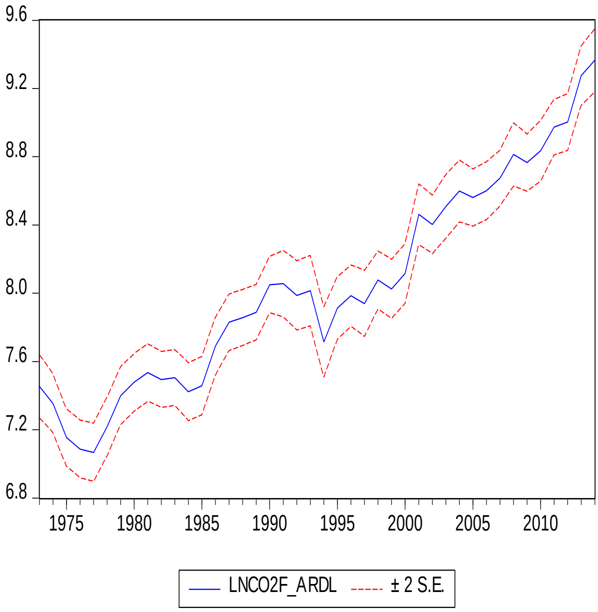


Source: Own computation, 2021

3.7 ARDL model robustness evaluation for CO_2 emission forecast

The robustness of ARDL model is also checked for CO_2 emission forecast as compared with Least Square (LS), Fully Modified Ordinary Least Squares (FMOLS), and Auto Regressive Conditional Heteroscedasticity (ARCH) models. Figure 4 (a-d) shows that ARDL (a) is the best-fit model as compare to LS (b), ARCH (c), and FMOLS (d). The Root-mean-square errors and Theil inequality coefficient in the ARDL model show the lowest value than the others. The ARDL root-mean-square error of CO_2 emission (0.0544) is preferable for forecasting since it is closest to the actual value than the rest models. The Theil inequality coefficient, often between 0 and 1, approach zero in the ARDL model (0.0033) as compare to the others. In addition, the three aspects of Theil proportions (the Bias, variance, and covariance) show ARDL is the best model. So, we can conclude that the CO_2 emission prediction based on the ARDL model is robust and best.

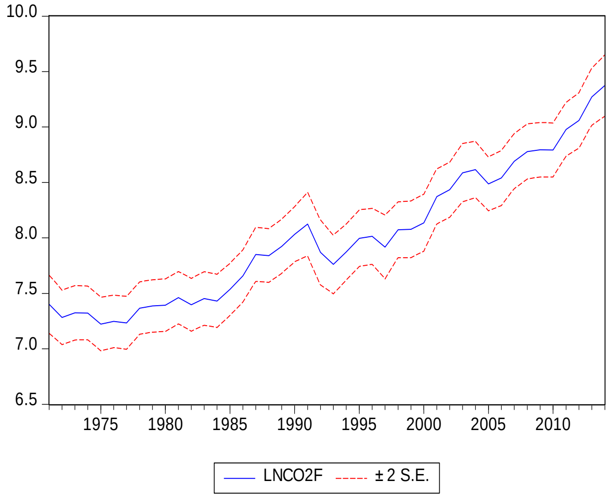
Figure 4a: *CO_2* emission forecast from the ARDL models



Forecast: LNCO2F_ARDL	
Actual: LNCO2	
Forecast sample: 1971 2014	
Adjusted sample: 1973 2014	
Included observations: 42	
Root Mean Squared Error	0.054462
Mean Absolute Error	0.037917
Mean Abs. Percent Error	0.485777
Theil Inequality Coefficient	0.003378
Bias Proportion	0.000000
Variance Proportion	0.002518
Covariance Proportion	0.997482
Theil U2 Coefficient	0.395279
Symmetric MAPE	0.485237

Source: Own computation, 2021

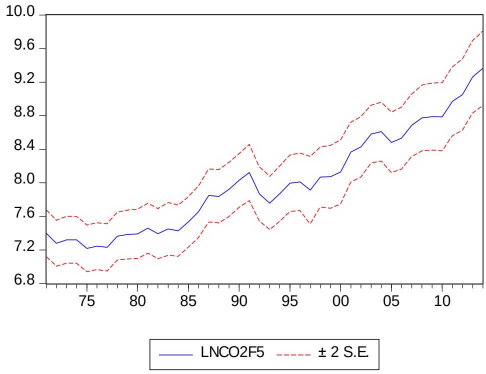
Figure 4b: CO_2 emission forecast from the LS models



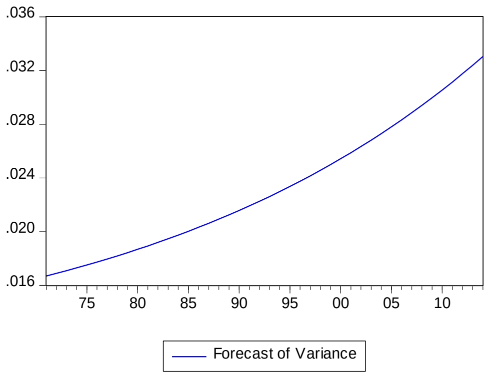
Forecast: LNCO2F	
Actual: LNCO2	
Forecast sample: 1971 2014	
Included observations: 44	
Root Mean Squared Error	0.099285
Mean Absolute Error	0.072871
Mean Abs. Percent Error	0.953404
Theil Inequality Coefficient	0.006181
Bias Proportion	0.000000
Variance Proportion	0.006682
Covariance Proportion	0.993318
Theil U2 Coefficient	0.680891
Symmetric MAPE	0.952408

Source: Own computation, 2021

Figure 4c: CO_2 emission forecast from the ARCH models

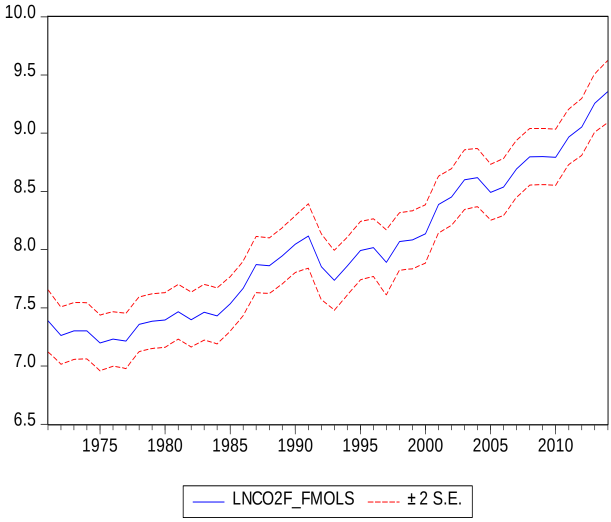


Forecast: LNCO2F5	
Actual: LNCO2	
Forecast sample: 1971 2014	
Included observations: 44	
Root Mean Squared Error	0.099398
Mean Absolute Error	0.073494
Mean Abs. Percent Error	0.960493
Theil Inequality Coefficient	0.006189
Bias Proportion	0.001798
Variance Proportion	0.010122
Covariance Proportion	0.988080
Theil U2 Coefficient	0.680790
Symmetric MAPE	0.959870



Source: Own computation, 2021

Figure 4d: CO_2 emission forecast from the FMOLS models



Forecast: LNCO2F_FMOLS	
Actual: LNCO2	
Forecast sample: 1971 2014	
Included observations: 44	
Root Mean Squared Error	0.100226
Mean Absolute Error	0.072520
Mean Abs. Percent Error	0.946540
Theil Inequality Coefficient	0.006240
Bias Proportion	0.000761
Variance Proportion	0.002381
Covariance Proportion	0.996858
Theil U2 Coefficient	0.681365
Symmetric MAPE	0.946873

Source: Own computation, 2021

4 Discussions

The study finds that *ln* CO_2 emission has a strong relationship with *ln* $GDPPC^2$, *ln EU*, *ln PD*, *ln AL*, and with *ln GC*. An increase in ln $GDPPC^2$ reduces *ln* CO_2 emission in the short run. Our finding is in line with most of the studies (Ahmed and Long, 2012; Boutabba, 2014; Charfeddine, 2017; Chen et al., 2016; Hanif, 2017; Kasman and Selman, 2015; Özokcu and Özdemir, 2017; Saboori et al., 2012; Shahbaz et al., 2012) and against the findings of some authors (Alam et al., 2016; Ara et al., 2015; Inglesi-lotz and Dogan, 2018; Salahuddin et al., 2018). In fact, it is a general truth that an increase in personal-income led people to conduct quality life and shift from fossil and fuelwood energy sources to hydroelectric power, wind energy, and solar (Kebede et al., 2002) which is expected to contribute to CO_2 emission reduction. Since most Ethiopians have lived in rural areas with poor electricity infrastructure, as their personal income improves, they tend to shift from traditional energy sources to electricity from the hydropower (Kebede et al., 2002).

The other important variable which contributes to CO_2 emission, in the long run, is energy use. As explained by Erbato and Hartkopf (2011) and Beyene et al. (2018), the dominant source of energy in Ethiopia comes from fuelwood, animal dung, charcoal, and the likes. So, it is obvious that these sources have contributions to the increment of CO_2 emission. So, energy use in Ethiopia, in line with some studies (Acheampong, 2018; Ahmed and Long, 2012; Ahmed et al., 2017; Al-mulali and Ozturk, 2016; Boontome et al., 2017; Boutabba, 2014; Charfeddine, 2017; Hanif, 2017; Javid and Sharif, 2016; Jayanthakumaran et al., 2012; Kahouli, 2018; Kasman and Selman, 2015; Özokcu and Özdemir, 2017; Rauf et al., 2018; Saad and Belloumi, 2017; Sarkodie and Owusu, 2017; Shahbaz et al., 2012, 2015; Shahzad et al., 2017) came mostly from non-renewable sources and have enhancing effect on CO_2 emission (Alam et al., 2016; Asumadu-Sarkodie and Owusu, 2017).

The expansion of agricultural land also increases CO_2 emissions in the long run. It may be associated with the soil structure, crop cover, and land management (Schahczenski and Hill, 2009; Toochi, 2018). In spite of the fact that forest and bushlands have reduced the effect on the overall CO_2 emission than annual crops (Schahczenski and Hill, 2009; Wang et al., 2017), the expansion of agricultural land at the expense of forests (EPMES, 2017) enhances CO_2 emission in the long run (Di Vita et al., 2017). Furthermore, the agricultural practice might not be carbon-intensive and the use of biomass and crop residue as fuel and burning in the farmyard tend to increase CO_2 emission (Di Vita et al., 2017; Ko et al., 2017).

The anthropogenic CO_2 emission is related not only to energy use but also to population expansion (Asumadu-Sarkodie and Owusu, 2017). Like agricultural land, an increase in population density causes land use land cover change in Ethiopia. So, an increase in population enhances CO_2 emission which supports the findings of several studies (Ahmed and Long, 2012; Ara et al., 2015; Kasman and Selman, 2015; Zhu et al., 2016) among others but against the case of Brazil (Alam et al., 2016). In contrast, government change reduces the effect on CO_2 emission in the short run. In reality, government change in Ethiopia has not been in a democratic way rather through military action. Hence, in the short run government might give focus on peace and security to stabilize the country rather than encouraging people's socio-economic activities which is expected to inhibit the energy use (it is not co-integrated with CO_2 emission in the short run).

Like most agrarian countries, the GDP in Ethiopia is more dependent on the agricultural sector. Agriculture shares around 56% in 2000/01, 52% in 2005/6, and 43% in 2012/13 (Ferede and Kebede, 2015) of the GDP. In addition, the contribution of agriculture to the total export earning is almost 80 percent (EPMES, 2017). However, its contribution to GDP has been declining and overtaken by service and manufacturing sectors (IMF, 2020). So, it is not amazing that agricultural land negatively related to *ln GDPPC*. Similarly, energy also contributes to *ln GDPPC* improvement in the short run which is in line with studies done in various countries (Azam et al., 2015; Baranzini et al., 2012; Bekun et al., 2019; Bildirici, 2014; Dagher and Yacoubian, 2012; Saad and Taleb, 2018). Hence, it is better to expand the energy supply particularly from renewable sources to sustain economic growth. In addition, government change in Ethiopia brings economic reform in the country (Shiferaw, 2017) which improves the *ln GDPPC* as compared to the Derg regime. Government change is nothing by itself but the associated socio-economic reform and the stance of politicians for their commitment positively contribute to *ln GDPPC.*

Our result also shows bidirectional causality between *ln* CO_2 emission and energy use in the long run which is in agreement with the findings in Sri Lanka (Asumadu-Sarkodie and Owusu, 2016). Likewise, energy use and *ln GDPPC* have bidirectional causality in the short run in line with the findings of some studies (Bildirici, 2016; Bildirici, 2014; Wang et al., 2016). An increase in energy use enhances *ln GDPPC* and at the same time, an increase in *ln GDPPC* improves energy use. That is to say, means an increase in *ln GDPPC* encourages peoples to use more energy. So, it is a good opportunity for Ethiopia to boost the economy without affecting the environment by exploiting untouched renewable energy resources such as hydropower, the solar, wind, geothermal energies (Erbato and Hartkopf, 2011). In addition, biofuel from jatropha and castor oil also serve as alternative energy sources and at the same time, they can conserve soil and sequestrate carbon (Negash and Riera, 2014).

An increase in population density reduces the energy use in the short run against the findings of some scholars (Asumadu-Sarkodie and Owusu, 2016; Sarkodie and Owusu, 2017). While our finding is in agreement with Ji and Chen, (2017) and Osorio et al. (2017), as the population density increases it induces an energy-saving effect particularly in the urban areas. On the other hand, the negative effect of population density on energy use might be due to the incompatibility of energy supply with the population growth rate.

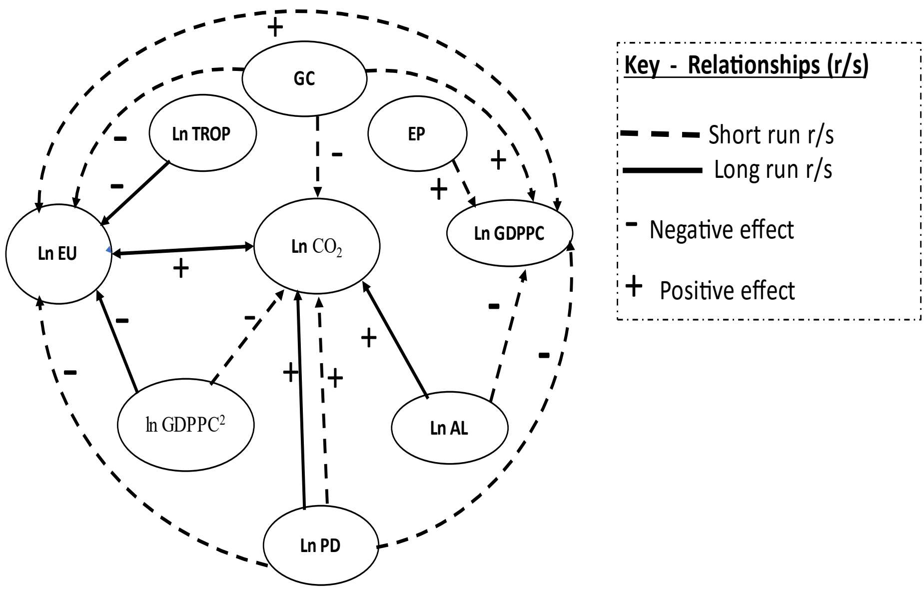
5. Conclusion and Policy Implications

5.1 Conclusion

This study identifies the nexus of CO_2 emission, economic growth, and energy use, keeping other variables constant. As summarized in Figure 5, CO_2 emission has a bidirectional positive relationship with energy use in the long run, while *ln* $GDPPC^2$ has a unidirectional and negative effect on CO_2 emission in the short run. On the one hand, *ln GDPPC* has no effect on CO_2 emission, but *ln*

$GDPPC^2$ it reduces it. This result is an evidence for the ECK hypothesis not holds true in Ethiopia. On the other hand, even though *ln GDPPC* has no direct effect on *CO_2* emission, it affects *CO_2* emission indirectly through energy use. Moreover, agricultural land has a negative effect on *ln GDPPC* in the short runs while its expansion enhances *CO_2* emission in the long run. Similarly, an increase in population density enhances *CO_2* emission in the long and short runs while it reduces energy use and *ln GDPPC* in the short run. Hence, it is possible to conclude that the energy sector is an engine towards economic growth and for *CO_2* emission reduction. So, due emphasis should be given to the type and source of energy is used in the economy.

Figure 5: Nexus of CO_2 emission and macroeconomic variables



Source: Own computation, 2021

5.2 Policy Implications

To sustain the per capita economic growth and at the same time to reduce *CO_2* emission government should exploit renewable energy sources like hydroelectric power, solar, wind, and geothermal energy sources. So, it is a good opportunity for Ethiopia to utilize the untouched renewable sources to meet the CRGE strategy and the SDGs. Furthermore, since agriculture is the backbone of the Ethiopian economy, mechanized and intensified agricultural practice likely to enhance its productivity by reducing the expansion of agricultural land which in turn retards CO_2 emission. So, emphasis should be given to the use of productive and environmentally friendly climate-smart agricultural technologies instead of expanding agricultural land to reduce CO_2 emissions.

An increase in *ln* $GDPPC^2$ and energy use potential tend to decline and enhance CO_2 emission, respectively, while the energy use enhances *ln GDPPC*. So, these relationships provide vibrant lessons to boost the implementation of the CRGE strategy. Furthermore, the environmental policy of Ethiopia does not have a significant effect on CO_2 emission and on energy use, so it is substantial to review and improve the policy. For the future, we recommend further studies that consider the forest resource and mining to assess the economy-environment nexus.

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