The Critical Role of Education and ICT in Promoting Environmental Sustainability in Eastern and Southern Africa: A Panel VAR Approach

Shobande, Olatunji and Asongu, Simplice A

2 January 2022

A G D I   Working Paper

WP/22/006

The Critical Role of Education and ICT in Promoting Environmental Sustainability in Eastern and Southern Africa: A Panel VAR Approach

Olatunji A. Shobande
Business School, University of Aberdeen, UK
E-mails :olatunji.shobande@abdn.ac.uk /
o.shobande.19@abdn.ac.uk

Simplice A. Asongu
African Governance and Development Institute,
P.O. Box 8413, Yaoundé, Cameroon
E-mails: asongusimplice@yahoo.com /
asongus@afridev.org

2022 African Governance and Development Institute WP/22/006

Research Department

The Critical Role of Education and ICT in Promoting Environmental Sustainability in Eastern and Southern Africa: A Panel VAR Approach

Olatunji A. Shobande & Simplice A. Asongu

January 2022

Abstract

The struggle to combat climate change remains complex and challenging. Currently, two climate change approaches, namely, mitigation and adaptation, have been widely supported. These are empirical, requiring further explanation of the main drivers of carbon emissions. This research seeks to tackle this problem by providing a strategy to reduce climate change impacts. This study contributes to the existing empirical literature in several ways. It investigates whether education and information and communication technology (ICT) matter to promote environmental sustainability in the Eastern and Southern Africa. The empirical evidence is based on the third-generation panel unit root test and panel cointegration tests that account for the potential issue of structural breaks in the series. We further dissect the long and short run dynamics using the panel Granger causality approach. Our findings show the possibility of using education and clean technology investment in a complementary strategy for mitigating carbon emissions and promoting environmental sustainability in the sampled countries.

JEL Classification : C52 ; O38 ; O40; O55; P37

Keywords: Environmental Sustainability; ICT; Education; Eastern Africa; Southern Africa

1. Introduction

Climate issues have continued to yield considerable literature seeking to provide solutions for promoting environmental sustainability. This is not surprising, as consensus has been reached among scientists and environmentalists that carbon dioxide (CO_2) emissions are the greatest concern for global warming (Khajuri & Ravindranath, 2012; Aueswald et al., 2018; Asongu, 2018a, 2018b; Ahmed, 2020a, 2020b). This study developed and tested an augmented stochastic impact by regression on population, affluence, and technology (STIRPAT) framework incorporated in a panel VAR model to explore the role of education and information and communication technology (ICT) in promoting environmental quality in Eastern and Southern Africa. The study aims to discover new insights that could help mitigate climate change in the Eastern and Southern Africa.

In a series of studies, Asongu et al. (2018) suggested that ICT promotes environmental sustainability in sub-Saharan Africa, contingent on the attainment of some ICT penetration thresholds. Moreover, in a recent study, Ahmed et al. (2020) discovered that ICT supports environmental sustainability in Latin American and Caribbean countries. Their findings provide a far deeper insight into the link between ICT and environmental sustainability. Still, the lack of a consensus among scholars on whether the effect of ICT on environmental sustainability is direct or indirect motivates renewed interest, particularly in Eastern and Southern Africa, where the need to improve education and ICT usage/adoption is a major objective.

Three important factors call for an inquiry into the environmental impact assessment of Eastern and Southern African countries. First, Eastern and Southern Africa are among the oldest communities and home to a variety of agricultural products. These regions contribute to a substantial proportion of the agricultural production of the entire continent, which makes their environmental impact assessment important for the food security of the continent (Salami et al., 2010; Wing & Keats, 2013); thus, a sudden outbreak of negatively externalities resulting from climate change is likely to have an overall unfavourable impact on the food supply chain. There is increasing concern that the Eastern and Southern African countries are likely to be highly vulnerable to climate change due to exposure to extreme weather conditions and increasing evidence of sea-level changes (Wing & Keats, 2013). A similar report has shown that climate change is expected to trigger future disease outbreaks in the coming decades, which are likely to generate public health crises in which equatorial and subtropical Eastern and Southern African countries may be most affected (Funk et al., 2005). Other reports have shown that the EAC and Southern Africa will be confronted with weather events and exposed to health-related risks arising from poor environmental quality (Magadza, 2000).

Second, the Eastern and Southern African regions have abundant natural resources that require understanding of integrated climate change strategies to mitigate CO_2 emissions. For instance, improving technology resources is needed to promote the integration of climate-smart species, efficient wildlife management, and marine planning.

Third, Eastern and Southern African countries' populations have continued to increase disproportionately with natural resources, yet there is a dearth of empirical studies assessing climate variability and its consequences on potential human capital (health and education). The Eastern and Southern African countries constitute a coastal area where there is a growing population. Trading networks have been affected by rising sea levels and mangroves are threatened by deforestation and erosion problems (Magdza, 2000). Additionally, the Eastern and Southern African communities have human capital deficits when compared to other sub regions with relatively better education and health institutions such as West Africa. These factors make the attendant communities important candidates for our inquiry.

In the light of the above, the main research question this study aims to address is the following: does education and ICT promote environmental sustainability in Eastern and Southern Africa? Hence, the study uses a panel approach to investigate whether education and ICT promote environmental quality and makes three important contributions: (a) By controlling for confounders, the study makes inference on the causation link among the factors. (b) By accounting for structural breaks and addressing the cross sectional dependency issue, the study uses the Bai and Carrion (2009) panel unit root tests and the Westerlund and Edgerton (2008) test to check the convergence of the variable to the long-term mean. (c) The study further employs the panel Granger causality test which help to decompose the long and short run dynamics among the factors and provide information on the speed of convergence of the variable to the long run mean which is important for policy implication. The findings show cointegration among the factors and highlight the importance of education and ICT for promoting environmental sustainability in Eastern and Southern Africa.

The positioning of the study is consistent with Aspiration 1 of Africa's Agenda 2063 on a prosperous Africa that is based on inclusive growth and sustainable development (African Union Commission, 2015). Accordingly, goals surrounding this aspiration clearly articulate the need for countries to leverage on ICT and education, *inter alia*, in order to ensure environmental sustainability on the African continent. Accordingly, education and ICT are variables of interest in this study by which environmental sustainability can be ensured. Moreover, some Programmes/Agreements implemented/instituted by Eastern and Southern African countries in relation to climate change that further justify the study include: (i) "*The COMESA-EAC-SADC (Common Market for Eastern and Southern Africa, East African Community, and the South African Development Community) Tripartite Programme Management Units of the Programme on Climate Change Adaptation and Mitigation in Eastern and Southern Africa*" (IISD, 2014) and (ii) the Southern Africa Sub Regional Framework of Climate Change Programmes (SADC, 2010).

This study contributes to the existing empirical literature, which is concisely discussed in Section 2. Section 3 describes the data, modelling strategy, and research method. Section 4 presents and discusses the findings, while section 5 concludes with policy recommendations.

Literature Review

2.1 Conceptual Framework

In contemporary studies, the link between education, ICT, and the environment relies on the STIRPAT framework (see Ibrahim et al., 2017; Shahbaz et al., 2016, 2019, 2020). The framework was developed by Erlich and Hodren (1972) but was reformed by Dietz and Rosa (1997). Today, the STIRPAT framework is useful for stimulating policy needs to promote environmental sustainability. However, it contains important indicators that are key drivers of climate change (Bargoui et al., 2014); thus, the augmented version is used in the present study.

2.2 Related studies

2.2.1 Education and the Environment

Education is a crucial factor for the success of a global response to climate change (United Nation, 1992). Mitigation and adaptation strategies are commonly used to address climate change, and effective implementation of either strategy necessitates a well-informed population and citizenry education. Several studies have looked at the possibility of using education to reduce carbon emissions and reassure sustainable environment (Cordero et al., 2008). For example, education and air quality (Johnson et al., 2012), education and improved farming practice (Magadza, 2000) as well as education and ICT. Some studies have found that through education, people can be aware of the danger of environmental degradation (Kollmuss & Agyeman, 2002; Lyons et al., 2006; De Leeuw et al., 2015; Craig & Allen, 2015). Few studies have argued that students should be required to learn about the effects of climate change and the role of human activities in degrading the environment (Monroe et al., 2019; Wise, 2010; Lee et al., 2015). Monroe et al. (2019) suggests that a systematic education strategy that provides in-depth understanding of climate change should be developed. Wise (2010) suggests that earth science teachers should include climate and climate change in their curriculum to raise sustainability awareness. Rodriguez et al. (2011) and Aderson (2012) indicate that if the government invests in science education, it will help to reduce global warming.

The importance of climate education is now the focus of many policy circles because whereas the impacts of climate change are affecting the lifestyles and lives of citizens directly, it is imperative for networks of committed 'agents of change' to be created in order to fast-track processes of securing wonderful landscapes, interesting flora and fauna as well as preserving the wellbeing of generations to come. It is in this light that 'education of the future' aims to bring climate awareness and education to young people and children such that policy makers can leverage on their creativity, willingness to learn and energy to help develop sustainable solutions, especially by means of ICT (World Economic Forum, 2021).

2.1.2 ICT and the Environment

Several studies have attempted to explain the relationship between ICT and the environment, with mixed and conflicting results. Asongu et al. (2017) investigated whether ICT penetration and carbon emissions in sub-Saharan Africa can contribute to environmental sustainability by reducing CO_2 emissions using the Generalised Method of Moments for the period 2000–2012 and found that ICT can be used to mitigate the negative impact of CO_2 emission on inclusive development. Zhou et al. (2019) examined how ICT drives carbon emissions using a sectorial level analysis for China and discovered that ICT drives China's carbon emissions. Ahmed et al. (2020a)examined the criticality of ICT and human capital for environmental sustainability in Latin America and Caribbean countries between 1995 and 2017 and reported that ICT and trade openness Granger cause CO_2 emissions. Shabani and Shahnazi (2019) examined the link between carbon emissions and ICT via energy consumption for the period 2002 to 2013 and discovered a negative relationship between ICT and CO_2 emissions. Shabani and Shahnazi (2019) attributed these results to industrial output. Amri et al. (2019) investigated the link between CO_2 emissions, total factor productivity, and ICT in Tunisia and reported that the level of ICT in Tunisia promoted environmental sustainability. Asongu et al. (2018) showed that ICT can have a significant impact on CO_2 reduction. Lee and Brahmasrene (2014) investigated the impact of ICT on CO_2 emissions and economic growth in ASEAN countries between 1991 and 2019, reporting that ICT has a positive impact on CO_2emissions during the examined period. Gouvea et al. (2018) examined the link between ICT and environmental sustainability and observed that human capital plays an important role in the relationship between ICT and environmental sustainability. Shobande and Ogbeifun (2021) investigated whether information and communication technology (ICT) can help improve environmental quality, concluding that ICT can help raise awareness, track emitters, and improve the environment.

2.2.3 Economic Growth and Environment

There are many arguments on the link between economic growth and the environment. Some studies contend that initial growth is associated with a rise in carbon emissions but after a certain level of growth, a decline in carbon emissions is expected. While the hypothesis has gained ground among scholars, empirical evidence remains inconclusive. For example, Apergies and Oztirks (2015) find evidence in Asian economies, Shahbaz (2013) for Pakistan, Ongan et al. (2021) for the United States, Murshed et al. (2021) for Bangladesh, Ahmed et al. (2021) for Chinese provinces, Isik et al. (2021) for the OECD. Among the most influential studies, the question of whether economic growth is associated with lower pollution remains unanswered. Similarly, studies that have looked into whether growth leads to increased resource overuse and environmental degradation have found mixed results. For example, Kahuthu (2006) provide a global perspective, Jamel and Derbali (2016) focus on Asia, Alam et al. (2007) are concerned with Pakistan, Ullah et al. (2021) are oriented toward Pakistan and Indian, and Hao et al. (2021) focus on G-7 countries.

2.2.4 Trade Openness and environment

The role of trade on environmental degradation is well spelt-out in the pollution haven hypothesis (Leal & Marques, 2021; Shobande & Asongu, 2021a). According to the hypothesis, increased trade and weaker environmental policies have serious consequences for climate change. Similarly, polluting industries migrate to countries with weaker environmental policies when one country's pollution policies are tightened (Usman et al., 2020; Gasimil et al., 2019; Ahmed & Le, 2021). While the pollution haven hypothesis enables researchers to track the channels through which global trade influences emissions, critics argue that global trade actually improves the environment. For example, Shen (2008) examined the impact of trade liberalisation in China for the period 1993 to 2002 and reported that increase in trade leads to more emissions. Sinha et al. (2017) reported that trade leads to unsustainable environment among emerging economies. On the contrary, Nasir et al. (2021) examined the role of trade on environmental depredation and reported that trade has no meaningful impact on the environment. Muradian and Martinez – Alier (2001) examined whether global trade should be blamed for environmental degradation and reported that trade has a positive influence on the environment. Wang and Zhang (2021) examined the effects of trade openness on decoupling carbon emissions in 182 countries and reported that trade openness can help reduce emissions during the period examined.

2.2.5 Agriculture and environment

The prospects for global warming and the link between human activities through agricultural production have become a never-ending debate for carbon emissions when weighing climate-change policies. Many studies have concluded that agricultural education is critical for reducing carbon emissions, especially in Africa. For example, Magadza (2000) suggests that poor education of farmers contributes to increase in carbon emissions. Shobande (2019) suggest that agricultural extension programs geared are towards educating farmers on new farming methods can boost productivity while also ensuring long-term viability. According toLi et al. (2021) failing to pay attention to farmers' education will result in environmental degradation. Recent studies have shown that carbon emissions from agricultural activities have continued to double, posing a climate threat if not addressed (Malhi et al., 2021; Khanal et al., 2021).

In light of the above review, previous studies have provided deeper information on the link between education, ICT, and carbon emissions. However, the majority of evidence is still far from generalised. At best, the different methodologies and changes in these studies' environments are likely to explain this inconsistency. Similarly, the majority of empirical studies are country-specific, as they do not reflect the circumstances of the region. Meanwhile, specific studies focusing on Eastern and Southern Africa are still missing; whereas reports have shown that the environments of attendant regions may be the worst hit by climate change (Madadza, 2000; Funk et al., 2005). Thus, this study is timely as it seeks to examine the link between education, ICT, and CO_2 emissions tailored to provide information that will help reduce the unfavourable effects of climate change.

3. Data and Methodology

3.1 Data

This research investigates whether education and ICT matter for environmental sustainability for a panel of 12 African countries which includes: (i)the 5countries of the Eastern Africa(Tanzania, Kenya, Rwanda, Burundi & Uganda), 3 Eastern African extension (Ethiopia, Djibouti, and Sudan), and4 Southern African countries (Madagascar, Mozambique, Zambia & Mauritius). The study used annual series data obtained from the World Bank covering the period 1995 to 2018. The availability of data constrains the period covered. Consistent with existing literature (Shobande & Enemona, 2021; Shobande, 2020; Shobande & Asongu, 2022), CO_2 emissions in metric tons per capita are used to capture the environmental impact, and the data are available in the World Development Indicators (WDI) of the World Bank. The three ICT indicators include internet users (cyber); mobile cellular subscription (mobile), fixed broadband subscription (broadband). The internet users can be internet used via a computer, mobile phone, personal digital, game, and digital television (Ahmed et al., 2016, 2020). (Shobande & Asongu, 2021b), the education variable is captured with school enrolment, tertiary (% gross) obtained from WDI. Other variables considered include GDP per capita, population, agriculture, and trade openness (trade) which is also sourced from WDI. This choice of the variables conformed with the earlier studies (see Asongu, 2018, 2019, 2020; Ahmed et al., 2016, 2020; Tchamyou et al., 2019), and description is in Appendix Table A, while the list of countries is in Appendix B.

Descriptive Statistics

This section presents the summary statistics of the series. The goal is to have prior information on the series' past behaviour before undertaking any serious analysis. Table 1 presents the descriptive statistics of the variables.

Table 1

Evidence from Table 1 suggests an average of carbon emission (CO_2) per capita and corresponding standard deviation stood at 0.32 (0.11), whereas education, 0.4 (0.2), and respectively.

Principal Components Analysis

The first step in choosing the candidate variable for our ICT is to use the Panel Principal Component Analysis (PPCA). The PPCA contains a standardised variable model that helps determine the eigenvectors using a correlation matrix from well-constructed data. To analyse our PPCA, we used the three ICT variables to uncover the factors' variation and contribution. In PPCA, the covariance function is expressed as

$$\Sigma = {}^{1}/_{k} \sum_{i=1}^{k} (\vec{u}_i - \vec{u})\,(\vec{u}_i - \vec{u})^T = {}^{1}/_{k} XX^T \tag{11}$$

The correlation matrix is defined as $(\vec{u}_1 - \vec{u}) \dots\dots\dots\dots\dots\dots (\vec{u}_i UK - \vec{u}) \in \mathcal{R}^{n*k}$, and the bar $(\vec{u})$ is taking as the sample's average value. The PPCA indicates the various eigenvalues and the difference in variation in each variable and the proportional contribution. Table 2 presents the empirical results of the PPCA for the ICT variables examined.

Table 2

From the findings presented in Table 2, the first principal component is retained as proxy for ICT because it has an Eigen value that is higher than one and contains about 93% of combined information in the three ICT variables. The choice of the first principal component is based on the Kaiser 1 criterion (Kaiser, 1974; Jolliffe, 2002) in the light of recent literature (*see* Tchamyou, 2017; Asongu, 2017).

Tests for cross-section dependency and homogeneity

In panel analysis, ignoring cross-sectional dependency (CD) will have serious implications on the results. Two major problems are often discussed regarding CD. First, ignoring the CD might results in loss of efficiency as the T-statistics is unlikely to be valid. Second, important information about the variable's prior behaviour is likely to be uncovered during the CD tests. Three statistical tests were used. The first is suggested by Breusch and Pagan (1979) for testing disturbance in linear regression framed in the Lagrangian Multiplier (LM). The second is suggested by Pesaran (2004, 2015) developed to rectify the challenges observed with Breusch-Pagan LM. The third is Pesaran (2004) for testing CD in large samples. Unfortunately, the Breusch and Pagan (1979) LM is not without problem, research has shown that when N is becoming larger, the Breusch and Pagan (1979) LM is unlikely to be efficient (Baltagi, 2008; Baltagi et al., 2007, 2012, Baltagi & Li, 1995; Baltagi & Kao, 2001). Table 3 presents empirical results of the CD tests.

Table 3

Evidence from Table 3 suggests the existence of cross-sectional dependency among the countries. This suggests *inter alia*: potentially high economic integration, benefits of globalisation through trade and sharing of common shocks among the countries. To further validate the findings of the first-generation CD test, we implement the Pesaran and Yagamata (2008) slope heterogeneity test and the empirical evidence are presented in Table 4.

Table 4

The overall evidence presented in Table 4 confirmed the earlier finding from the first-generation tests on the existence of cross-sectional dependency among the countries.

3.2 Methodology

3.2.1 Theoretical Model

As earlier discussed, this study adopts the STIRPAT framework and detailed as follows.

$$I_{i,t} = \alpha\, P_{i,t}^{\varpi_1} A_{i,t}^{\varpi_2} T_{i,t}^{\varpi_3} v_{i,t} \qquad (1)$$

Where I denotes environmental impact ($C0_2$ emissions), P is population; A is the affluence factor (GDP) and T captures technology (ICT). v is the shock or error term; i is index of the individual country and t is time. Next, the STIRPAT framework is linearised and respecified as:

$$\log co_{2i,t} = \alpha + \varpi_1 \log Pop_{i,t} + \varpi_2 \log gdp_{i,t} + \varpi_1 \log ict_{i,t} + v_{i,t} \quad (2)$$

As before, CO_2 is captured carbon dioxide emissions per capita, pop is population, and ICT (cyber, mobile, broadband). We then include other covariates that are likely to impact on CO_2 in the environment of study such as $Agricultural$ ($agric$) and $Trade\ Openness$ ($trade$); $Education$ (Edu). Thus, our model is respecified along with a uniformed parameter as:

$$\log O2_{i,t} = \beta_0 + \beta_1 \log pop_{i,t} + \beta_2 \log gdp_{i,t} + \beta_3 \log ict_{i,t} + \beta_4 \log agric_{i,t} + \beta_5 \log trade_{i,t} + \beta_6 \log edu_{i,t} + v_{i,t} \quad (3)$$

Where $\beta_0\ and\ \beta_{1-6}$ are parameters, the former is the intercept while the latter is the elasticity of each variable, v is the shock.

3.2.2 Long and Short Run Dynamics

In this study, the empirical strategy's is framed in Panel VAR/VEC Granger causality. Granger (1969, 1988) proposed a dynamic model that can decompose the short and long run tendencies among factors. The Granger causality tests have become the fundamental for both time series and panel data analyses. The approach is widely applied in all disciplinary studies, given that Granger causality does engender causal concepts (see Haavelmo, 1944, Holland, 1986; Spanos, 1989, Pindyck & Rotemberg, 1990; Reboredo, 2013). Three conditions must be satisfied before implementing a Panel Granger causality which are: (a) all the series must be stationary after differencing; (b) there must be evidence of cointegration among the series (Pesaran, 2015); (c) lag selection criteria must be satisfied. Fortunately, the aforementioned conditions appeal to our analysis.

4. Empirical Results

This section discusses the empirical results and offers a thorough explanation of the findings. It also contrasts findings with the previous study.

4.1 Panel Unit root tests

In the preceding section, the PPCA, summary statistics, CD tests, and slope heterogeneity test have been conducted. It is fair to check the series' stationarity properties to uncover more information on the series. Three serious implications may arise if the panel unit root tests are overlooked—first, the possibility of using a spurious regression to understand its behaviour.

Second, the neglect of using a series which exhibits a random walk with long cycle without treatment, making the results invalid as the series is unlikely to follow a normal distribution (Stock & Watson, 2007). Third, the failure to check the potential stationarity in the dataset may lead to misinterpretation of results. The Levin et al. (2002) (hereafter, LLC) and Im et al. (2003) (hereafter, IPS) panel unit root tests are implemented. The empirical results of the panel unit root tests are presented in Table 5.

Table 5

The overall evidence from Table 5 suggests non stationarity of all the variables at level series. This is not surprising because it is unusual for macroeconomic variables to exhibit reasonable stationarity in level series owing to business cycle disturbances that can loom substantially (Asongu, 2014). Particularly, in the climate change variables that exhibit some volatility (see Shahbaz et al., 2018). To circumvent the problem, if a variable is not stationary, contemporaneous, and lagged, the option suggested by Stock and Watson (2007 and Brooks (2019) is transformation, by taking the first difference of the variables. All the variables become stationary after taking the first differences in both LLC and IPS tests. So, we conclude that all the variables are stationary and integrated with order *1(1).*

Prior research has cautioned that the LLC and IPS panel unit roots tests are unlikely to suffice because one significant flaw is their failure to account for the potential issue of structural breaks and idiosyncratic components of the unobservable elements in the series (Bai & Carrion-i-Silvestre, 2009; Liu et al., 2021). Therefore, we reconsidered the third-generation unit root tests developed by Bai and Carrion-i-Silvestre (2009). The Bai and Carrion -i-Silvestre (2009) panel unit root test offers a unique solution as it helps to check for potential issues of cross-sectional dependence, heterogenous slope coefficients and structural break in the series. Table 6 present the empirical results of the Bail and Carrion panel unit tests.

Table 6

Interestingly, the results of the Bai and Carrion- i- Silvestre panel unit roots tests indicates that all the variables are stationary at first different which is consistent with the earlier results of the LLC and IPS unit root tests.

4.2 Lag Selection Criteria

In the proceeding section, the variables only become stationary after first differencing, which implies that testing for cointegration is crucial to validate whether the variables can converge to their long term mean values. To realise cointegration, lag selection is required. We then use three main criteria to determine the appropriate lag. The criteria used are as follows: the Akaike (AIC), Schwartz Bayesian (SC), and Hannan-Quinn (HQ) Information Criteria and the results are presented in Table 7.

Table 7

Overall evidence from Table 7 suggests that lag 3 is selected as optimal from all the lag criteria. This enables us to proceed to move on to check the cointegration of the series.

4.3 Panel Cointegration tests

We now turn to the check cointegration after two important conditions have been satisfied. First, the series are stationary at first difference; second, an optimal lag of 3 has been selected. To check cointegration among the series, two Panel cointegration tests are implemented. The first is based on the Pedroni (1999, 2001, 2004) cointegration test (STATA Xtpedroni) that checks the existence of cointegration among non-stationary series in panel data. Pedroni cointegration provides seven important criteria for validating whether a series is cointegrated. Table 7-9 present empirical results of the panel cointegration tests with the associated hypothesis.

Table 8

Table 9

The overall evidence from Tables 8 and 9 confirmed the existence of cointegration among the variables. Specifically, the seven statistical criteria contained in the Pedroni panel cointegration tests and the Kao cointegration tests admitted that cointegration exists among the variables for the Eastern and Southern African countries examined.

The reliability of Pedroni and Kao panel cointegration tests is not without serious shortcomings. One issue with these first-generation panel cointegration tests is that they are not designed to deal with structural breaks that are common in time series when analysing data with time trends and long cycles (Blomquist & Westerlund, 2013). To address the problem of first-generation panel cointegration tests, we use third-generation panel cointegration tests developed by Westerlund and Edgerton (2008). The Westerlund and Edgerton (2008) cointegration approach is considered because it accounts for heteroskedastic and serial correlated errors, unit root specific time trend, cross sectional dependence and unknown structural break. Another important motivation for using the Westerlund and Edgerton panel cointegration test is that it increases statistical power through the pooling of information across units. Table 10 presents the empirical results of the Westerlund and Edgerton's panel cointegration tests.

Table 10

The empirical evidence supported the existence of cointegration among the variables and was found to be consistent with Pedroni and Kao's cointegration test results. These results enable us to proceed and conduct the panel Granger causality tests.

4.4 Panel Granger Causality / Block Exogeneity Wald

As earlier mentioned, the cointegration theory is important for establishing whether the variables can revert to their long term mean but does not uncouple the dynamic relationship connecting the short run to the long run (Granger, 1969; Bressier & Seth, 2011; Dimitrescu & Hurlin, 2012; Kuruppuarachchi & Premachandra, 2016). One main approach that often serves as motivation is the Panel VAR/VEC Granger causality approach to bridge this gap. The approach is justified as it provides an avenue to explain the short run and long run among the variables. Table 11 summarises the empirical evidence from the Panel VAR/VEC Granger causality tests showing the long and short run dynamics among the variables.

Table 11

The overall evidence from Table 11 is discussed as follows. First, there was existence of long and short run relationships among the variables. Second, the convergence speed was relatively slow, indicating a delay in the convergence of the variable to their long-term mean. Third, education and ICT unidirectionally Granger causes CO2 emission. The evidence suggests that education can provide a foundation for science; technology and innovation that could help create awareness about the consequences of global warming on the population.

For example, environmental education at all levels of education can help change the attitude of the people towards the environment. Similarly, an improve connectivity through newer and broader ICT coverage can help reduce carbon emissions and promote sustainability through access to resources, carbon monitoring and knowledge sharing.

Fourth, the mechanism through which education and ICT explain CO2 emissions per capita in Eastern and Southern Africa has been identified as agriculture and population. Precisely, evidence also suggests that agriculture bidirectionally Granger causes CO2 emissions per capita among in the Eastern and Southern African countries. The evidence confirmed the contribution of agricultural activities to climate crisis and education can help resolve the problem. For example, farmers and fishers still rely on traditional means of production and access to education could help in more innovation-driven practices and effective usage of ICT facilities in order to improve the environment. Likewise, the evidence of bidirectional Granger causality between population and carbon emission suggests that proportionate growth in population contributes to climate crisis and significant effort is needed to educate the population on the consequences of overpopulation on climate risk. This can help prevent tragic loss of life, particularly in the climate related hotspots. Fifth, education and agriculture unidirectional Granger cause trade openness, whereas bidirectional causality between education and ICT is observed. Our results are consistent with Ahmed et al. (2020) and Shahbaz et al. (2014, 2016, 2019).

Implication of findings: The unidirectional causality between education and ICT and carbon emissions pose a serious consequence for the sampled Eastern and Southern African countries. First, the sampled countries are poorly educated, and ICT investment is slowly growing, which is reflected from the results. Second, the sampled countries have teeming populations and depend on agriculture as a means of livelihood, which explains the bidirectional relationships observed between population, agriculture and CO_2 emissions per capita. Similarly, the unidirectional causality flow running from agriculture and education to trade openness is not surprising. This is because the regions are centres of tourist attraction and appear to be among the oldest trading networks for agricultural production.

5. Conclusion, implications, and future research directions

Recent empirical research is divided into whether education and ICT support environmental sustainability. This motivates the need to confirm the criticality of education and ICT for carbon abatement in Eastern and Southern African communities. The empirical contribution of our study is discussed in a panel approach. The empirical evidence is based on time series method and the step-by-step analysis is discussed as follows. First, we carried out an initial assessment of the variables used for ICT using the panel principal component analysis, which enabled us to determine the appropriate indicator to capture technology. Next, we carried out an initial preliminary check on the variables using cross-sectional dependency tests and slope heterogeneity test, while combining the LLC and IPS and Carrion -i-Silvestre (2009) panel unit tests to check the stationarity of the series and examining the appropriate lag selection using AIC, SC, and HQ criteria. Second, three robust panel cointegration approaches based on the Pedroni (1999, 2001), Kao (1999), Westerlund and Edgerton's (2008) procedures were implemented. Finally, we used the panel VAR/VECGranger causality to uncouple the short- and long-run dynamics and the speed of convergence of the variables to their long-term mean. Our findings confirmed the existence of cointegration among variables with a relatively low speed of convergence. Further results show that education and ICT matter for carbon abatement in the sampled countries. Our study's results confirm evidence from another region reported by Ahmed et al. (2016, 2019, 2020) and Shahbaz et al. (2014, 2016, 2020). In contrast, the evidence does not support the earlier findings ofAsongu et al. (2018) who established that the effect of ICT is contingent on ICT thresholds and Khan et al. (2018) who found no evidence of ICT reducing carbon emissions, except when contingent on GDP and Research and Development (R&D).

Our findings are important for the strategic planning of climate change policies tailored to reduce climate impact in East African and Southern African countries. Similarly, environmental and economic planning must be taken seriously to ensure environmental sustainability and improve regional growth.

Two implications can be derived from the findings. First, policymakers must encourage sustainable values, synthesise, and use emerging ICT through understanding of the risk of environmental degradation. Second, policymakers should invest in Africa teaching, science, community engagement and university management. Third, there is an immediate need to encourage creativity through ICT focused on best sustainable practises that can be accomplished by improving positive behaviours and behaviour change, all meant to ensure a continent that is environmentally resilient.

Future studies can evaluate the dynamics of farmers' education and ICT in promoting environmental sustainability in the Eastern and Southern Africa. This suggested future research direction complements the findings of the present study.

Table 1. summary statistics

Variables	Mean	Std. Dev.	Obs.
Co_2	0.3	0.11	288
edu	0.4	0.12	288
ict	0.42	0.21	288
gdp	29940.2	37892.5	288
pop	808.3	2877.8	288
agric	67.0	46.5	288
trade	46.45	21.46	288

Notes. *Carbon emissions per capita (co2), edu, education, ict, Technology, gdp, growth; population (pop), agric, agricultural, trade, Trade openness.*

Table 2. Principal Component Analysis

Variables	Eigenvalue	Difference	Proportion	Cumulative proportion
PC1	2.79	2.62	0.93	0.93
PC2	0.17	0.14	0.05	0.98
PC3	0.033		0.011	1.0
Eigenvectors Components	PC1	PC2	PC3	Unexplained
cyber	0.589	-0.51	0.629	0
Broadband	0.581	-0.26	-0.762	0
mobile	0.562	-0.81	0.14	0
Correlation Matrix	*cyber*	*broadband*	*mobile*	
cyber	1			
broadband	0.96	1		
mobile	0.84	0.85	1	

Table 3. Residual Cross Section Dependency Tests

Tests	T-stat	P-value
Breush-Pagan LM	340.8***	0.00
Pasaran Scaled LM	23.9***	0.00
Pesaran CD	8.633***	0.00

Notes. The signs and is the statistical significance level at 1%, 5%m and 10% respectively.
$*** \ p < 0.001$

Table 4. Pesaran and Yamagata (2008) Slope Heterogeneity Tests

Statistics	CO2	edu	ict	gdp	pop	agric	trade
Delta tilde ($\hat{\Delta}$)	6.51***	8.19***	6.49***	8.21***	9.37***	6.02***	8.03***
Delta tilde$\hat{\Delta}$ $\boldsymbol{adj}$	7.24***	8.56***	7.01***	8.60***	9.84***	6.59***	8.49***

*Notes. Carbon emissions per capita (co2), edu, education, ict, Technology, gdp, growth; population (pop), agric, agricultural, trade, Trade openness. *** denotes significance at the 10%; 5%; 1%*

Table 5. Panel unit roots tests

Variables	At level		At first differences		
	No time effect	Time effects	No time effect	Time effects	Remarks
LLC tests					
CO_2	1.68	-5.8	-12.8**	-10.4**	I (1)
edu	-1.24	-7.3	-14.3**	-12.5**	I (1)
ict	-2.2	-5.2	-9.85**	-11.97**	I (1)
gdp	1.65	-4.3	4.4**	-4.5**	I (1)
pop	1.28	-1.5.6	5.56**	-6.8**	I (1)
agric	-2.78	-5.07	-3.16**	-3.15**	I (1)
trade	-1.40	-4.56	-3.61**	6.3**	I (1)
IPS test					
Co_2	-1.35	-2.23	-4.9**	-5.26**	I (1)
edu	-2.06	-3.52	-6.24**	-6.26**	I (1)
ict	-0.84	-1.28	-3.95**	-4.1**	I (1)
gdp	-1.3	-2.07	-5.3**	-4.61**	I (1)
pop	-1.27	-3.85	-5.54**	-6.46**	I (1)
agric	1.30	1.85	-2.45**	-6.34**	I (1)
trade	-2.29	-3.90	-8.11**	-8.9**	I (1)

Notes. *Carbon emissions per capita (CO2), Edu, education, Technology (ICT), GDP, growth; population (pop), Agricultural (Agric), Trade openness (Trade). ** denotes the rejection of null hypothesis at the5% significant level.*

Table 6. Bai and Carrion – i- Silvestre (2009) Panel Unit Root Tests

Variable	Level			First Difference		
	Z statistics	P_m statistics	P statistics	Z statistics	P_m statistics	P statistics
CO_2	0.61	-0.36	36.45	-1.82**	2.56**	62.33***
edu	-0.33	-0.38	37.20	-2.41**	2.70**	56.49***
ict	-0.12	-1.24	35.19	-1.91*	2.43**	61.49***
gdp	0.81	-1.26	31.47	-1.88*	1.86**	53.90**
pop	-0.48	-0.53	34.16	-1.65*	2.75***	61.54***
agric	-0.65	-1.22	35.61	-2.13***	2.93***	63.51***
trade	-0.53	-1.38	32.02	-1.82**	2.56**	55.18***

Critical Values

Criteria	Z statistics	P_m statistics
1%	2.23	56.06
5%	1.64	48.90
10%	1.28	44.60

Notes.*Co_2, Carbon emissions per capita, edu, education, ict, Technology, gdp, growth; population (pop), agric, agricultural, trade, Trade openness. ***; **; * denotes the rejection of null hypothesis at 1%,5% and 10% significant levels respectively.*

Table 7. VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-9712.977	NA	3.55e+26	80.99981	81.10133	81.04072
1	-9433.387	4407.208	3.45e+18	72.41156	64.22371	63.73879
2	-8398.791	64.86781	3.40e+18	65.53159	65.05437	63.54516
3	-7368.450	55.11907*	3.37e+18*	62.68708*	63.92049*	64.58698*

Notes: * indicate the Automatic lag length selection based on AIC, SC, HQ criterion. Each value of LR statistics at 5%

Table 8: Panel cointegration test results

Pedroni Cointegration Test	**Panel $v-stat$**	**Panel $\sigma-stat$**	**Panel $\rho\rho-stat$**	**Panel $adf-stat$**	**Group Panel $\sigma-stat$**	**Group Panel $\rho\rho-stat$**	**Group Panel $adf-stat$**
Statistic	-3.50**	2.32**	-4.1**	-4.58	-3.4**	-5.5**	4.69**
P-value	(0.00)	(0.01)	(0.00)	(0.003)	(0.023)	(0.053)	(0.01)

***Notes.** ** denotes the rejection of null hypothesis at the 5% significant level.*

Table 9: Kao Cointegration tests results

Cointegration Test	Statistic	P-value
ADF	-2.2305**	0.0001

Notes. ** denotes the rejection of null hypothesis at the 5% significant level.

Table 10. Westerlund and Edgerton's (2008) Panel Cointegration Tests

Test Statistics	Mean Shift	Regime Shift
$\mathbf{Z_{\varphi}(N)}$	-1.748** (0.005)	-2.540** (0.001)
$\mathbf{Z_{\tau}(N)}$	-2.731** (0.004)	-5.107** (0.00)

Notes. ** denotes the rejection of null hypothesis at the 5% significant level.

Table 11. Granger Causality Tests – VAR/VEC Approach

Independent Variable	The Direction of Causality Dependent variable							Long run
	Δco_{2t}	Δedu_t	Δict_t	Δgdp_t	Δpop_t	$\Delta agric_t$	$\Delta trade_t$	vct_{t-1}
$\mathbf{\Delta co_{2t-k}}$	-	2.27	3.68 [0.16]	0.27 [0.17]	4.92** [0.00]	15.6** [0.00]	0.005 [0.22]	-0.82** (0.09) [-10.23)
$\mathbf{\Delta edu_{t-k}}$	11.9*** [0.00]	-	18.9** [0.00]	0.35 [0.23]	5.32** [0.00]	1.16 [0.36]	10.1** [0.00]	-0.02** (0.01) [-1.79)
$\mathbf{\Delta ict_{t-k}}$	4.7** [0.00]	4.57** [0.01]	-	0.45 [0.48]	0.49 [0.49]	10.2** [0.00]	1.52 [0.16]	-0.4** (0.00) [-2.91]
$\mathbf{\Delta gdp_{t-k}}$	7.5** [0.00]	0.58 [0.24]	1.96 [0.37]	-	0.004 [0.12]	14.9** [0.00]	1.49 [0.50]	0.01 (0.02) [0.72]
$\mathbf{\Delta pop_{t-k}}$	31.9** [0.00]	4.07 [0.20]	0.66 [0.18]	0.008 [0.50]	-	18.0** [0.00]	0.13 [.43]	-0.41** (0.01) [-3.06]
$\mathbf{\Delta agric_{t-k}}$	21.2** [0.00]	1.96 [0.44]	1.78 [0.13]	5.04*** [0.00]	0.14 [0.31]	-	25.0*** [0.00]	0.81** (0.81) [0.01]
$\mathbf{\Delta trade_{t-k}}$	3.53 [0.15]	3.23 [0.19]	14.3** [0.00]	5.63*** [0.00]	0.15 [0.57]	22.9*** [0.00]	-	0.60 (0.01) [0.01]

Notes. *Carbon emissions per capita (co2), edu, education, ict, Technology,gdp, growth; population (pop), agric, agricultural, trade, Trade openness. ***; **; * ,denotes the rejection of null hypothesis at 1%,5% and 10% significant levels respectively.*

Appendix A: Descriptions and sources of variables

Variables	***Abbreviations***	***Descriptions***	***Sources.***
Environmental impacts	Co_2	CO_2 emissions (metric tons per capita)	World Bank
Education	edu	School enrolment, tertiary (% gross)	World Bank
ICT Variable	ict	Internet users are individuals who have used the Internet (from any location).	World Bank
Income per capita	gdp	Real GDP per capita	World Bank
Population	pop	Population total	World Bank
Agric	agric	Real Agricultural, forestry, and fishing, value added	World Bank
Trade Openness	trade	Trade (% of GDP)	World Bank

Appendix B: East Africa Countries

1	Kenya	8	Sudan
2	Uganda	9	Mozambique
3	Tanzania	10	Zambia
4	Ethiopia	11	Mauritius
5	Rwanda	12	Zimbabwe
6	Djibouti		
7	Madagascar		

Appendix C

Equation (4) is respecified in the Panel Granger causality capturing the long run and short run dynamics of the factors.

$$\log co_{2i,t} = \beta_{10} + \sum_{k=1}^{q} \beta_{11ik} \log co_{2i,t-k} + \sum_{k=1}^{q} \beta_{12ik} \log pop_{i,t-k} + \sum_{k=1}^{q} \beta_{13ik} \log gdp_{i,t-k}$$
$$+ \sum_{k=1}^{q} \beta_{14ik} \log ict_{i,t-k} + \sum_{k=1}^{q} \beta_{15ik} \log agric_{i,t-k} + \sum_{k=1}^{q} \beta_{16ik} \log rade_{i,t-k}$$
$$+ \sum_{k=1}^{q} \beta_{17ik} \log edu_{i,t-k} + \alpha_{1i} ECM_{it-1} + \mu_{1i,t} \quad (4)$$

$$\log pop_{i,t} = \beta_{20} + \sum_{k=1}^{q} \beta_{21ik} \log pop_{i,t-k} + \sum_{k=1}^{q} \beta_{22ik} \log co_{2i,t-k} + \sum_{k=1}^{q} \beta_{23ik} \log gdp_{i,t-k}$$
$$+ \sum_{k=1}^{q} \beta_{24ik} \log ict_{i,t-k} + \sum_{k=1}^{q} \beta_{25ik} \log agric_{i,t-k} + \sum_{k=1}^{q} \beta_{26ik} \log trade_{i,t-k}$$
$$+ \sum_{k=1}^{q} \beta_{27ik} \log edu_{i,t-k} + \alpha_{2i} ect_{it-1} + \mu_{2i,t} \quad (5)$$

$$\log gdp_{i,t} = \beta_{30} + \sum_{k=1}^{q} \beta_{31ik} \log gdp_{i,t-k} + \sum_{k=1}^{q} \beta_{32ik} \log pop_{i,t-k} + \sum_{k=1}^{q} \beta_{33ik} \log co_{2i,t-k}$$
$$+ \sum_{k=1}^{q} \beta_{34ik} \log ict_{i,t-k} + \sum_{k=1}^{q} \beta_{35ik} \log agric_{i,t-k} + \sum_{k=1}^{q} \beta_{36ik} \log trade_{i,t-k}$$
$$+ \sum_{k=1}^{q} \beta_{37ik} \log edu_{i,t-k} + \alpha_{3i} ect_{it-1} + \mu_{3i,t} \quad (6)$$

$$\log ict_{i,t} = \beta_{40} + \sum_{k=1}^{q} \beta_{41ik} \log ict_{i,t-k} + \sum_{k=1}^{q} \beta_{42ik} \log pop_{i,t-k} + \sum_{k=1}^{q} \beta_{43ik} \log gdp_{i,t-k}$$
$$+ \sum_{k=1}^{q} \beta_{44ik} \log co_{2i,t-k} + \sum_{k=1}^{q} \beta_{45ik} \log agric_{i,t-k} + \sum_{k=1}^{q} \beta_{46ik} \log trade_{i,t-k}$$
$$+ \sum_{k=1}^{q} \beta_{47ik} \log edu_{i,t-k} + \alpha_{4i} ect_{it-1} + \mu_{4i,t} \quad (7)$$

$$\log agric_{i,t} = \beta_{50} + \sum_{k=1}^{q} \beta_{51ik} \log agric_{i,t-k} + \sum_{k=1}^{q} \beta_{52ik} \log pop_{i,t-k} + \sum_{k=1}^{q} \beta_{53ik} \log gdp_{i,t-k} + \sum_{k=1}^{q} \beta_{54ik} \log ict_{i,t-k} + \sum_{k=1}^{q} \beta_{55ik} \log co_{2i,t-k} + \sum_{k=1}^{q} \beta_{56ik} \log trade_{i,t-k} + \sum_{k=1}^{q} \beta_{57ik} \log edu_{i,t-k} + \alpha_{5i} ect_{it-1} + \mu_{5i,t} \quad (8)$$

$$\log trade_{i,t} = \beta_{60} + \sum_{k=1}^{q} \beta_{61ik} \log trade_{i,t-k} + \sum_{k=1}^{q} \beta_{62ik} \log pop_{i,t-k} + \sum_{k=1}^{q} \beta_{63ik} \log gdp_{i,t-k} + \sum_{k=1}^{q} \beta_{64ik} \log ict_{i,t-k} + \sum_{k=1}^{q} \beta_{65ik} \log agric_{i,t-k} + \sum_{k=1}^{q} \beta_{66ik} \log co_{2i,t-k} + \sum_{k=1}^{q} \beta_{67ik} \log edu + \alpha_{6i} ect_{it-1} + \mu_{6i,t} \quad (9)$$

$$\log edu_{i,t} = \beta_{70} + \sum_{k=1}^{q} \beta_{71ik} \log edu_{i,t-k} + \sum_{k=1}^{q} \beta_{72ik} \log pop_{i,t-k} + \sum_{k=1}^{q} \beta_{73ik} \log gdp_{i,t-k} + \sum_{k=1}^{q} \beta_{74ik} \log ict_{i,t-k} + \sum_{k=1}^{q} \beta_{75ik} \log agric_{i,t-k} + \sum_{k=1}^{q} \beta_{76ik} \log trade_{i,t-k} + \sum_{k=1}^{q} \beta_{77ik} \log co_{2i,t-k} + \alpha_{7i} ect_{it-1} + \mu_{6i,t} (10)$$

In equation 4-10, $\beta_{10}, \beta_2, \beta_{30}, \beta_{40}, \beta_{50}, \beta_{60}, \beta_{70}$, are taken as intercepts associated with an individual model for each variable; $\beta_{11-16}, \beta_{21-26}, \beta_{31-36}, \beta_{41-46}, \beta_{51-56}, \beta_{61-66}, \beta_{71-22}$ are parameters and elasticities for each model associated with endogenous factors; p is the lag length, and it is selected using the AIC, SC and HQ criteria; $\mu_{1i,t}, \mu_{2i,t}, \mu_{3i,t}, \mu_{4i,t}, \mu_{5i,t}, \mu_{6i,t}, \mu_{7i,t}$ are the shocks arising from each variable transmitted to climate change from each endogenous model; Δ is the difference operator; α, is the short-run dynamic coefficient to be estimated and the serially uncorrelated error term is $\mu_{i,t}$; q which is the optimal lag length reduced by 1, α is the speed of adjustment parameter with a negative sign, and ect_{t-1} is the error correction term, which is the lagged value of the residuals obtained from the cointegration regressions of the dependent variable on the regressors. Thus, the past disequilibrium term (i.e., ect) determines if the long-run causality holds.

Pedroni (1999, 2002) describe the seven statistical criteria as follows.

(a) Panel $v-.stat$istic

$$Panel\ v\text{: } T^2N^{2/3}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{L}_{11i}^{-2}\,\tilde{e}_{i,t-1}^{2}\right)^{-1} \quad (15)$$

(b) Panel $\rho - Stat$istic

$$T\sqrt{N}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{L}_{11i}^{-2}\,\tilde{e}_{i,t-1}^{2}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{L}_{11i}^{-2}\left(\tilde{e}_{i,t-1}-\Delta\tilde{e}_{i,t}-\tilde{\lambda}_i\right)(b) \quad (16)$$

(c) Panel $t - Statistic\ (non\ parametric)$

$$(\tilde{\sigma}_{N,T}^{2}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{L}_{11i}^{-2}\,\tilde{e}_{i,t-1}^{2}\right)^{-1/2}\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{L}_{11i}^{-2}\ \left(\tilde{e}_{i,t-1}-\Delta\tilde{e}_{i,t}-\tilde{\lambda}_i\right) \quad (17)$$

(d) Panel $t - Statistics\ (parametric)$

$$(\tilde{s}_{N,T}^{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{L}_{11i}^{-2}\,\tilde{e}_{i,t-1}^{2})^{-1/2}\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{L}_{11i}^{-2}\ \ (\tilde{e}_{i,t-1}-\Delta\tilde{e}_{i,t} \quad (18)$$

(e) Group $\rho - Statistic$

$$T\ {}^{1}\!/_{\sqrt{N}}\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{L}_{11i}^{-2}\,\tilde{e}_{i,t-1}^{2})^{-1/2}\sum_{i=1}^{T}(\tilde{e}_{i,t-1}-\Delta\tilde{e}_{i,t}-\tilde{\lambda}_i) \quad (19)$$

(f) Group $t - Statistic\ (non\ parametric)$

$${}^{1}\!/_{\sqrt{N}}\sum_{i=1}^{N}(\widetilde{\sigma}_i^{2}\sum_{t=1}^{T}\tilde{L}_{11i}^{-2}\,\tilde{e}_{i,t-1}^{2})^{-1/2}\sum_{i=1}^{T}(\tilde{e}_{i,t-1}-\Delta\tilde{e}_{i,t}-\tilde{\lambda}_i) \quad (20)$$

(g) Group $t - Statistics\ (parametric)$

$${}^{1}\!/_{\sqrt{N}}\sum_{i=1}^{N}\sum_{t=1}^{T}\widetilde{S_{11i}^{-2}}\,\tilde{e}_{i,t-1}^{2})^{-1/2}\sum_{i=1}^{T}\tilde{e}_{i,t-1}\ -\Delta\tilde{e}_{i,t} \quad (21)$$

The panel t and $Panel\ \rho$ are called with dimension residual based on cointegrated tests. The group panel dimension is the group $t,$ and $group\ \rho$which is the null of no cointegration statistics, and others, respectively.

The null hypothesis of no panel cointegration in each statistic is expressed as:

$$H_0 : \theta_I = 1 \; for \; all \; i = 1 \dots \dots \dots \dots \dots . N,$$

The alternative hypothesis of the between dimension based on the statistics procedure is stated as

$$H_1 : \theta_I < 1 \; for \; all \; i = 1 \dots \dots \dots \dots \dots . N,$$

A similar value of $\theta_I = \theta$ is not essential.

References

African Union Commission (2015). Agenda 2063: the Africa We Want. *African Union Commission*. https://www.afdb.org/fileadmin/uploads/afdb/Documents/PolicyDocuments/Agenda2063_Popular_Version_English.pdf (Accessed: 21/12/2021).

Ahmed, Z., & Le, H. P. (2021). Linking Information Communication Technology, trade globalization index, and CO 2 emissions: evidence from advanced panel techniques. *Environmental Science and Pollution Research*, *28*(7), 8770-8781.

Ahmed, Z., Asghar, M. M., Malik, M. N., & Nawaz, K. (2020a). Moving towards a sustainable environment: The dynamic linkage between natural resources, human capital, urbanization, economic growth, and ecological footprint in China. *Resources Policy*, *67*, 101677.

Ahmed, Z., Nathaniel, S. P., & Shahbaz, M. (2020b). The criticality of information and communication technology and human capital in environmental sustainability: Evidence from Latin American and Caribbean countries. *Journal of Cleaner Production*, 125529.

Ahmad, M., Jabeen, G., & Wu, Y. (2021). Heterogeneity of pollution haven/halo hypothesis and environmental Kuznets curve hypothesis across development levels of Chinese provinces. *Journal of Cleaner Production*, *285*, 124898.

Alam, S., Fatima, A., & Butt, M. S. (2007). Sustainable development in Pakistan in the context of energy consumption demand and environmental degradation. *Journal of Asian Economics*, *18*(5), 825-837.

Anderson, A. (2012). Climate change education for mitigation and adaptation. *Journal of Education for Sustainable Development*, *6*(2), 191-206.

Apergis, N., & Ozturk, I. (2015). Testing environmental Kuznets curve hypothesis in Asian countries. *Ecological Indicators*, *52*, 16-22.

Asongu, S. A., (2014). African financial development dynamics: big time convergence, *African Journal of Economic and Management Studies*, 5(2): 160-194.

Asongu, S. A., (2017). Knowledge Economy Gaps, Policy Syndromes, and Catch-Up Strategies: Fresh South Korean Lessons to Africa, *Journal of the Knowledge Economy*, 8(1), 211-253.

Asongu, S. A., Le Roux, S., &Biekpe, N. (2017). Environmental degradation, ICT and inclusive development in Sub-Saharan Africa. *Energy Policy*, *111*, 353-361.

Asongu, S. A., (2018a) ICT, openness and CO_2 emissions in Africa. *Environmental Science and Pollution Research*,25(10): 9351–9359.

Asongu, S. A., (2018b) CO_2 emission thresholds for inclusive human development in sub-Saharan Africa. *Environmental Science and Pollution Research*, 25(26): 26005–26019.

Asongu, S. A., Le Roux, S., &Biekpe, N. (2018). Enhancing ICT for environmental sustainability in sub-Saharan Africa. *Technological Forecasting and Social Change*, *127*, 209-216.

Asongu, S. A., &Nwachukwu, J. C.(2016) The mobile phone in the diffusion of knowledge for institutional quality in sub-Saharan Africa. *World Development* 86(October): 133–147.

Asongu, S. A., & Nwachukwu, J. C. (2018). Educational quality thresholds in the diffusion of knowledge with mobile phones for inclusive human development in sub-Saharan Africa. *Technological Forecasting and Social Change*, *129*: 164-172.

Asongu, S. A., Nwachukwu, J. C., &Orim, S. M. I. (2018). Mobile phones, institutional quality and entrepreneurship in Sub-Saharan Africa. *Technological Forecasting and Social Change*, *131*: 183-203.

Auerswald, H., Konrad, K. A., &Thum, M. (2018). Adaptation, mitigation and risk-taking in climate policy. *Journal of Economics*, *124*(3): 269-287.

Baltagi, B. (2008). *Econometric analysis of panel data*. John Wiley & Sons.

Baltagi, B. H., Egger, P., &Pfaffermayr, M. (2007). Estimating models of complex FDI: Are there third-country effects? *Journal of econometrics*, *140*(1): 260-281.

Baltagi, B. H., Feng, Q., & Kao, C. (2012). A Lagrange Multiplier test for cross-sectional dependence in a fixed-effects panel data model. *Journal of Econometrics*, *170*(1): 164-177.

Baltagi, B. H., & Kao, C. (2001). Nonstationary panels, cointegration in panels and dynamic panels: A survey. In *Nonstationary panels, panel cointegration, and dynamic panels*. Emerald Group Publishing Limited.

Baltagi, B. H., & Li, Q. (1995). Testing AR (1) against MA (1) disturbances in an error component model. *Journal of Econometrics*, *68*(1): 133-151.

Barbieri, L. (2008). Panel cointegration tests: a survey. *RivistaInternazionale di ScienzeSociali*, 3-36.

Bargaoui, S. A., Liouane, N., &Nouri, F. Z. (2014). Environmental impact determinants: An empirical analysis based on the STIRPAT model. *Procedia-Social and Behavioral Sciences, 109*: 449-458.

Blomquist, J., &Westerlund, J. (2013). Testing slope homogeneity in large panels with serial correlation. *Economics Letters*, *121*(3), 374-378.

Bressler, S. L., & Seth, A. K. (2011). Wiener–Granger causality: a well-established methodology. *Neuroimage*, *58*(2), 323-329.

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica: Journal of the Econometric Society*, 1287-1294.

Brooks, C. (2019). *Introductory econometrics for finance*. Cambridge university press.

Christian, B., & Christoph, H. (2009). *Combining Non-Cointegration Tests* (No. 012).

Cordero, E. C., Todd, A. M., &Abellera, D. (2008). Climate change education and the ecological footprint. *Bulletin of the American Meteorological Society*, *89*(6), 865-872.

Craig, C. A., & Allen, M. W. (2015). The impact of curriculum-based learning on environmental literacy and energy consumption with implications for policy. *Utilities Policy*, *35*, 41-49.

De Leeuw, A., Valois, P., Ajzen, I., & Schmidt, P. (2015). Using the theory of planned behavior to identify key beliefs underlying pro-environmental behavior in high-school students: Implications for educational interventions. *Journal of environmental psychology*, *42*, 128-138.

Dietz, T., & Rosa, E. A. (1997). Effects of population and affluence on CO2 emissions. *Proceedings of the National Academy of Sciences*, *94*(1): 175-179.

Dumitrescu, E. I., &Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic modelling*, *29*(4), 1450-1460.

Ehrlich, P. R., &Holdren, J. P. (1971). Impact of population growth. *Science, 171*(3977): 1212-1217.

Fuchs, C. (2008). The implications of new information and communication technologies for sustainability. *Environment, Development and Sustainability*, *10*(3): 291-309.

Furini, F., &Bosello, F. (2020). Accounting for adaptation and its effectiveness in International Environmental Agreements. *Environmental Economics and Policy Studies*, 1-27.

Funk, C., Senay, G., Asfaw, A., Verdin, J., Rowland, J., Korea, D., ... &Choularton, R. (2005). Recent drought tendencies in Ethiopia and equatorial-subtropical eastern Africa:

Washington DC, US Agency for International Development. *Also available at http://earlywarning. USGS. gov/fews/pubs/FEWSNET_2005. pdf*.

Gasimli, O., Naradda Gamage, S. K., Shihadeh, F., Rajapakshe, P. S. K., & Shafiq, M. (2019). Energy, trade, urbanization and environmental degradation Nexus in Sri Lanka: bounds testing approach. *Energies*, *12*(9), 1655.

Gouvea, R., Kapelianis, D., &Kassicieh, S. (2018). Assessing the nexus of sustainability and information & communications technology. *Technological Forecasting and Social Change*, *130*: 39-44.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society*, 424-438.

Granger, C. W. (1988). Some recent development in a concept of causality. *Journal of econometrics*, *39*(1-2): 199-211.

Jamel, L., &Derbali, A. (2016). Do energy consumption and economic growth lead to environmental degradation? Evidence from Asian economies. *Cogent Economics & Finance*, *4*(1), 1170653.

Johnson, B., Duffin, M., & Murphy, M. (2012). Quantifying a relationship between place-based learning and environmental quality. *Environmental Education Research*, *18*(5), 609-624.

Haavelmo, T. (1944). The probability approach in econometrics. *Econometrica: Journal of the Econometric Society*, iii-115.

Hao, L. N., Umar, M., Khan, Z., & Ali, W. (2021). Green growth and low carbon emission in G7 countries: How critical the network of environmental taxes, renewable energy and human capital is?. *Science of The Total Environment*, *752*, 141853.

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association*, *81*(396): 945-960.

Hoover, W. G. (2012). *Computational statistical mechanics*. Elsevier.

Ibrahim, S. S., Celebi, A., Ozdeser, H., &Sancar, N. (2017). Modelling the impact of energy consumption and environmental sanity in Turkey: A STIRPAT framework. *Procedia computer science*, *120*: 229-236.

IISD (2014). Climate Change Programme in Eastern and Southern Africa Strengthens Capacity, Builds Resilience. IISD. http://sdg.iisd.org/news/climate-change-programme-in-eastern-and-southern-africa-strengthens-capacity-builds-resilience/ (Accessed: 26/12/2021).

Jolliffe, I. T., (2002). Principal Component Analysis (2ndEd.), New York: Springer.

Kaiser, H. F., (1974). An index of factorial simplicity. *Psychometrika*, 39, pp. 31–36.

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of econometrics*, *90*(1): 1-44.

Kahuthu, A. (2006). Economic growth and environmental degradation in a global context. *Environment, development and sustainability*, *8*(1), 55-68.

Khajuria, A., &Ravindranath, N. H. (2012). Climate change in context of Indian agricultural sector. *Earth Science and Climate Change*, *3(1)*: 1-4.

Khan, N., Baloch, M. A., Saud, S., & Fatima, T. (2018). The effect of ICT on CO 2 emissions in emerging economies: does the level of income matters? *Environmental Science and Pollution Research*, *25*(23), 22850-22860.

Khanal, U., Wilson, C., Rahman, S., Lee, B. L., & Hoang, V. N. (2021). Smallholder farmers' adaptation to climate change and its potential contribution to UN's sustainable development goals of zero hunger and no poverty. *Journal of Cleaner Production*, *281*, 124999.

Kollmuss, A., & Agyeman, J. (2002). Mind the gap: why do people act environmentally and what are the barriers to pro-environmental behavior?. *Environmental education research*, *8*(3), 239-260.

Kuruppuarachchi, D., &Premachandra, I. M. (2016). Information spillover dynamics of the energy futures market sector: A novel common factor approach. *Energy Economics*, *57*: 277-294.

Leal, P. H., & Marques, A. C. (2021). The environmental impacts of globalisation and corruption: Evidence from a set of African countries. *Environmental Science & Policy*, *115*, 116-124.

Lee, T. M., Markowitz, E. M., Howe, P. D., Ko, C. Y., & Leiserowitz, A. A. (2015). Predictors of public climate change awareness and risk perception around the world. *Nature climate change*, *5*(11), 1014-1020.

Lei, Y., Yang, K., Wang, B., Sheng, Y., Bird, B. W., Zhang, G., & Tian, L. (2014). Response of inland lake dynamics over the Tibetan Plateau to climate change. *Climatic Change*, *125*(2): 281-290.

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of econometrics*, *108*(1): 1-24.

Loh, Y. A. (2015). Approaches to ICT for development (ICT4D): vulnerabilities vs. capabilities. *Information Development*, *31*(3): 229-238.

Li, W., Ruiz-Menjivar, J., Zhang, L., & Zhang, J. (2021). Climate change perceptions and the adoption of low-carbon agricultural technologies: Evidence from rice production systems in the Yangtze River Basin. *Science of The Total Environment*, *759*, 143554.

Liu, J., Murshed, M., Chen, F., Shahbaz, M., Kirikkaleli, D., & Khan, Z. (2021). An empirical analysis of the household consumption-induced carbon emissions in China. *Sustainable Production and Consumption*, *26*, 943-957.

Lyons, A. C., Chang, Y., &Scherpf, E. (2006). Translating financial education into behavior change for low-income populations. *Journal of Financial Counseling and Planning*, *17*(2), 27-45

Magadza, C. H. (2000). Climate change impacts and human settlements in Africa: prospects for adaptation. *Environmental Monitoring and Assessment*, *61*(1): 193-205.

Malhi, G. S., Kaur, M., & Kaushik, P. (2021). Impact of Climate Change on Agriculture and Its Mitigation Strategies: A Review. *Sustainability*, *13*(3), 1318.

Monroe, M. C., Plate, R. R., Oxarart, A., Bowers, A., &Chaves, W. A. (2019). Identifying effective climate change education strategies: a systematic review of the research. *Environmental Education Research*, *25*(6), 791-812.

Muradian, R., & Martinez-Alier, J. (2001). Trade and the environment: from a 'Southern'perspective. *Ecological Economics*, *36*(2), 281-297.

Nasir, M. A., Canh, N. P., & Le, T. N. L. (2021). Environmental degradation & role of financialisation, economic development, industrialisation and trade liberalisation. *Journal of Environmental Management*, *277*, 111471.

Ongan, S., Isik, C., &Ozdemir, D. (2021). Economic growth and environmental degradation: evidence from the US case environmental Kuznets curve hypothesis with application of decomposition. *Journal of Environmental Economics and Policy*, *10*(1), 14-21.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and statistics*, *61*(S1), 653-670.

Pedroni, P. (2001). Fully modified OLS for heterogeneous cointegrated panels. In *Nonstationary panels, panel cointegration, and dynamic panels*. Emerald Group Publishing Limited.

Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric theory*, 597-625.

Pesaran, H. M. (2004). General diagnostic tests for cross-sectional dependence in panels. *University of Cambridge, Cambridge Working Papers in Economics*, *435*.

Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, *34*(6-10): 1089-1117.

Pesaran, M. H., Schuermann, T., & Weiner, S. M. (2004). Modeling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business & Economic Statistics*, *22*(2): 129-162.

Pesaran, M.H., Yamagata, T., 2008. Testing slope homogeneity in large panels. J Econom 142 (1), 50–93.

Reboredo, J. C. (2013). Modeling EU allowances and oil market interdependence. Implications for portfolio management. *Energy Economics*, *36*: 471-480.

Rodríguez, M., Boyes, E., Stanisstreet, M., Skamp, K. R., Malandrakis, G., Fortner, R., ... & Yoon, H. G. (2011). Can science education help to reduce global warming? An international study of the links between students' beliefs and their willingness to act. *The International Journal of Science in Society*, *2(3)*, 89.

SADC (2010). Southern Africa Sub Regional Framework of Climate Change Programmes: Adaptation and Mitigation Actions, Supported by Enabling Measures of Implementation. Southern Africa Climate Change Framework. https://www.sadc.int/files/4813/5293/3518/Southern_Africa_Framework_of_Subregional_Climate_Change_Programmes.pdf

Salami, A., Kamara, A. B., &Brixiova, Z. (2010). *Smallholder agriculture in East Africa: Trends, constraints and opportunities*. Tunis: African Development Bank.

Shabani, Z. D., &Shahnazi, R. (2019). Energy consumption, carbon dioxide emissions, information and communications technology, and gross domestic product in Iranian economic sectors: a panel causality analysis. *Energy*, *169*: 1064-1078.

Shahbaz, M., Raghutla, C., Song, M., Zameer, H., & Jiao, Z. (2020). Public-private partnerships investment in energy as new determinant of CO2 emissions: the role of technological innovations in China. *Energy Economics*, *86*, 104664.

Shahbaz, M., Rehman, I. U., Sbia, R., & Hamdi, H. (2016). The role of information communication technology and economic growth in recent electricity demand: fresh evidence from combine cointegration approach in UAE. *Journal of the knowledge economy*, *7*(3): 797-818.

Shahbaz, M., Sbia, R., Hamdi, H., & Rehman, I. U. (2014). *The Role of Information Communication Technology and Economic Growth in Recent Electricity Demand: Fresh Evidence from Combine Cointegration Approachin UAE* (No. 2014-523).

Shobande, O. A. (2020). The effects of energy use on infant mortality rates in Africa. *Environmental and Sustainability Indicators*, *5*, 100015.

Shobande, O. A. (2019). Effect of economic integration on agricultural export performance in selected west African countries. *Economies*, *7*(3), 79.

Shobande, O. A., &Enemona, J. O. (2021). A Multivariate VAR Model for Evaluating Sustainable Finance and Natural Resource Curse in West Africa: Evidence from Nigeria and Ghana. *Sustainability*, *13*(5), 2847.

Shobande, O. A.&Ogbeifun, L. (2021). HasInformation and Communication Technology and Environmental Quality in OECD: *International Journal of Sustainability & Ecology*

Shobande, O. A., & Asongu, S. A. (2021). Has knowledge improved economic growth? Evidence from Nigeria and South Africa. *Journal of Public Affairs*, e2763.

Shobande, O., & Asongu, S. (2022). *The rise and fall of the energy-carbon Kuznets curve: Evidence from Africa* . Management of Environmental Quality. DOI: 10.1108/MEQ-08-2021-0185

Shen, J. (2008). Trade liberalization and environmental degradation in China. *Applied Economics*, *40*(8), 997-1004.

Sinha, A., Shahbaz, M., &Balsalobre, D. (2017). Exploring the relationship between energy usage segregation and environmental degradation in N-11 countries. *Journal of Cleaner Production*, *168*, 1217-1229.

Spanos, A. (1989). On rereading Haavelmo: A retrospective view of econometric modeling. *Econometric Theory*, 405-429.

Stock, J. H., & Watson, M. W. (2007). Why has US inflation become harder to forecast? *Journal of Money, Credit and Banking*, *39*: 3-33.

Tchamyou, V. S, (2017). The Role of Knowledge Economy in African Business, *Journal of the Knowledge Economy*, 8(4): 1189–1228.

Tchamyou, V. S., (2020). Education, Lifelong learning, Inequality and Financial access: Evidence from African countries.*Contemporary Social Science*, 15(1): 7-25.

Tchamyou, V.S., Erreygers, G., &Cassimon, D., (2019). Inequality, ICT and Financial Access in Africa, *Technological Forecasting and Social Change*,139(February): 169- 184.

Ullah, S., Andlib, Z., Majeed, M. T., Sohail, S., & Chishti, M. Z. (2021). Asymmetric effects of militarization on economic growth and environmental degradation: fresh evidence from Pakistan and India. *Environmental Science and Pollution Research*, *28*(8), 9484-9497.

United Nations (1992). United Nations Framework Convention on Climate Change. New York: United Nations, General Assembly.

Usman, O., Alola, A. A., & Sarkodie, S. A. (2020). Assessment of the role of renewable energy consumption and trade policy on environmental degradation using innovation accounting: Evidence from the US. *Renewable Energy*, *150*, 266-277.

Wang, Q., & Zhang, F. (2021). The effects of trade openness on decoupling carbon emissions from economic growth–evidence from 182 countries. *Journal of cleaner production*, *279*, 123838.

Westerlund, J., Edgerton, D.L., 2008. A simple test for cointegration in dependent panels with structural breaks. Oxf Bull Econ Stat 70 (5), 665–704.

Wiggins, S., & Keats, S. (2013). Leaping and Learning. Linking Smallholders to Markets in Africa. London: Agriculture for Impact: Imperial College and Overseas Development Institute.

Wise, S. B. (2010). Climate change in the classroom: Patterns, motivations, and barriers to instruction among Colorado science teachers. *Journal of Geoscience Education*, *58*(5), 297-309.

World Economic Forum (2021). Climate Education MX. World Economic Forum. https://www.weforum.org/projects/climate-education-mx (Accessed: 26/12/2021).