How ICT, Globalization, Electricity Generation, and Economic Growth Impacted the Environment Quality: A Case of Low-Middle-Income Countries

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Abstract:

The environmental quality is influenced by several issues; among them are Information and Communication Technology (ICT) in the form of Mobile penetration and Internet usage, globalization measured through openness to trade, Electricity Generation, and Economic Growth. This research mainly aims to quantify the impact of these five indicators on the environmental quality considered in the Carbon dioxide (CO_2) emissions in thirty selected countries; variables figures cover the period from 2000 to 2020. The employed statistical tools: Stata was adopted to analyze the corresponding collected figures. Various tests were employed; a cross-section dependence and panel : (unit root, cointegration, VAR) and Panel Impulse Response function Analysis (IRF). The findings demonstrated that environmental degradation was considerably influenced by electricity generation, economic expansion, and internet use. In terms of environmental quality, as evaluated by CO2 emissions, all three variables are inelastic, which means that a 1% rise in any of them leads to a less than 1% increase in CO2 emissions. Yet , openness to trade has a detrimental effect on environmental degradation, which indicates that as trade is opened up more, environmental degradation would likely slow down. However, mobile penetration has a negligible impact on environmental pollution in these low-middle-income countries suggesting that mobile phone use is not yet a significant factor in these nations' environmental impact.

Keywords: Mobile penetration, Internet usage, Electricity Generation, Trade Openness, Economic Growth, Environment Quality, Carbon Dioxide (CO2)

1. Introduction

Global warming, which is the slow rise in the earth's temperature, is a component of climate change. It is mostly caused by human activities like farming and the burning of fossil fuels, which result in an increase in the quantities of greenhouse gases in the atmosphere. The preceding eight years were on track to be the eight warmest on record, according to the World Meteorological Organization's provisional Status of the Global Climate in 2022 assessment, driven by rising greenhouse gas concentrations and accumulated heat. In addition, this year's severe heatwaves, drought, and catastrophic flooding have affected millions of people and cost billions. The poor and those who are economically disadvantaged are the ones who are most at danger from the negative impacts, while everyone feels these effects to some level. The progressive rise in the earth's temperature, known as global warming, is one type of climate change. Climate experts have determined that if we want to avoid a future in which daily life is characterized by some of climate change's worst effects, such as catastrophic droughts, wildfires, floods, tropical storms, and other calamities, we must keep global warming to 1.5 degrees Celsius by 2040.

Throughout the past few decades, several studies have been done exploring the relationship between economic growth and its influence on environmental quality. Achieving balanced environmental conservation with stable economic growth constitute a great challenge for many countries especially the developing ones. As economies develop, people consume energy more frequently, which raises CO_2 emissions; as a result, pollution is a direct result of economic expansion and development. The impacts of economic expansion on the environment have been well studied in the past, with a range of outcomes. Finding out whether there is a connection between GDP and CO_2 missions in low- and middle-income nations is one of the objectives of this study. Will increasing per capita

GDP-driven economic growth raise living standards on its own or in combination with other factors?

The productivity and energy consumption of many economic sectors have increased during the past 30 years as a result of the enormous rise of ICT during the globalization era, leading to an ongoing discussion concerning the impact of ICT on the environment. According to several research, the ICT industry's quick expansion puts pressure on electricity use, leading to high worldwide emissions that have an impact on environmental quality. Several research revealed that the internet might reduce CO2 emissions and that the digital revolution has brought about advantages and opportunities. The truth is that depending on how we use modern technology, it can have both positive and negative effects on the environment. Takase and Murota (2004) discovered that internet use can boost the energy efficiency of Japan and the US, which is in line with the academics who believe that using the internet might cut CO2 emissions. In addition, Khan et al. (2018) noted that building a home energy management controller and reducing energy use are both doable by utilizing the internet, which will save energy costs. The interplay between ICT and the environment is thought to have three different effects (Charfeddine and Kahia, 2021). First-order effects include those brought on by ICT directly, such as the energy expended and waste generated during the creation of ICT products or services. The focus of the second-order repercussions is on how increased ICT adoption and use might impact sustainability . Gains from first-order effects may be offset by third-order effects, such as increased power consumption resulting from lower energy prices gained through increased energy efficiency. As a result, if energy consumption rises as a result of ICT performance gains, carbon emissions could also rise (Awad, 2022).

Global trade is another crucial factor that has a significant impact on environmental quality. Theoretically, trade openness and the environment are related, although this is controversial. It is possible to show the connection between commerce and greenhouse gases using three impacts. First, the "scale effect" argues that higher production and energy use come from global trade, which may negatively influence the environment. Second, the "composition effect" contends that in response to trade, industrial activities migrate to sectors with ongoing competitive advantages. The overall impact on greenhouse gas emissions will mostly depend on whether or not expanding sectors use less energy than decreasing ones. Finally, the "technique Impact" claims that trade promotes the use of advanced, efficient, and. environmentally friendly technology, lessening the burden on GHGs, in accordance with the "technique impact." Hence, trade may have both positive and negative effects on the environment.

By analyzing the link between the aforementioned variables for a group of lower middle-income countries that have been given a categorization by the World Bank, this research adds to the body of literature. The new study is unique from the existing body of literature in a number of ways. (I) No well-known literature has examined the relationship between the variables EG, RGDP, CO2, MOB, NET, and TO for the chosen set of nations. (II) Just a small number of well-known studies have looked at the impact of mobile penetration on carbon emissions in the lower middle-income countries classified by the World Bank. (III) This study uses the PVAR approach using a system GMM methodology to evaluate the nexus between the variables. In addition to accounting for the endogeneity problem, this methodology is asymptotically unbiased. . Also, the cross-sectional dependence (CD) test described by Pesaran (2004) is used to determine if the variables are cross-sectionally dependent.

The following describes the organization of this study. The next section, titled "Literature Review," provides a summary of the literature. The section after that, titled "Research Framework and Hypotheses," describes the theoretical framework, empirical techniques, and data sources employed in the study. Empirical Findings & Discussion is mostly concerned with discussing observations and the research findings. The Policy Implications section, which comes last, provides recommendations for the next research, findings, and policy dealing with climate change and its effects.

2. Literature Review

The literature review can be divided into five categories relating environmental quality to electricity generation, economic growth, trade openness, and ICT through net usage and mobile penetration. This section focuses on panel data studies and the following are some of the academic studies on the variables that would affect CO2 emissions.

The first strand of literature judges the possible link between electricity generation and CO2 emissions. The burning of coal, oil, and other fossil fuels is the primary cause of global warming and the ensuing climate changes, according to strong scientific data provided by climate scientists. Numerous studies are raising awareness of the use of fossil fuels and their connections to environmental deterioration. For instance, Gani, 2021 investigated the supply-side impact of fossil fuel energy generation (coal, natural gas, and oil) on environmental quality where an expanded version of the Stochastic Impacts by Regression on Population Affluence and Technology (STIRPAT) model is employed. The model includes a balanced panel of 59 countries that use coal, 77 countries that use gas, and 96 countries that use oil from 2002 to 2016. The findings showed that coal and oil had significant negative coefficients on the quality of the environment at the 5% level. These findings confirm that burning coal and oil for energy is a significant factor in the deterioration of the environment's quality.

A recent study by Majeed et al., (2021) examined how the abundance of natural resources, economic globalization, and disaggregated energy consumption have affected the environmental quality in Gulf Countries (GCC) between 1990 and 2018. For both short-run and long-run estimates, the study used an advanced econometric method called the cross-sectional autoregressive distributed lags (CS-ARDL) estimator. The results demonstrated that the GCC economies' emission levels are mitigated by economic globalization and the consumption of renewable energy, whereas environmental quality is markedly worsened by urbanization, economic expansion, and the use of non-renewable energy sources. Also, Alola, and Joshua (2020), looked at the effects of globalization, the consumption of fossil fuels, and renewable energy on CO_2 emissions from 1970 to 2014 for cases of high-income, low-income, lower-middle-income, and upper-middle-income countries. The study, which used the (ARDL) approach, discovered that in the panel of examined income classifications, the consumption of fossil fuels worsens environmental risks over the short- and long-term, while the share of renewable energy usage only improves the environment over the short term. Therefore, the study suggested policy guidelines for each of the four income-categorized countries and territories, particularly the lower-middle-income economies, in the context of enhanced energy portfolio diversification.

Similarly, Mujtaba, et al., (2020) examined the relationship between economic development, energy consumption, population, trade openness, and carbon dioxide (CO2) emissions in 25 countries in the upper middle-income group between 1985 and 2014. Fully Modified Ordinary Least Square (FMOLS) and Dynamic Ordinary Least Square (DOLS) methodologies were used in the study to examine the strength of the associations and relationships between the variables. According to FMOLS findings, energy consumption, population growth, and carbon dioxide emissions are all positively correlated. Majeed and Aisha, (2020) employed first and second-generation tests in their study to investigate the effects of urbanization, industrialization, and energy consumption on carbon emissions for a panel of 156 countries and different income categories between 1990 and 2014. GMM, common CCEMG and dynamic CCEMG estimation approaches were used to address the challenges of heterogeneity, endogeneity, and cross-sectional dependence. The outcomes reveal that energy consumption coefficients show that energy use affects CO2 emissions positively and significantly in all income levels. These findings supported the idea that, regardless of income level, energy consumption is drawn at the expense of an increase in carbon emissions. Sohag et al., (2017) analyzed how middle-income economies' sector value addition to GDP affects CO2 emissions while controlling for factors like population growth, energy use, and trade openness covering the period from 1980 to 2012. Through the use of the cross-correlated effect mean group (CCEMG) and augmented mean group (AMG), the results showed that CO2 emissions in middle-income economies are positively triggered by energy use and the expansion of the industrial and service sectors concluding the importance of having a strong foundation for creating a sustainable and pro-growth policy for middle-income nations.

The second part of the literature considers the possible link between trade openness and CO2 emissions. Trade openness to international markets is a potential pathway via which the environmental quality of a given nation or group of nations may be positively or badly impacted. Since the issue varies between nations, no agreement has yet been achieved regarding the long-term impact of trade openness on environmental degradation.

With respect to the positive effect of trade openness on environmental quality, Lv and Xu, (2019) attempt to empirically examine the heterogeneous effects of trade openness and urbanization on CO2 emissions in 55 middle-income countries from 1992 to 2012 using the Pooled Mean Group (PMG) method. They discovered that, in the short run, trade openness has favorable effects on the environment. In 2019, the associations between the production of renewable and non-renewable electricity, CO_2 emissions per person, real gross domestic product per person, trade openness, and financial development for a group of countries consisting of twelve MENA region nations throughout the years from 2005 to 2014 were the subject of the investigation performed by Amer, (2019). With regard to PCO_2, trade openness has a negative significant influence on CO_2 emissions. Such results indicate that The MENA countries might have recognized the value of implementing ecologically friendly import and export practices to some extent based on the negative correlation between PCO_2 emissions and trade openness. Likewise, Sohag et al.,(2017) used the MG, Cross-Correlated MG, and Augmented MG methodologies to examine the effects of trade openness, economic development, population growth, and energy use on CO_2 emissions for 82 middle-income countries over the period of 1980 to 2012. In the case of upper-middle-income nations, the authors calculated that a one-unit increase in openness resulted in a 0.003-unit reduction in CO_2 emissions. For the entire sample of nations and lower-middle-income countries, the findings regarding the impact of trade openness were equivocal. Additionally, Ang, (2009) made the case that trade openness encourages improved productivity for resources, especially energy, which may result in decreased marginal emission from consuming energy when compared to the growth in output. Also, Yanikkaya, (2003) claimed that because of the openness to trade, innovations from trading nations are now easily accessible in a country resulting in more economic effects that would enhance the quality of economic growth or lower externalities in the form of decreased CO2 emissions.

On the other hand, Adebayo et al., (2021) utilized the MINT countries (Mexico, Indonesia, Nigeria, and Turkey) to evaluate the asymmetric influence of trade (import and export) and economic growth on consumption-based carbon emissions (CCO2). The Nonlinear ARDL was used to evaluate this link using data from 1990 to 2018. The results of the NARDL estimates showed import shocks have positive effects on CCO2 emissions in every MINT country. According to Mahmood et al., (2019), there is a strong correlation between trade openness and CO2 emissions in Tunisia during the period of study from 1971 to 2014. Their study used a structured model revealing that trade openness is one of many factors that contribute to greater emissions. Nevertheless, using instrumental variables in examining the overall effect of trade on environmental quality, Managi et al., (2009) reached a conclusion that global trade can reduce emissions in non-advanced economies, with a contradictory reaction in advanced economies: They explained such increase as due to the scale and composition effects of trade.

In conclusion, numerous research supports the claim that the world's environmental circumstances are significantly influenced by the global trade network where trade networks have grown in importance for countries that influence their environmental qualities either positively or negatively. For instance, Aller et al., (2015) argued that trade networks have an indirect effect on environmental quality for developing countries but a direct impact on wealthy countries. As a result, when viewed in a broader context, trade policies can be used as a tool for countries to reexamine their environmental policies and trade agreements made with other countries which are considered a crucial step in maintaining an appropriate perspective on the environment.

The third part of the literature judges the relationship between ICT and environmental degradation. In this reserach, ICT comes in the form of internet usage and mobile penetration. ICT in helping promote more economic expansion could have a negative influence on the environment at the same time.

Unquestionably, the digital revolution has brought about advantages and opportunities, but there are also clear drawbacks, which is why people are now talking about how it will affect the environment. The truth is that modern technology has both beneficial and harmful consequences on the environment, depending on how we use it. Among the academics who agree with the assumption that internet usage might reduce CO2 emissions, Takase and Murota, (2004) found that internet use can increase the energy efficiency of Japan and the US. Furthermore, Khan et al., (2018) pointed out that using the internet makes it possible to build a home energy management controller and cut energy use in order to lessen energy expenditures. Additionally, Kumari et al., (2020) pointed out that the transformation of the current grid brought about by the energy industry's usage of the internet has resulted in a smart grid that can meet consumer demand and reduce the cost of energy use by permitting the bidirectional flow of data and energy.

On the contrary, Özpolat, (2022) found that intent usage resulted in environmental degradation in the G7 countries during the period from 1990 to 2015 by applying the Augmented Mean Group methodology. He came to the conclusion that it is critical that ICT manufacturers provide goods with minimal negative environmental effects where ICT makes up about 2% of the carbon footprint, per data from 2007. Also, Wang and Xu, 2021 empirically explored the relationship between internet usage, human capital, and CO2 emissions under different degrees of economic development by utilizing the system GMM and a threshold regression model, based on the panel data of 70 nations from 1995 to 2018. The findings showed when human capital is below the threshold value, internet use can raise CO2 emissions; however, when human capital is above the threshold value, internet use can dramatically reduce CO2 emissions. In other words, there is an inverted U-shaped nonlinear link between internet use and CO2 emissions as human capital increases. With the world becoming more and more virtual and about 84%

(Infomineo,2022) of people using smartphones, it is getting much harder to ignore the facts and statistics about the negative impacts of cell phones on nature and the environment. Significant numbers from numerous studies and research indicate that smartphones significantly contribute to the issue of climate change. Because they contain heavy metals like lead, arsenic, copper, and mercury, cell phones have the potential to have a significant negative impact on the environment. Ecological footprint analysis and life cycle energy modeling have demonstrated that the steps of acquiring raw materials and manufacturing require the most land area and energy. In reality, hardly many academics have truly examined how cell phones might affect the environment's quality. The novelty of our study is supported by the fact that the majority of research was conducted by businesspeople and corporations rather than academic research publications. To my knowledge, no paper has looked into how mobile cellular subscriptions, as a unique variable of ICT, affect CO2 emissions.

According to Infomineo, 2022, more than half of the global transportation industry's carbon footprint will be made by the ICT sector by 2040, which includes personal computers, laptops, smartphones, and tablets in addition to its digital infrastructures like data centers and communication networks. Global smartphone usage has roughly doubled over the last five years. In 2016, there were slightly over 3.6 billion smartphone users globally. By 2021, that number had risen to an estimated 6.3 billion users, and by 2026, it was projected to have surpassed 7.5 billion. Naturally, the mass manufacture of smartphones in mega factories has a significant negative impact on the environment. Between 85% and 95% of a smartphone's total carbon footprint is generated during production. Also, Edquist and Bergmark, (2022) examined the relationship between carbon dioxide (CO_2) emissions and relative mobile broadband penetration. Based on data from 181 nations between 2002 and 2020, the study used a two-stage model that takes fixed broadband into account as well as four additional control variables, the results showed that on average, a 10 percentage point increase in mobile broadband penetration results in a 7 percent reduction in CO_2 emissions per person. As a result, the findings suggest that longer-term investments in mobile infrastructure can help to slow down global warming. According to an article produced by Honest Mobile, 2020, the environmental impact of your daily phone use is greater than the environmental impact of its manufacture. The infrastructure and data centers that enable you to make video chats, upload selfies, and stream TV consume a lot of energy. For instance, making a mobile call for one minute emits 0.1g of carbon dioxide (CO_2), sending an SMS emits 0.014g of CO_2, and utilizing one gigabyte of data emits 0.3kg of CO_2. A typical Mobile subscriber uses the service and generates about 16.7kg of CO_2 per year through charging. This is equivalent to about 25% of the carbon footprint of your smartphone.

Yet, with respect to the effect of mobile use on economic growth, Röller and Waverman (2001), in previous research found that fixed-line telephones increased OECD country output growth by 1/3. The growth rate increased by 1.5 percent for every 10 percent increase in the penetration rate of telecommunications (including mobile and fixed-line telecoms). The use of mobile phones allowed for the rapid dissemination of information without the costly installation of physical phone lines. In 2006, Abraham conducted research on the impact that mobile phones had on India's fishing sector. The research showed that when mobile phone use increases, markets become more efficient as a result of less risk and uncertainty, increased market integration, and increases in production. The researcher conducted a poll of Indian fishermen and discovered that 80 percent of them felt cell phones be helpful. Also, Lum (2011) addressed the different ways that mobile phones might improve market efficiency as well as the role that information and knowledge dissemination plays in development for 182 nations between 1980 and 2007. Overall, it was shown that the real per capita GDP and GDP growth rate of nations are positively and significantly impacted by the number of mobile cellular subscriptions.

The fourth section of the literature review finally covered the relationship between CO2 emissions and economic growth. For 15 MENA countries, Farhani and Ben Rejeb (2012) examined the link between energy consumption, GDP, and CO2 emissions using data from 1973 to 2008. The findings of this study demonstrated that neither short-term CO2 emissions nor energy consumption, nor GDP and energy consumption, are causally related. Al-mulali et al. (2015) investigated the effects of economic growth, the adoption of renewable energy, and financial development on CO2 emissions in 18 Latin American and Caribbean nations between 1980 and 2010. By using the Fully Modified OLS (FMOLS) model, the findings revealed that the connection between CO2 and GDP had an inverted U-shape. The VECM Granger causality results showed both short- and long-term feedback causation between GDP, power use from renewable sources, financial development, and CO2. Additionally, Granger causality analyses showed that since power consumption, GDP, and financial development all have a causal effect on CO2, they can all be effective ways to lessen environmental damage.

Magazzino (2016) used a panel VAR to investigate the relationship between CO2 emissions, economic growth, and energy use for ten Middle Eastern nations between 1971 and 2006. For the six GCC nations, the computed coefficients and impulse response function both demonstrate a negative relationship between economic growth and CO2 emissions. CO2 emissions appear to be influenced by both energy consumption and its own historical values. The other four non-GCC nations' growth, which is determined by their own lagged numbers, does not appear to be impacted by either CO2 emissions or energy use. In their 2017 study, Antonakakis et al.,(2017), used panel VAR to examine the relationship between increasing energy consumption, increase in CO2 emissions, and rising real GDP per capita. An analysis using 106 nations divided into different income categories from 1971 to 2011 revealed that the effects of different types of energy consumption on economic growth and emissions vary depending on the country group. The feedback hypothesis is further supported by the bidirectional causal relationship between economic growth and energy use. Using the Tapio decoupling index and the Log Mean Divisia Index (LMDI) decomposition approach, Ozturk et al. (2021) investigated the decoupling of CO2 emissions from economic growth for Pakistan, India, and China (PIC) throughout the 1990–2014 period. The results of the Tapio elasticity analysis show that in the relevant PIC countries, the environmental effect has been observed to be disconnected from economic growth in recent years. However, India primarily suffered poor decoupling and expensive coupling, whereas China demonstrated weak decoupling across a number of years. Pakistan, on the other hand, experienced expensive negative decoupling. Additionally, the Tapio decoupling elasticity research revealed that energy intensity is the primary driver of decoupling in PIC countries.

The effects of real income, financial development, and trade openness on the ecological footprint (EF) of consumption in the 27 largest emitting nations from 1991 to 2012 were examined by Uddin et al., (2017). The variables are co-integrated, according to the results of Pedroni co-integration tests. The panel DOLS show a long-term, significant positive correlation between EF and real income and a small, but negative, correlation between EF and trade openness. Real income and EF are causally related in a unidirectional causality according to the vector error correction model. Results from impulse response functions and variance decomposition analyses show that real income will continue to have an increasing impact on EF in the future.

In their study, Shokoohi et al. (2022) examined the effects of energy intensity and economic growth on environmental quality, taking into account Iran, Iraq, and Turkey as three populous Middle Eastern countries. The ecological footprint (EF) and carbon dioxide (CO2) emission indicators from 1971 to 2015 were compared in order to evaluate the environmental Kuznets curve (EKC) hypothesis. The existence of short- and long-run correlations was investigated using the auto-regressive distributed lag (ARDL) methodology. By using two environmental indicators in Turkey, the empirical findings supported the inverted U-shaped relationship between per capita income and environmental deterioration. The EF index was also used to corroborate the theory, and CO2 emissions in Iran and Iraq were used to refute it.

3. Research Framework and Hypotheses

3.1. Research Framework Overview

Previous studies looked at variables such as economic growth Mobile penetration, Internet usage, globalization (trade openness), Electricity Generation, and Economic Growth on CO2 emissions, which were chosen and evaluated to create the model for the research. The research framework, which incorporates the hypotheses, is shown in Figure 1 below.

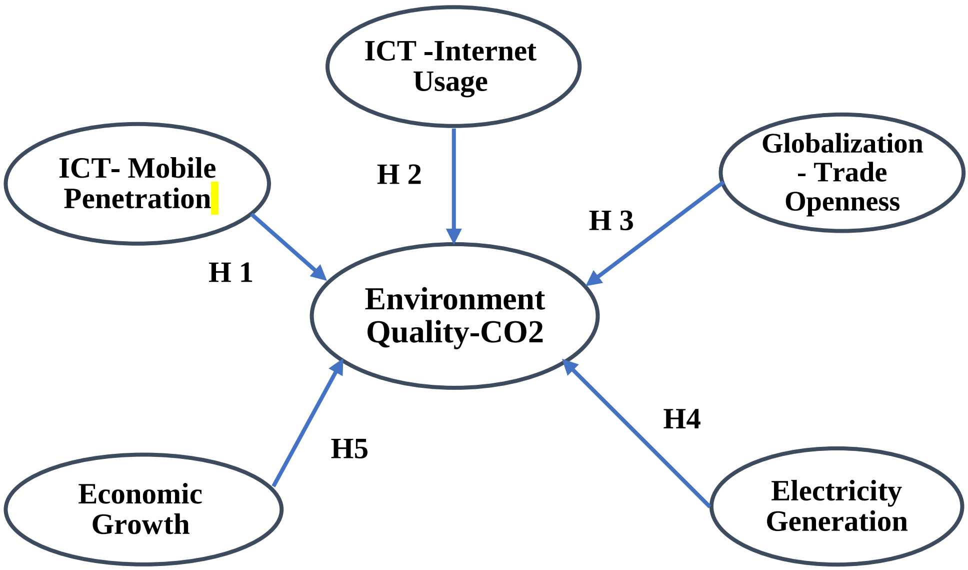

Figure 1: Research Framework

4. Data and Methodology

4.1. Data

The acquired corresponding secondary data was from BP Statistical Review of World Energy and the World Development Indicators (WDI) in 2019 websites. The used variables are: carbon dioxide emissions per capita (PCO2), per capita electricity generation (EG), economic growth (PRGDP), ICT measured by the Mobile cellular subscriptions per 100 people(MOB) and Individuals using the Internet as % of population and last variable is the trade openness (TO).

4.2 Methodological Framework

4.2.1 Cross-Section Dependence Problem

When working with panel data, cross-section dependence among the panel units is becoming more and more crucial. The occurrence of cross-sectional dependency in the errors of the panel data models may be caused by the presence of common shocks and unobserved components that become part of the error term. To study the cross-sectional dependency in panel data, Pesaran (2004) will be used in this analysis.

Consider the following panel data model

$$y_{it} = \alpha_i + \beta_i X_{it} + u_{it} \quad i = 1,2,\ldots\ldots,N, t = 1,2,\ldots\ldots,T \qquad (1)$$

Here, i represents the cross-section dimension while t stands for the time series dimension , X_{it} constitute different regressors to be used, and α_i denotes time-invariant parameters. For each cross section unit , u_{it} is independent and identically distributed , for all t, yet it's still possible to have some sort of cross sectional correlation but no serial correlation. The null hypothesis of zero cross-equation error correlations can be expressed using the correlations between the disturbances in different cross-section units as follows:

$$H_0: \hat{\rho}_{ij} = \hat{\rho}_{ji} = Corr(u_{it}, u_{jt}) = 0 \text{ For } i \neq j$$

Versus

$$H_0: \hat{\rho}_{ij} = \hat{\rho}_{ji} = Corr(u_{it}, u_{jt}) \neq 0 \text{ For } some\ i \neq j$$

Pesaran (2004) has proposed the CD test to inspect cross-sectional dependency :

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left[\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right] \xrightarrow{d} N(0,1) \qquad (2)$$

This test has an asymptotically standard normal distribution and is used when N and T are both sufficiently large. It depends on the sum of the squares of the correlation coefficients among the cross section disturbances. The alternate hypothesis with cross section independence applies.

4.2.2. Panel Unit Root Tests

To prevent the potential of misleading regression, the integrational features of the series must first be established. First generation panel-unit root tests can produce erroneous estimates, according to Banerjee et al., (2005), if there are large levels of error cross-section dependence and this is disregarded. In light of this, the use of second-generation panel unit root tests is only recommended when it is certain that the panel exhibits a considerable level of error cross section dependence. In this research, after identifying cross section correlation among the errors a second generation tests were conducted.

The assumption of cross-sectional independence is relaxed by the second generation of tests. Equation (3) is called the cross-sectionally augmented Dickey-Fuller (CADF) test and takes the following form:

$$\Delta y_{it} = a_i + \rho^*{}_i\, y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \varepsilon_{i,t} \qquad (3)$$

Where $\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{i,t}$, represents the average at time t of all n observations, $\Delta \bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} \Delta y_{i,t}$ and the regression error is $\varepsilon_{i,t}$.

For every panel unit, a simple CADF regression is performed in case of no serial correlation where the cross-sectional averages, $\bar{y}_{t-1}$ and $\Delta \bar{y}_t$, are included into (3) as a proxy for the unobserved common factor where (N) is sufficiently large. If serial correlation in the error term or the factor term exists, the regression must be augmented as usual by lagged first differences of both y_{it} and $\bar{y}_t$ and the augmentation degree can be selected using any information criterion.

After performing this CADF regression for each unit in the panel, Pesaran averages the t-statistics on the lagged value (also known as CADFi) to create the CIPS statistic. A modified version of the IPS t-bar test called CIPS for Cross-sectionally Augmented (IPS), which concurrently takes into account for cross-section dependence and residual serial correlation, is created using the individual CADF data. The form of the CIPS test statistic is as follows:

$$\text{CIPS} = \frac{1}{N} \sum_{i=1}^{N} CADF_i \qquad (4)$$

Where the cross sectional augmented dickey fuller statistic (CADF i) is calculated using the t-ratio of the OLS estimate of $\rho^*{}_i$ in the CADF regression (3). The t-test built using this regression has no cross-sectional dependence.

These tests can be used for both cases when $N > T$ or $T > N$. In CADF test, the null hypothesis is that cross unit (i) in the panel has a unit root and the alternative hypothesis is that ($\rho^*{}_i < 1$) while in the CIPS, which is a joint panel test statistic ,the null hypothesis is that all the panel units have unit root ($\rho^*{}_1 = \cdots = \rho^*{}_N = 1$) and the alternative is that ($\rho^*{}_i < 1$) for at least some i (Westerlund, 2007).

4.2.3 Panel Cointegration Tests/ Error Correction Based Cointegration Test

The use of cointegration analysis is important, especially when dealing with non-stationary variables that could presuppose the presence of long-term relationships. The need of testing for cointegration seems to be of importance and significance in order not to have a spurious regression and to distinguish whether a long run or short run relationship is available between the variables under examination. Second generation cointegration tests like those developed by Westerlund's (2007) will be used in this research.

Westerlund (2007) tests the null hypothesis of no cointegration by testing the error-correction term in a panel error-correction model. In order to account for cross-sectional dependencies, unit-specific short-run dynamics, and unit-specific trend and slope characteristics, all of the new tests are normally distributed and appropriately wide. Two tests are designed to examine the alternative hypothesis that the panel is cointegrated overall, while the other two test the alternative theory that at least one unit is cointegrated and bootstrap distribution is employed when cross-sectional dependence occurs. It should be highlighted that the only requirement for these tests is that the regressors utilized have low exogeneity. Weak exogeneity ensures that both the test for the lack of cointegration and the test for the lack of error correction in the equation may be carried out..(5)

$$\Delta y_{it} = \delta_i' d_t + \alpha_i y_{it-1} + \lambda_i' x_{it-1} + \sum_{j=1}^{pi} \alpha_{ij} \Delta y_{it-j} + \sum_{j=0}^{pi} \gamma_{ij} \Delta x_{it-j} + e_{it} \qquad (5)$$

Here, $t = 1,\ldots,T$ *represnts the time series and* $i = 1,\ldots,N$ stands for cross-sectional units, respectively. The deterministic components are contained in d_t. λ_i' = -$\alpha_i \beta_i'$ The parameter α_i specifies the speed of adjustment at which the system returns to the equilibrium relationship $(y_{it-1} - \beta_i' x_{it-1})$when a shock occurs. α_i is calculated through least squares providing a valid test of H_0 against H_1. If α_i is less than zero, then cointegration do exist between y_{it} and x_{it} , whereas if α_i is eqaula to zero, then, cointegration is absent. This suggests that the following may be used to illustrate the null hypothesis of no cointegration for cross-sectional unit i

$$H_{0:}\ \alpha_i = \text{Zero}$$

4.2.4 Panel Vector Auto regression (VAR) Methodology

This section's goal is to thoroughly explain how panel VAR models are estimated using a system GMM, as well as the impulse response functions that will be covered at the end of this section. The Vector Auto Regression Model (VAR) uses a system approach to model the relationship between the relevant variables, accounting for the important interactions between the variables under consideration. According to Abrigo, and Love, (2016), because each variable in the system is viewed as potentially endogenous in this method, there is no endogeneity bias when endogenous regressors are introduced .

A lagged dependent variable among the regressors is typically what distinguishes a dynamic relationship. In a panel VAR model, a dynamic equation with just the two variables x and y can be assumed to have the following representation:

$$y_{it} = \lambda_{1,1}\, y_{it-1} + \lambda_{1,2}\, x_{it-1} + u_{1it} \qquad (6)$$

$$x_{it} = \lambda_{2,1}\, y_{it-1} + \lambda_{2,2}\, x_{it-1} + u_{2it} \qquad (7)$$

Where i=one... $,N$ (cross-sectional dimension) and t=1$\ldots,T$ (time dimension) and $u_{it} \sim i.i.d.$ y_{it} is a $(1xk)$ vector of dependent variable and x_{it} is a $(1xk)$ vector of independent variables in addition to the possibility of adding constant, dummy variables and deterministic trend. When utilizing the VAR approach on panel data, it is required to impose the restriction that the underlying structure be the same for each cross-sectional unit. Although this constraint is likely to be violated in practice, one approach to get around it is to introduce fixed effects, which are denoted by (μ_i) in the model and which allow for "individual heterogeneity" in the levels of the variables. Assuming that u_{it} consists of the following;

$$u_{it} = \mu_i + v_{it} \qquad (8)$$

u_{it} consisits of two error elements; μ_i and v_{it} the unobservable individual eff ects and the remainder error term respectively, and μ_i ~IID $(0, \sigma_\mu^2)$ and v_{it} ~IID $(0, \sigma_\mu^2)$.

As for equations (6) and (7), it is possible to determine that the dynamic panel data regression is featured over time by persistence from two sources: the autocorrelation brought on by the existence of a lagged response variable among the regressors, and the individual effect demonstrating the heterogeneity among the individuals. For this reason and to overcome these two problems , the Blundell and Bond (1998) method known as "system" GMM (SYS-GMM), which combines "level" and "difference" GMM, will be employed. A "system" GMM, despite what its name suggests, treats the data system as a single-equation problem:

$$\begin{pmatrix} \Delta y_{it} \\ y_{it} \end{pmatrix} = \alpha \begin{pmatrix} \Delta y_{i,t-1} \\ y_{i,t-1} \end{pmatrix} + \beta \begin{pmatrix} \Delta X_{i,t-1} \\ X_{i,t-1} \end{pmatrix} + \begin{pmatrix} \Delta u_{it} \\ u_{it} \end{pmatrix} \quad (9)$$

The SYS-GMM estimator combines the equations in first-differences with lagged levels as instruments to another set of equations that enter in levels with correctly lagged first-differences as instruments, as shown in equation (8).It should be highlighted that incorporating a longer set of lags can increase the effectiveness of estimates and produce more accurate estimates. But it has the unpleasant trait of lowering observations, particularly with unbalanced panel.

Besides, a different kind of transformation from differencing known as "forward mean differencing or orthogonal deviations" is also used by the system GMM to remove the fixed effect (the Helmert procedure). In order to remove the fixed effects, all model variables are converted in deviations from their forward means.Let y_{it}^{m} and u_{it}^{m} indicate a variable and a disturbance as follows;

$$y_{it} = (\, y_{it}^{1}\, , y_{it}^{2}\, \ldots\ldots ., y_{it}^{M}\,)\text{ 'and } \quad u_{it} = (\, u_{it}^{1}\, , u_{it}^{2}\, , \ldots \ldots ., u_{it}^{M}\,)$$

The following are the means derived from the future values.

$$\bar{y}_{it}^{m} = \sum_{s=t+1}^{T_i} \frac{y_{is}^{m}}{(T_{i-1})} \qquad (10)$$

For a given country series, $T_i$is the last year the obtainable data. The transformed variable and error term are as follows :

$$\tilde{y}_{it}^{m} = \delta_{it}(y_{it}^{m} - \bar{y}_{it}^{m}) \qquad (11)$$

$$\tilde{u}_{it}^{m} = \delta_{it}(u_{it}^{m} - \bar{u}_{it}^{m}) \qquad (12)$$

Where:

$$\delta_{it} = \sqrt{\frac{T_{i-t}}{T_{i-t+1}}} \qquad (13)$$

Nevertheless, since there are no future values to use in the derivation of the forward means, the data from the most recent period cannot be estimated. The forward means differencing (FOD) method offers the benefit of maintaining sample size in panels with gaps, which is one advantage it has over the first-difference (FD) process (Roodman, 2009). The first-difference method's drawback is that it accentuates gaps in unbalanced panels. Hence, the transformed model becomes:

$$\tilde{y}_{it}^{m} = \alpha_1 \, \tilde{y}_{it}^{m} + \tilde{u}_{it}^{m} \qquad (14)$$

Where

$\tilde{y}_{it}^{m} = (\tilde{y}_{it}^{1}, \tilde{y}_{it}^{2}, \dots \dots .., \tilde{y}_{it}^{M})$ ‘ And $\tilde{u}_{it}^{m} = (\tilde{u}_{it}^{1}, \tilde{u}_{it}^{2}, \dots \dots .., \tilde{u}_{it}^{M})'$

It is clear from the discussion thus far that the FOD transformation reduces the average of all possible future observations relative to the current value. The FOD transformation, on the other hand, drops the first observation for each individual data while the FD transformation removes the last observation for each individual data in the panel. Finally, it should be mentioned that the estimators do not rely on having high-quality instruments from sources other than the dataset because they are intended for general use. In actuality, the instruments used are internal from inside the model that is, depends on the lags of the available regressors. Lastly, PVAR in differences should be used if the variables are non-stationary at the level.

4.2.5. Panel Impulse Response Functions

Impulse-response functions (IRF) of the panel VAR model are produced to assess the two-way effects between the model variables. When holding all other shocks to zero, the IRF is a valuable tool for displaying how one variable responds to innovation in another component of the system (Love and Zicchino, 2006). One of the key advantages of the VAR system is that it makes it possible to evaluate the impact of the orthogonal shocks, or the impact of a shock on one variable on another while maintaining the same value for all other variables. Additionally, it follows that the impulse responses are equal to zero if none of the variables Granger-cause the others taken together.

In order to examine the impulse response functions, 95% significance levels will be taken into consideration. Since the calculated PVAR coefficients are used to build the matrix of impulse response functions, it is crucial to take into account their standard errors.

5. Empirical Results and Discussion

5.1 Preliminary Investigation

The variables in the provided model are all changed to double log form to get the data relative normal distribution. The results should be simple to understand since the estimated coefficients in this form indicate the elasticities of the explanatory factors. The sample period is from 2000 to 2020. The mean, maximum, and minimum are displayed in Table 5.1, in addition, other statistics of the normality distribution tests and standard deviation of the data are reported and explained.

Presented in Table 5.1 below are the mean, maximum and minimum values for all six variables for the whole panel. Considering the (JB) test by Jarque-Bera (1980), the PRGDP, PCO2, PEG and TO accept that the data is normally distributed at the 1 percent significance level, only the NET and MOB variables could not accept the null hypothesis $H_{0,}$, indicating that the sampled data are not normally distributed.

Table 5.1: Summary statistics for all the variables (2000-2020)

	PRGDP	PCO2	PEG	TO	NET	MOB
Mean	2091.3	1.474775	763.5406	66.87142	17.00883	60.87104
Maximum	5614.118	8.8702	4363.691	211.4998	84.12036	165.5482
Minimum	486.5413	.0768	5.139	20.72252	.0470226	0.024420
J-B Probability	2.90 (0.2343)	6.17 (0.0458)	3.68 (0.1592)	6.97 (0.0307)	13.07 (0.0014)	39.23230 (0.00000)
S.D.	1074.996	1.722865	865.624	30.53094	18.61831	45.40051
Observations	630	630	630	630	630	630

Source: Research based Calculation. S.D. is the standard deviation.

Also, as was already noted, the data's log transformation enhances the distribution's normality. Regarding the standard deviation, it can be said that regressors do have high values of standard deviation indicating that data is spread out leading them to be more precise.

Table 5.2: Estimations of Unconditional Correlations on Panel Data Set

	PRGDP	PCO2	PEG	TO	NET	MOB
PRGDP	1.000					
PCO2	0.7373*	1.0000				
PEG	0.6332*	0.8331*	1.0000			
TO	0.1707*	0.2264*	0.2150*	1.0000		
NET	0.5339*	0.4321*	0.4733*	0.0830*	1.0000	
MOB	0.3750*	0.2281*	0.2870*	0.1565*	0.8525*	1.0000

Source: Research based Calculation.

Table 5.2 reports unconditional correlation on the selected variables. According to the results of the correlation analysis, most of the variables have a positive significant correlation with each other at the 5% significant level. Only trade openness and internet usage tend to be uncorrelated. In the subsequent empirical study, we further investigate their link.

5.2 Panel Unit Root Tests

In order to prevent issues with spurious regression, panel-unit root tests were run on each series to see if the data were stationary. In order to establish whether first-generation or second-generation tests of stationarity will be used, lags must first be chosen, and a pretest assessment of the cross-sectional independence among the panel units must be carried out.

5.2.1 Lag Order Selection

Due to the relatively small sample size, only three lags are allowed to select from; as the maximum lag order for the AIC criterion. Based on Wooldridge (2016) one or two lags are sufficient in case of modest sample size and the data is annual in order to maintain degrees of freedom.

Table 5.3: Lag Order Selection

Lags	LPCO2	LPRGDP	LPEG	LTO	LNET	LMOB
1	-1126.2378*	-2206.09	-986.4892*	-883.578*	-184.43998	-218.4616
2	-1060.9236	-2218.276*	-942.8126	-824.78	-229.8764	-487.8254
3	-994.711	-2104.504	-909.96	-776.2818	-342.68088*	-556.2294*

Source: Research based Calculation. * indicates lag order selected

According to the results of Table 5.3, one lag is being selected for the variables; per capita electricity generation, per capita CO2, and trade openness while two lags are being selected for PRGDP, finally three lags are selected for the internet usage and mobile penetration. Lags chosen, as shown in Table 5.3, are used for cross-section dependency tests and panel unit root analyses.

5.2.2 Testing for Cross-Section Dependence

Table 5.4 shows the findings from the examination of the cross-sectional correlation among the panel units. The ADF regressions for the panel series applied the lags as indicated in Table 5.3

Table 5.4: The Pesaran 2004 (CD)

	With Intercept	With trend
Variables	Pesaran CD-statistic (P-value)	Pesaran CD-statistic (P-value)
LPRGDP	27.91***	26.63***
LPCO2	9.683 ***	8.616 ***
LPEG	7.046 ***	7.351***
LTO	29.09***	28.65***
LNET	0.3564	2.624***
LMOB	3.156***	3.731***

Source: Research based Calculation.

According to the results of Table 5.4 being with intercept only, only the internet variable cannot reject the null hypothesis at the 5 percent level of significance while the other variables significantly reject the null. On the other hand, all of the variables reject the null at the 1 percent significance level when a trend is included. As a result, it is safe to decide that the panel units are cross-sectionally dependent based on the majority of outcomes in both cases.

5.2.3 Panel Unit Root Tests

Second-generation panel unit root tests will be applied since the panel has proven the cross-sectional dependence issue. The tests will be applied for both specifications of having an intercept only and intercept and trend. Lags have been applied according to the results of Table 5.3.

Table 5.5: Second generation panel unit root tests; The Pesaran (2007)

Specification	With intercept CIPS(2007)		With Trend CIPS(2007)	
	Level		First Difference	
LPRGDP	-1.671	-2.869**	-1.416	-2.666**
LPEG	-1.995	-3.580**	-2.235	-4.007**
LTO	-1.730	-3.521**	-2.424	-3.669**
LPCO2	-2.444**	_	-2.473	-4.374**
LNET	-2.384**	-	-2.945	-4.118**
LMOB	-1.554	-2.871**	-1.471	-2.666**

Source: Research based Calculation.

(1) the critical values for the CIPS statistic, in the case of intercept only, are -2.07,-2.15, and -2.3 for variables in level and -1.47,-1.58, and -1.76 for differenced variables. (2) the critical values for the CIPS statistic, when there is a trend, for the variables

in level are -2.58, -2.66, and -2.81, and -2.07, -2.15, and -2.32 for variables in difference. (2) the number units in the panel =30 and time periods=21 for the variables in level and *, **, *** is used to indicate significance at the 10%, 5%, and 1% levels.

The findings demonstrate that in the event of an intercept only, only the per capita CO2 emissions and the internet variables are stationary at the 5 percent significance level, whilst the other variables are stationary at the first difference. On the other hand at their first difference; all the variables are stationary at the 5 percent level of significance when a trend is taken into account. As a result, it is possible to infer that the majority of the variables are stationary at their first difference according to the tests that were used, and that it is preferable to continue testing for co-integration relationships between the variables.

5.2.4 Panel Co-integration Tests

The next stage is to determine whether or not the variables have a long-term relationship or co-integration. A second-generation test of Westerlund's (2007) is utilized since cross-sectional correlation is present; this test should be more trustworthy when cross-sectional units are suspected of being associated.

After bootstrapping for all of the variables, both Pt and Pa came to the conclusion that the panel is not cointegrated based on the panel statistics and failed to reject the null hypotheses. Table 5.6 displays the findings, with each variable serves as a dependent variable. The panel can be thought of as non-cointegrated because the PCO2 is the primary dependent variable. After determining that the panel is not cointegrated, the following stage entails using panel VAR to investigate short-run relationships.

Table 5.6: Panel co-integration tests of the second generation

Statistic	Response variables	Value	Z-Value	P-Value	Robust P-Value
Pt	LPCO2	-13.577	-0.814	0.208	0.500
Pa		-0.455	7.139	1.000	0.800
Pt	LPRGDP	-3.225	9.040	1.000	0.123
Pa		-0.387	7.183	1.000	0.140
Pt	LPEG	-6.094	6.387	1.000	0.570
Pa		-0.354	7.205	1.000	0.810
Pt	LTO	-9.548	3.191	0.999	0.090
Pa		-0.198	7.307	1.000	0.980
Pt	LNET	-3.754	8.551	1.000	0.490
Pa		-0.369	7.195	1.000	0.660
Pt	LMOB	-6.203	6.286	1.000	0.320
Pa		-0.340	7.214	1.000	0.750

Source: Research based Calculation .

5.2.5 Panel VAR Outcomes

Panel VAR in difference will be used to estimate the endogenous behavior of the variables based on the results of the co-integration tests and lacking co-integration between the model variables. Choosing the lag length is the first step in estimating PVAR; the proper lag in this case, as stated in Table 5.7, is one period based on the AIC criteria.

Table 5.7: Criteria for Lag Order Selection

Lags	BIC	AIC	QIC
1	-516.1871*	-72.38836*	-247.3059*
2	-353.5182	-57.65239	-174.2641
3	-168.6014	-20.66851	-78.97437

Source: Research based Calculation .* indicates the lag order selected .

The PVAR model will be estimated using a system GMM framework after the lag length has been chosen. The default setting for the system GMM uses just one lag as an instrument because it uses an instruments number equal to the number of regressors in each equation. Considering the dynamic equation in first difference form, it is a typical procedure that the country-specific effects should be removed. Besides, the endogeneity of the regressors should be taken into account when estimating the first difference equation. In reality, utilizing the instrumentation approach is crucial to avoid inconsistent and imprecise estimates because the right-hand lagged dependent variable is by construction linked with the error term. Accordingly, Blundell et al., (2001) emphasized that using the system GMM (SGMM) estimator increases the precision by incorporating an additional set of instrumental variables. As a consequence, we estimated the regressions using the system GMM estimation method taking into account what Blundell et al., (2001) recommended.

It should be noted as well , the PVAR analyzes the effects of ICT variables and electricity generation on environmental quality controlling for the gross domestic product ($PRGDP_{it}$) and the level of trade openness (TO_{it}) of a country i in period t.

Additionally, using the variables in their first differences brings serial correlation into the model by default; thus, the only way to address this issue is by introducing more lags to the system acting as instruments. Hansen's j test is employed to surveying of the over-identifying validity when further lags have been added to the system. Therefore, determining whether a serial correlation exists or not; is a necessary step before computing the PVAR, as shown in **Table 5.8**

Table 5.8: Autocorrelation Wooldridge Test

Response Variable	F-Statistic
PCO2	21.708***

Source: Research based Calculation .

Further lags should be added as instruments since, as indicated in **Table 5.8**, the serial correlation was determined to be significant at the 1% level of significance. Hansen's over-identification test should be used to confirm the precision of these instruments. The next step is to apply the PVAR.

Table 5.9: Panel VAR model

Response variables	(SGMM Estimates) Regressors					
	ΔLPCO2 (-1)	ΔLPEG (-1)	ΔLTO (-1)	ΔLNET (-1)	ΔLMOB (-1)	ΔLPRGDP (-1)
D.LPCO2	-.1376319**	.1341202***	-.0523203*	.0365152**	-.0001444	.4266614**
D.LPEG	-.0536867	.2010702**	.0985213**	.0102588	-.0152987	.1308056
D.LTO	.1090649**	-.0562244	.1420391***	-.011863	.0101158	.073456
D.LNET	.0634067	-.0002677	.0972592	.2939868***	.0153471	.4793947**
D.LMOB	-.123052**	.0805111	.06864	-.0127098	.3623394***	.5926888*
D. LPRGDP	-.0055709	-.0047569	.0164211	.0025031	.020135***	.2733584***

Source: Research based Calculation . *, **, *** are the significance levels at the 10%, 5%, and 1% and Hansen's J chi^2 = 70.210795 (p = 0.538).

Table 5.10: Panel Granger Causality Test Results

	Chi^{2}-Probabilities					
Response variables	ΔLPCO2	ΔLPEG	ΔLTO	ΔLNET	ΔLPRGDP	Δ.LMOB
DLPCO2	-	13.666***	3.050*	4.190**	5.166**	0.000
D.LPEG	1.742	-	6.035**	0.293	0.870	0.673
D.LTO	4.887**	1.282	-	0.363	0.110	0.254
D.LNET	0.426	0.000	1.534	-	3.580**	0.049
D. LPRGDP	0.170	0.166	1.690	0.258	-	8.143***
D.LMOB	4.060**	2.579	1.074	0.180	2.865*	-

Source: Research based Calculation. *, **, * indicate significance at the 10percent, 5percent, and 1percent levels of significance.**

Over the past three decades, there has been a steady growth in the percentage of the population with access to electricity in lower-middle-income countries. In examining the impact of the expansion of electricity generation and economic well-being on per capita CO2 emissions, results show that these middle-income countries are likely to face a trade-off between economic growth and environmental quality as well as a trade-off between electricity generation and environmental quality as well. A 1 percent increase in economic growth and electricity generation results in a 0.42 percent and 0.13 percent increase in emissions respectively. As a result, these nations may need to establish policies that complement the production of renewable energy and enhance energy efficiency while at the same time stimulating the economic growth of these countries. Granger causality analysis reveals a unidirectional causal link going from electricity generation to CO2 as well as a unidirectional causal link between economic growth and CO2 emissions. However, there was no evidence of a Granger causal relationship between the production of electricity and economic growth, confirming the neutrality hypothesis i.e., there exists no cause-and-effect relationship between both variables. Such a result shows that policies to conserve electricity generation from fossil fuels could be implemented safely without sacrificing the country's economic growth, a matter that should also help in detachment of CO2 emissions from economic growth.

Additionally, the development of trade policies must take into account how international trade affects environmental quality. Regarding how trade liberalization affects the environment, results show that trade openness negatively and significantly influences environmental quality where for every 1 percent increase in openness to trade, the quality of the environment is improved by 0.05 percent. This outcome is comparable to that of Shahbaz et al. (2013), who discovered that trade openness enhances environmental quality in Indonesia as a result of increased research on foreign direct investment. Additionally, using data from 14 MENA countries from 1990 to 2011, Omri, (2013) analyzed the relationship between CO2 emission and international trade and confirmed a negative but statistically negligible effect of trade openness on CO2 emissions for the panel as a whole and for individual nations. Additionally, evidence in some of the examined countries in our panel shows that trade openness improves environmental quality; The dynamic effects of trade openness and CO2 emissions were examined by Ali et al. (2019) using the autoregressive distributed lag-bound testing technique for Nigeria, for the period 1971–2010, demonstrating that trade openness improves environmental quality . Also, Rafindadi (2016) demonstrated that trade openness improves environmental quality by lowering CO2 emissions in Nigeria as well.

To conclude, technological effects can explain the inverse association between trade openness and carbon emissions. Cleaner and more effective technology practices spread throughout partner countries as commerce creates a channel for spillover effects. In the end, trade openness fosters a positive cycle that supports economic growth by increasing employment opportunities, regulating capital flows, and fostering competitiveness. Accordingly, these lower middle-income countries ought to support preferential trade policies, with a focus on technical value addition, which can be fostered by reciprocal trade liberalization and the removal of trade restrictions. To uphold their commitment to environmental protection, these nations must set regulations that promote the development of so-called non-polluting industries or more ecologically friendly production methods. In addition, they must use legal instruments to limit CO_2 emissions from the manufacturing sector, such as a carbon tax, environmental tax, or green tax. As a result, it is crucial to proceed cautiously when interpreting our findings that, for low-middle-income countries, trade will typically tend to cut emissions in the short run. This is because the net impact of trade on pollution may vary depending many factors.

Considering the effects of internet usage, in general, it accounts for 3.7 percent (energuide,2023) of all global greenhouse gas emissions. This number is anticipated to double by 2025, excluding the Covid-19 effect. In reality, just using the internet results in an annual average CO_2 output of 400 g per resident. ICT influences the environmental quality due to its need for generating energy. For instance, a one-megabyte email (= 1 MB) emits 20 g of CO_2 throughout the course of its lifetime, which is the same amount as a 60 W lamp that has been lighted for 25 minutes. Over the course of a year, 20 emails per user produce the same amount of CO2 emissions as a car traveling 1000 kilometers.

Additionally, a web address search takes up 3.4 Watt hours (0.8 g CO2 equivalent). It is possible to calculate that an online user who conducts 2.6 web searches each day is releasing 9.9 kg of CO2 equivalent annually. As of July 31, 2022, the earth had 7,934,462,631 inhabitants, 69.02 percent of whom were internet users. The number of internet users increased by 614 percent in Europe, 2,467 percent in Asia, and 14,362 percent in Africa between 2000 and 2022 (Hilty et al., 2006). The Internet World Stats, IWS, estimates that there were 4.648 billion internet users globally in June 2020 which consequently has a significant impact on the ecological environment.

On the other hand side, internet penetration can improve environmental quality by facilitating the rapid flow of knowledge and information at a reduced cost, lowering CO2 emissions, and promoting sustainable economic growth. This can be achieved when internet technology in the production sector increases energy usage effectiveness and hence lower CO2 emissions. Additionally, the development of intelligent transportation systems and smart cities that make use of big data, block chain, and other internet technologies will significantly lower CO2 emissions (Salahuddin and Alam, 2016).However, the results of this paper show that internet usage significantly and positively affects emissions per capita where for every 1 percent increase in using the internet, CO_2 emissions increase by 0.03 percent. Yet, the fact that the coefficient is quite modest suggests that these countries increase in internet usage does not yet pose a threat to the environment. Similar to our results, Salahuddin and Alam, (2016) discovered that the OECD countries were unable to utilize information and communication technology efficiently, and hence, CO_2 emissions have increased. Likewise, Shabani and Shahnazi (2019) studied the relationship between internet use and CO_2 emissions using a panel causality model on Iranian economic sectors and found that internet use considerably increased CO_2 emissions. The results of this paper show that the use of the internet hasn't had a beneficial impact on reducing environmental pollution. This is likely due to the fact that the internet's technological advancements in lower-middle-income countries are insufficient to reduce CO_2 emissions, and that customers in these nations do not have the money to pay for and use internet-related items.

As previously mentioned, internet usage and mobile penetration are the two variables used to quantify ICT. While the former lowers environmental quality, the latter has no impact on the environment. In actuality, a smartphone contributes to climate change and global warming over its entire life cycle, from manufacturing to disposal. The energy-intensive mining required to obtain the heavy metals used in smartphones, such as lithium, cobalt, and gold, usually results in serious environmental damage. Results, however, indicate that using a mobile device has little effect on CO2 emissions. Furthermore, the economic growth in lower-middle-income countries does not appear to be impacted by the internet penetration rate. We discovered that there was little correlation between the former and the latter. This finding contrasts with that of Bhattacharya and Ghosh, (2020), used panel data regression methodologies, and discovered that internet use had a generally favorable impact on economic growth in lower-middle-income and low-income nations between 2002 and 2011.

Also, the fact that this study looks at how mobile cellular penetration affects both environmental quality and economic growth adds to the body of literature. In general, empirical evidence of a positive correlation between economic growth and mobile phone adoption has been established over the past two decades by a small but growing number of research.. Numerous studies have discovered a connection between the use of mobile devices and economic expansion. In industries like agriculture, health, education, and finance, mobile phones have increased production, social inclusion, and economic activity. Fixed lines are often replaced by mobile phones in emerging nations. Mobile phones, according to WIPO Magazine, 2010, encourage business growth and improved market access, all of which advance the economy. In addition to voice calls, mobile phones can now give customers easy access to a variety of cutting-edge applications thanks to technological advancements. People are being given the opportunity to obtain market data, track healthcare, send money, and promote literacy in undeveloped countries.

The influence of mobile phone use on economic growth and development in sub-Saharan Africa is also explored in study by Aker and Mbiti (2010). People in Ghana, for instance, use their cellphones to talk to family members and look up the price of grains and tomatoes. But, people in Niger use their phones to look up employment vacancies. In Vietnam, people use their cell phones to look for new business opportunities. Many users find the technology handy since it enables them to keep track of transactions when they use them for mobile banking (Foster, 2007). By examining the effects of mobile penetration on economic growth and evaluating its influence on the environment as well as economic growth, this study fills in significant evidence gaps. Our findings demonstrate that a 1 percent increase in mobile penetration increases GDP per capita by 0.02 percent and that such a relationship is bi-directional where a 1 percent increase in economic growth raises mobile penetration by 0.59 percent. The bi-directional Causality between economic growth and telecommunications (mobile telephone), indicates that telecommunications are a consequence and a cause of economic growth. However, whereas internet usage reduces environmental quality, mobile penetration has an insignificant impact on the environment.

5.2.6 Panel Impulse Response Function:

The three shocks that will be looked at in this analysis are (I) the positive shock for mobile penetration on economic growth and per capita CO2 emissions, (II) the positive shock for internet usage on economic growth and per capita CO2 emissions, and (III) the positive shock for openness to trade on per capita RGDP and per capita CO2 emissions. An interval of 95% confidence is used to produce the impulse response functions. Finally, it should be highlighted that the PVAR must be stable, which it is in this instance as seen in Appendix C, for impulse response functions to be legitimate. The impulse response functions are illustrated in **Figures 5.1, 5.2, and 5.3:** The 10-year period responses of one variable to one standard deviation of innovations to another variable are taken into consideration, as in prior studies.

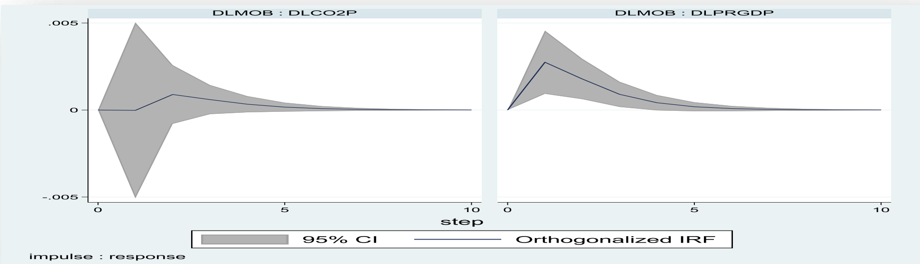

Figure 5.1: Response of ΔLPRGDP and Δ LPCO2 to a shock in ΔLMOB

Source: Research based Calculation.

The orthogonalization of the PVAR residuals assists in isolating the response of both per capita CO2 emissions and per capita real GDP to a shock on mobile penetration. Figure 5.1 shows that one standard deviation shock on mobile penetration, like for instance technological improvements that leads to lower mobile prices or better networks for a better connection between people, initially at the first period remains with no effect but then increases at the second period reaching its peak after then decreases till it stabilizes at the 8^{th} period. Similarly, the same shock on mobile penetration leads to a higher initial increase in the per capita RGDP in the first period reaching its peak and then decreasing till it stabilizes in the 7^{th} period. Both figures show that further developments in mobile penetration during its early stage gives a rise to both environmental degradation and more economic growth. This analysis proves the idea of having a trade-off between having better growth rates at the expense of environmental quality.

With respect to the response of the carbon dioxide emissions to a one standard deviation shock in internet usage, as shown in Figure 5.2, the emissions are exhibiting a positive behavior reaching their peak in the first year after which it is decreasing but still positive then stabilizes. As for the response of the economic growth, it is easy to see that at first, the shock positively affected the PRGDP but with a downward trend; it then fluctuates and stabilizes by the end of the 10 years period.

The analysis shows that using the internet still doesn't achieve the desired goals of having faster rates of economic growth while maintaining environmental quality.

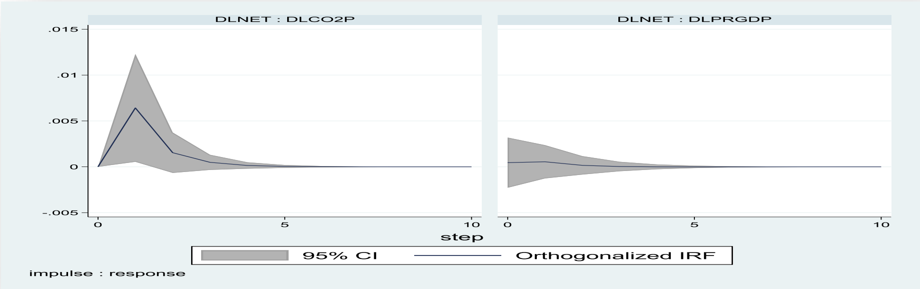

Figure 5.2: Response of ΔLPRGDP and Δ LPCO2 to a shock in ΔLNET

Source: Research based Calculation.

With respect to the response of the carbon dioxide emissions to a one standard deviation shock in trade openness, as shown in Figure 5.3, the emissions are exhibiting a negative behavior reaching their minimum in the first year after which it is gradually increasing through the periods from the 3rd to the seventh and then stabilizes. Initially, as previously indicated, the negative influence of trade openness on PCO2 emissions, at the early stage of the shock, could be the trade-related emissions that can be reduced thanks to technological advancement and global climate cooperation. However, the positive influence of trade, after that, on PCO2 emissions that can be imaginable by the positive unintended influence of the trade openness on emissions by electricity generation. As for the response of economic growth, initially the economic growth declines but then a gradual increase positively occurs where it stabilizes after the seventh period. This is due to the fact that trade openness has the ability to boost economic growth by increasing resource allocation efficiency and enhancing total factor productivity through the adoption of new technologies and the spread of knowledge.

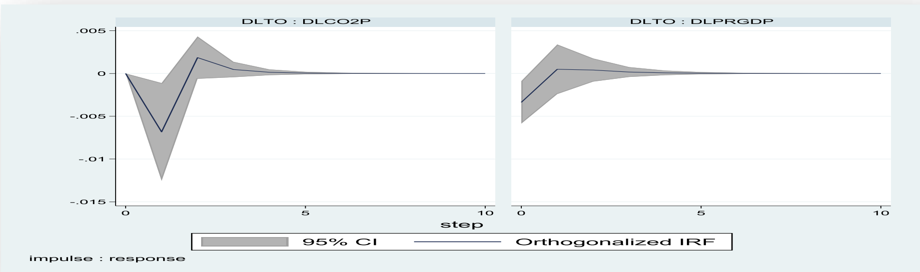

Figure 5.3: Response of ΔLPRGDP and Δ LPCO2 to a shock in ΔLTO

Source: Research based Calculation.

The important feature for the panel is that the impact of the positive shocks for the examined variables is always converging to zero taking an average period of seven years to adjust to the shock.

6. Policy Implications

The findings supported the claim that low- middle-income countries won't be able to grow their internet usage without experiencing negative environmental repercussions. Adoption of particular ICT goods and the ICT sector as a whole should be improved in order to lessen the environmental impact of internet usage. Recent events like (Covid-19) show that digitization is both unavoidable and certain. As a result, it is critical to create regulations that reduce emissions and prevent the spiraling impacts of ICT's energy demand. In addition, ICT can have a positive impact on economic growth by making information accessible to the general people via mobile phones in poor countries. Mobile devices can also improve the producers' and consumers' economic well-being. The two-causality relationship between mobile penetration and economic growth shows how crucial mobiles are to boosting greater growth rates in these nations. In conclusion, the consequences of ICT policy should help developing countries achieve greater growth while also looking for efficient energy delivery that would reduce environmental degradation.

Then again, there are a number of ways that trade with other countries affects GHG emissions. GHG emissions are produced during all stages of the manufacturing, transportation, distribution, and consumption of traded goods and services. Trade could help countries move to a low-carbon economy, which is necessary for advancing green technology. Therefore, technical improvement and international climate cooperation can help to cut trade-related emissions. Public policies are therefore essential in this scenario to encourage companies and customers to act and make decisions in a more sustainable manner. International cooperation is also essential to maximizing synergies in the initiatives to lower the carbon content of global trade, particularly through the adoption and spread of green technologies.

According to the aforementioned findings, policymakers of these countries should take all necessary steps to limit the use of fossil fuels for electricity generation .Such recommendation is consistent with the neutrality hypothesis between electricity generation and economic growth. The energy mix should also be improved by increasing the share of renewable energy generation. Since the richest nations must shoulder responsibility for limiting global warming, financial support is required. Additionally, one of the crucial steps towards the continued development and application of renewable energies is the expansion of knowledge and the reduction of political and economic obstacles.

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Appendix A : Research Variables and their Figures Source (s)

Variable	**Proxy**	**Definition**	**Source**
ICT	Mobile cellular subscriptions (per 100 people)	Mobile cellular telephone subscriptions are subscriptions to a public mobile telephone service that provide access to the PSTN using cellular technology. The indicator includes (and is split into) the number of postpaid subscriptions, and the number of active prepaid accounts (i.e. that have been used during the last three months). The indicator applies to all mobile cellular subscriptions that offer voice communications. It excludes subscriptions via data cards or USB modems, subscriptions to public mobile data services, private trunked mobile radio, telepoint, radio paging, and telemetry services.	World Bank www.worldbank.org
	Individuals using the Internet (% of the population)	Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV etc.	World Bank www.worldbank.org
Globalization	Trade (% of GDP)	Trade is the sum of exports and imports of goods and services measured as a share of the gross domestic product.	World Bank www.worldbank.org
Economic Growth	GDP per capita (constant 2015 US$)	GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for the depreciation of fabricated assets or for the depletion and degradation of natural resources. Data are in constant 2015 U.S. dollars.	World Bank

Electricity generation	Per capita electricity (KWH)	Annual average electricity generation per person is measured in kilowatts per hour.	BP Statistical Review of World Energy: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html
Environmental Quality	Per Capita CO2 emissions	Annual production-based emissions of carbon dioxide (CO2), are measured in tonnes per person.	BP Statistical Review of World Energy: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

Appendix B: The Investigated Low-Middle-Income Countries List

#	***Country***	***Location***
1	Algeria	Africa
2	Angola	Africa
3	Benin	Africa
4	Bangladesh	Asia
5	Bolivia	South America
6	Cambodia	Asia

7	Cameroon	Africa
8	Cote d'Ivoire	Africa
9	Egypt, Arab Rep.	Africa
10	El Salvador	North America
11	Ghana	Africa
12	Haiti	North America
13	Indonesia	Asia
14	India	Asia
15	Iran, Islamic Rep.	Asia
16	Kenya	Africa
17	Mauritania	Africa
18	Morocco	Africa
19	Nicaragua	North America
20	Nigeria	Africa
21	Pakistan	Asia
22	Philippines	Asia
23	Senegal	Africa
24	Solomon Islands	Oceania

25	Tanzania	Africa
26	Tunisia	Africa
27	Ukraine	Europe
28	Uzbekistan	Asia
29	Vietnam	Asia
30	Zimbabwe	Africa

Source:https://databank.worldbank.org/reports.aspx?source=2&country=UMC

Appendix C: PVAR Stability