BROADBAND, CLEAN TECHNOLOGY ADOPTION AND SUSTAINABLE DEVELOPMENT: A GLOBAL PERSPECTIVE.

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DECLARATION

I, Kwabena Fio Tangato, do hereby declare that the work which is being presented in the thesis, entitled "Broadband, clean technology adoption and sustainable development: A global perspective" in fulfilment of the requirements for the award of the degree of Doctor of Philosophy in Economics at the department of economics and social sciences and submitted to Marche Polytechnic University (Università Politecnica delle Marche) is the record of an authentic and independent research work carried out by me during my PhD period under the supervision and guidance of Prof. Roberto Esposti, full professor of economic policy at the Department of Economics and Social Sciences.

Moreover, I certify that this entire subject matter embodied in this PhD thesis is entirely my own research work, and not taken from the contents of other works with the exception of works that have been duly cited and acknowledged in the text of my own elaboration and development. Finally, I do declare that it has not previously formed the basis for the award of or been submitted in part or whole to any other institution for award of any Diploma, Associateship, Degree, Fellowship or related title.

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DEDICATION

This thesis is most dedicated to God Almighty, whose blessings, grace and kindness, that found me, brought me this far. I also dedicate it to my mother, Madame Yaa Kenin for her priceless support to me in life and my late father, Mr. Kobina Dombe. Besides, this dedication cannot end without a special mention of my one-time supervisor, Prof Giuseppe Canullo to whom I am highly indebted to in gratitude.

ACKNOWLEDGEMENT

Indeed, God shows grace and mercy on whom He will. I must confess that it is the favour and mercy of the Almighty God which found me, that made this feat a reality in my academic career. The hard work and determination were divinely inspired by the Almighty. I am therefore profoundly grateful to the ever-merciful God for His grace on me and how far He has brought me on the academic ladder.

ABSTRACT

Global warming and climate change are global challenges that need a holistic attention and measures to tackle. The potential of environmental technologies and in particular, the role of the information communication society and green technology innovation sector to influence sustainability of the environment has not only courted global attention but also generated a new line of research interests.

Given the range of evolving technologies that could play a crucial role toward carbon neutrality by the year 2050, investing in technologies that can be leveraged across households, firms, industries and countries of the world, whose adoption can contribute to mitigation of carbon emissions in the shortest possible time is of significant importance and worthwhile investigating. Broadband of ICT and clean green technology are some of these technologies.

This research study employed a dynamic GMM (Generalized Method of Moments) estimator in addition to a battery of static models and other statistical techniques to investigate the impact of broadband and clean green technologies as well as examine the validity of the EKC hypothesis on CO_2 emissions in a global context using unbalanced panel dataset of 190 countries to represent the global economy. Given the hypothesis that, emissions and accessibility of these technologies could vary among countries, the research study deemed it relevant to consider levels of development of countries of the global economy by classifying them broadly into two categories: developed countries and emerging-developing countries for further comparative analysis. The empirical results indicated that, overall, at the global level these technologies have mitigating impact on CO_2 emissions. At the development levels, while broadband technology had heterogenous outcome in mitigating CO_2 emissions between developed and emerging-developing countries, clean green technology had homogenous

outcome in mitigating CO_2 emissions between the two country groups. Additionally, consistent with the study period and data used, the results further confirmed evidence of the EKC at the global level and for emerging-developing countries in the diffusion of these technologies.

The environmental implication of the research findings showed that if broadband technology users and the general ICT sector rely heavily on green materials and energy or electricity consumption produced from clean, renewable sources, a significant chunk of the ICT sector and other anthropogenic footprints could be reduced which will subsequently facilitate the decarbonization efforts of the global environment. Relatedly, the mitigating impact of the indicator measures of clean green technology on carbon emissions discovered in the study consolidated the assertion that widespread development and diffusion of clean green technologies in general can potentially help to reduce over dependence on fossil sources to decarbonize the global economy and improve environmental quality.

From policy point of view, the study recommends these technologies not only be considered as important part of global short and long-term policy measures to support climate change mitigation strategies, but also their use maximized at different levels of development. Governments in countries of the global economy should come up with policy measures aimed at providing their private sectors which are critical players when it comes to these technologies development, application and diffusion with the right competitive environment. It is also important at the country levels for both developed and developing countries not to only increase the use of these technologies but should also make them more cheaper and accessible by encouraging investments in them and other emerging green and exponential technologies.

Keywords: CO_2 Emissions, Broadband Technology, Clean Technology, Environmental Kuznets Curve, Sustainable Development, Global Economy, Panel Data

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ABBREVIATIONS

AI	Artificial Intelligence
ASEAN	Association of Southeast Asian Nations
BRI	Belt and Road Initiative
BRICS	Brazil, Russia, India China, South Africa
CCS	Carbon Capture Storage
CO_2	Carbon dioxide emissions
DCITA	Department of Communications, IT and the Arts
DOLS	Dynamic Ordinary Least Squares
DSL	Digital Subscriber Line
EKC	Environmental Kuznets Curve
EU	European Union
FCC	Federal Communications Commission
FMOLS	Fully Modified Ordinary Least Squares
G20	Group of 20 World's Biggest Economies
GDP	Gross Domestic Product
GHGs	Greenhouse Gases
GLS	Generalized Least Square
GMM	Generalized Method of Moments
ICT	Information communication technology
IEA	International Energy Agency
IoT	Internet of Things
ITU	International Telecommunication Union
IPCC	Intergovernmental Panel on Climate Change
Kbs	Kilobit per second

MENA	Middle East and North African
Mbps	Megabit per second
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Square
R&D	Research and Development
RE	Random Effect
SDGs	Sustainable Development Goals
SEA	South-East Asia
SSA	Sub-Sahara Africa
STIRPAT	Stochastic Impacts by Regression on Population, Affluence and Technology
IPAT	Impact Population Affluence Technology
WDI	World Development Indicators
WBCSD	World Business Council for Sustainable Development
3G	Third generation
4G	Fourth generation
5G	fifth generation

CHAPTER ONE

INTRODUCTION

1.1 Background

The whole world is looking with worried eyes at the increasing rate of degradation of the global environment. The world is experiencing temperatures increase and effects of global warming and climate change more today than never before. Hurricanes and storms are getting stronger, weather patterns are changing drastically, food security is under threat in developing regions, and animal extinction is on the rise.

The global patterns of climate change have awakened the thought for clean green technologies in both developed and developing countries that are required to sustain development. Green technologies such as renewable technology help to conserve the environment. Renewable energy consists of solar, wind, hydropower, geothermal, tidal, biomass and biogas (World Bank, 2019). Broadband and ICT can also help to reduce carbon emissions when renewable energies such as wind, hydropower and solar are used to power broadband enabled services and facilities such as mobile and fixed broadband subscriptions and internet services. On the other hand, when the source of power for broadband and related applications and facilities are non-renewables (fossil, oil, gas etc), their use could negatively impact environmental quality. Besides, contemporary broadband and ICT applications are seen as direct mechanisms for facilitating the use of renewable resources (Andreopoulou, 2012). There are many ways in which broadband and ICT can promote the adoption and use of cleaner technologies and renewables in economies and one of these is through linking broadband and ICT application systems to smarten and green traditional energy grids that can help in the use of renewable resources for generation of small-scale electric power (Ahmed et al., 2017).

The emergence of the Covid-19 which peaked in April 2020, and the global lockdown it occasioned which induced significant drops (43%, 12% and 43% in transport, aviation, and power and industrial sectors respectively) (Le Quéré et al., 2020), in carbon emissions across different sectors and countries in the world economy is a clear indication that, the issue of global warming attributable to anthropogenic and other economic activities is a confirmed reality that needs urgent innovative measures to help in reaching the 1.5 - 2 ^{0}C Paris agreement temperature targets.

However, it is evident that, anthropogenic activities such as the burning of fossil fuels are the leading cause of climate change and global warming. Since the industrial revolution, the global economy has evolved and still evolving at a faster rate, resulting in a dramatic improvement in standard of living and productivity that are associated with severe degradation of the global environment. In 2017, the New Policies Scenario of the World Energy Outlook 2017 advised that global energy-related CO_2 emissions are increasing toward 2040. This is a clarion call for urgent effective measures to protect the global environment from climate disasters. Among the alternative paths of climate change mitigation and adaption, broadband accessibility and clean green technology adoption (including energy technology, energy efficiency technology, among others) are potential factors that could contribute to mitigation of carbon emissions (IEA, 2013; Du et al., 2019). It has also been argued that in different economies and regions of the world, R&D and diffusion of green technology are not the same. This presupposes that the impact of green technology innovations might depend on certain social and economic considerations (such as level of income among others), (IEA, 2015). Thus, according to Du et al. (2019), getting a detailed understanding of the relationship between human economic activity, green technology innovation and CO_2 emissions would help to protect the environment.

Given these developments in addition to other trajectories of global issues such as population growth, and inefficient use of energy among others, there is every reason for countries of the global economy to pursue paths of technology innovation, development and adoption towards green growth and other economic activities that are more eco-friendly as a concerted effort for mitigation of GHGs and preservation of the natural environment. But the much talked about sustainability of the global environment can only be realised when there is less deterioration of the environment through the implementation of an all-inclusive policies both at the national and international levels to ensure that the needs of future generations are not compromised, Guo et al. (2020). The role of broadband and clean green technologies is one of such policies. Thus, the main objective of this research study is to study the relationship between broadband technology, clean technology and environmental sustainability at the global level using a common dynamic framework of investigation (dynamic GMM).

1.2 Research Questions

Understanding the effects of broadband and clean green technologies usage in mitigating CO_2 emission is worth an empirical investigation. Based on existing literature therefore, this research study poses and seeks to answer the following fundamental questions:

I. Can broadband technology significantly contribute to mitigation of CO_2 emissions in the global economy?

II. Can clean green technology adoption significantly contribute to mitigation of CO_2 emissions in the global economy?

III. Do development (income) levels of countries of the global economy affect the impacts of these technologies in mitigating CO_2 emissions?

IV. Consistent with the study period, can the EKC hypothesis be confirmed for the global economy, developed and emerging developing countries in the diffusion of these technologies?

1.3 Contribution of the Research Study

The study aims to empirically investigate the above questions using a new panel dataset. Contributions of this study are as follows. First, existing studies mainly focus on the impact of general ICT and technological innovation on CO_2 emissions; only few studies investigate the role of broadband and clean green technologies. This study provides new evidence on the net effects of broadband and clean green technology use on CO_2 emissions.

Secondly, it contributes to literature by filling the gap created by most studies that focus only on cities, economic sectors, country levels, and economic blocs rather than in a global context. This is also relevant because aside the fact that, the generalization of the findings of such studies are limited to their settings of study, macroeconomic evidence is still not very rich and deserves further analysis at the global level.

Thirdly, to the best of knowledge, this is the first and the only study that attempts to examines the environmental mitigating role of broadband and clean green technology while, simultaneously taking into account the level of economic development of countries using a common dynamic framework of investigation in a global perspective. Using these technologies within the broader nexus between general ICT, environmental technology and sustainability could be helpful in explaining the extent to which broadband and clean green technology could be used as important policy of the environment. Besides, the study differs from other studies in terms of the dataset, methodology, study period and proxy indicators of variable measurement of interest. In addition, the study uses a battery of panel data estimation techniques that are robust in analysing cross-sectionally dependent and panel time series dataset.

Finally, it offers appropriate policy implications and recommendations that are beneficial to the global economy, developed countries and emerging-developing countries that could help in tackling global warming and climate change.

1.4 Motivation of the Research Study

The research study is motivated by the following considerations. First is concerns about degradation of the environment that could result from inefficient use of broadband and clean technology services and facilities in the global economy against the decarbonizing potentials of these technologies to improve environmental sustainability in the global environment, developed and emerging-developing countries; coupled with the fact that investigation of the role of these technologies usage is a new and ongoing debate, in which there exist gaps in extant literature of not including variables of these technologies.

Secondly, broadband and ICTs have become influential drivers of individual lifestyles, business operations, economic growth of countries, and development in almost every part of the globe (Rejeski, 2002). Energy consumption and carbon emissions concerns are also gaining attention in emerging and developing countries (Brazil, Russia, India, China, and South

Africa), although broadband and clean technologies have also been developing in these economies over recent decades. For instance, data and estimates from the International Energy Agency indicate that in 2013, BRICS countries emitted CO_2 emissions more than OECD countries, and are likely to be sustained into 2023, (Su et al., 2021).

Thirdly, to rethink and apply a different approach and scope of investigation of how certain component (broadband diffusion) of general ICT, energy utilization and innovative clean technology energy production could affect environmental quality in a global perspective is another motivation of the study. How broadband and clean technologies adoption could avoid or reduce carbon emissions has courted interest in the research community.

1.5 Outline of the research Study

The rest of the research study is organized as follows: Chapter 2 provides overview of broadband usage, clean technology and environmental sustainability. Chapter 3 is dedicated to a review of related literature. Chapter 4 deals with methodology and data presentation. In chapter 5 and chapter 6, empirical results are presented, discussed and analysed. Chapter 7 contains conclusion and findings, policy implications and recommendations of the research study.

CHAPTER TWO

OVERVIEW OF BROADBAND, CLEAN TECHNOLOGY AND ENVIRONMENTAL SUSTAINABILITY

2.1 Broadband Technology

The International Telecommunication Union defined broadband as a network connection with transmission speed equal to, or greater than, 256 Kbps (ITU, 2005, 2006). But modern definition goes beyond this traditional meaning of broadband to include improving bandwidth, speed, and functionality. According to the FCC, the definition of broadband internet is a minimum of 25 Mbps download and 3 Mbps upload speeds. Broadband provides high speed internet access via multiple types of its technologies including fibre optics, wireless, cable, DSL, and satellite. It is for this reason that it is also defined as "fast, "always-on" online access to digital content, applications and a range of services, some or all of which can occur simultaneously" DCITA (2006), and according to Dodd (2007), this definition is consistent with international understanding.

In recent decades, the world has witnessed an explosive use of information communication technologies (ICTs) that is unprecedented. Increasing number of people have switched from the use of fixed telephony services to smart cellular broadband devices and services, which could have both negative and positive impacts on the environment. Broadband technology has played an important role in globalizing and integrating the world over the last decades. It has helped in the reduction of information cost and asymmetry. Broadband technology has improved energy efficiency, financial development, economic growth and development, (Pradhan et al., 2014). It has also created opportunities for other technology innovations in the world.

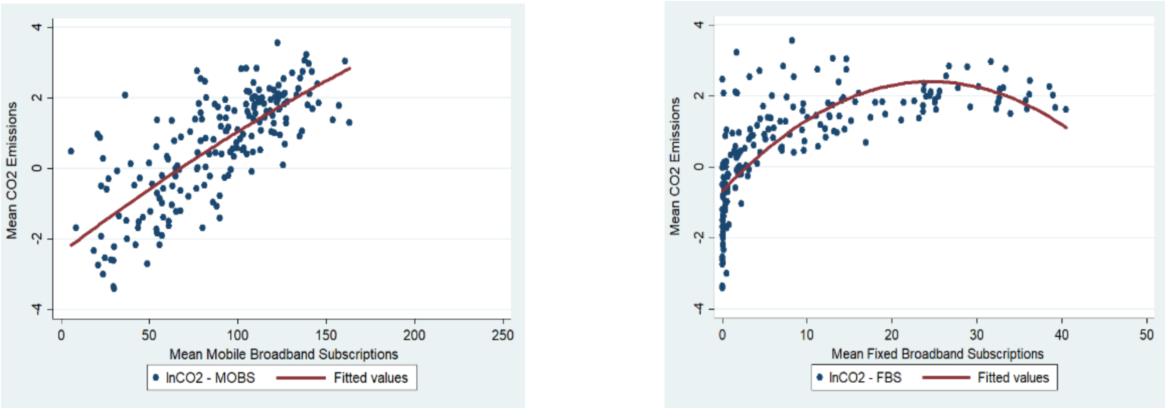
Lying at the heart of the evolution and development of general ICT is broadband technology (Lee et al., 2010). It has therefore become a very important ICT utility in the world to the extent that its enablement impact in the information communication industry goes beyond the infrastructure to practical application of the technology (Coonan, 2006; DCITA, 2006). It has also brought many changes in modern global economy, ranging from the way we work, interact, transact businesses, communicate, and access information. These changes have significant implications on environmental sustainability (Dodd, 2007).

As an enabler of ICTs, broadband (both mobile and fixed) has become the leading technological revolution indicator and utility of the information communication society. Since the 1990's, mobile information communications technology, especially mobile phone diffusion has transformed the economies of the world. New technologies and improved services have overtaken traditional telecommunication services. Telecommunication, information, and internet services have improved greatly with increasing subscriptions. The IEA in 2017, observed that mobile broadband subscription users of the world's total population were more than 4 billion subscribers with more than 3.5 billion people having access to broadband internet service. Between 1990 and 2015 alone, mobile cellular subscription in the global economy increased from 2.4 million to 7.6 billion subscribers (Saylor, 2012; The Mobile Economy, 2016). Projections showed that, this number was expected to continue increasing significantly in the coming years (Donner, 2008; ITU, 2003; Lavin, 2005). And this is happening across all levels and regions of development in today's world. Figures from ITU (2020) indicate that 93% of the world inhabitants had access to mobile-broadband networks, and between 2015 and

2020, 4G network coverage increased two-fold globally. In terms of 4G network coverage across levels of economic development in 2020, developed countries had 97% and developing countries had 82%. Fixed broadband subscriptions for the world, developed and developing countries were 15%, 34% and 12% respectively in the year 2020 (ITU, 2020). However, much as this increasing usage has brought about significant improvement in global economic growth and development, it has also added to the issue of global energy consumption and environmental pressures.

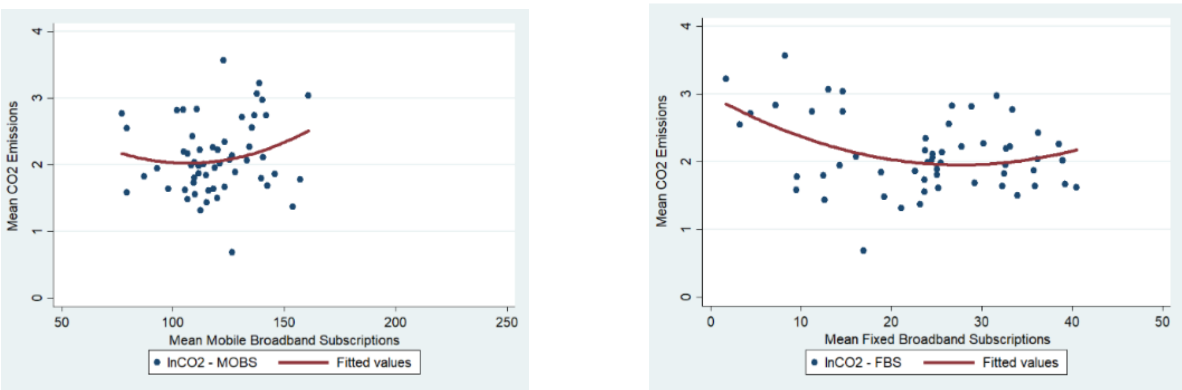
The relationship between the main utility of general ICT (i.e., broadband) and environmental performance is relatively a nascent area of inquiry and investigation. Although attempts have been made, existing literature still lacks general agreement on the exact impact of broadband technology on environmental performance. Broadband and ICT can reduce carbon emissions when renewable energies such as wind, hydropower and solar are used to power broadband enabled services and facilities such as mobile and fixed broadband subscriptions and internet services. On the other hand, when the source of power for broadband and related applications and facilities are non-renewables (fossil, oil, gas etc), their use could negatively impact environmental quality.

Figures (1-3) below, plot average values of mobile broadband and fixed broadband (proxy indicators of broadband technology) and CO_2 emissions, showing the relationship and distributional trend between CO_2 emissions and broadband technology for the global economy, developed countries and emerging-developing countries. From the scatter plots we can observe somewhat strong correlation between mobile broadband, fixed broadband and CO_2 emissions in the world environment and in emerging-developing countries but not so strong in developed countries. We can also observe some outlier points which warrant further investigations.



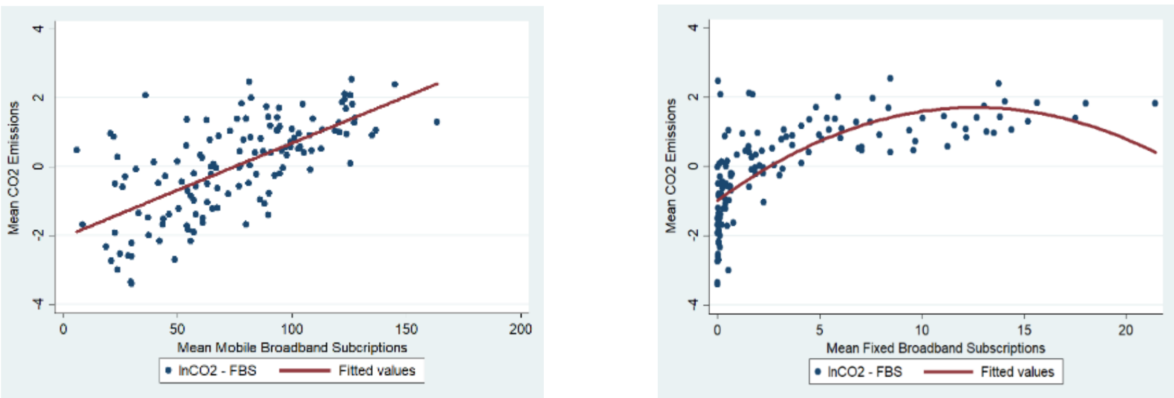
Global economy

Figure 1. Scatter plot of average CO_2 emissions, mobile and fixed broadband subscriptions for the global economy. Source: Author's computation using data from WDI.



Developed countries

Figure 2. Scatter plot of average CO_2 emissions, mobile and fixed broadband subscriptions for developed countries. Source: Author's computation using data from WDI.



Emerging-developing countries

Figure 3. Scatter plot of average CO_2 emissions, mobile and fixed broadband subscriptions for emerging-developing countries. Source: Author's computation using data from WDI.

2.2 Clean Technology

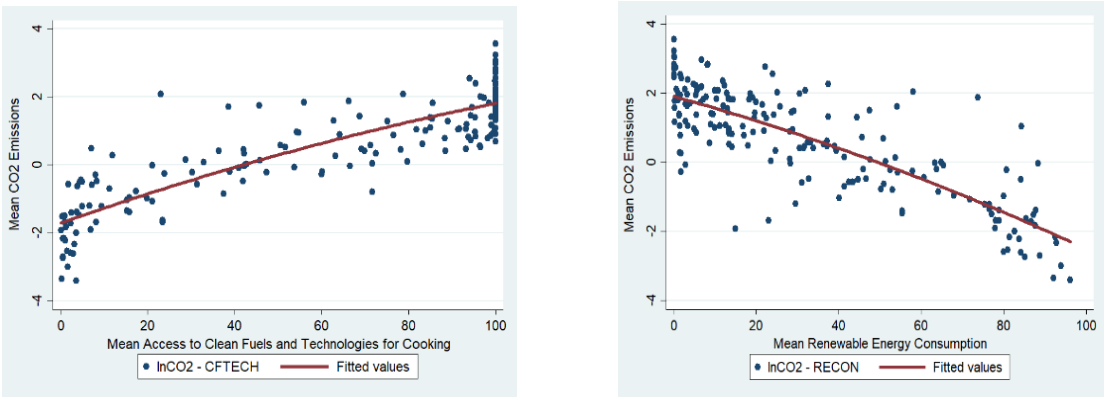
Economists, scientists, engineers and policy makers have always touted technology as a key factor to optimize resource utilization, increase productivity, and ensure wealth creation and sustainable development. Technological innovation and clean technologies are therefore preconditions towards the achievement of sustainable development (Walz et al., 2017).

According to Jain (2007), "Clean Technologies generally refer to: technologies that optimize use of resources (water, energy, land), minimize environmental impacts, produce minimum secondary wastes and are sustainable based on current and future economic and social societal needs. Thus, implementation of such technologies and associated challenges are of considerable interest from environmental, economic, and long-term societal view points". In this research study, clean technology is focused on the use of renewables, clean fuels and related green sources in production that avoids, reduces and optimizes the use of resources, decarbonizes the global environment and are sustainable. It involves the adoption and incorporation of eco-innovative technologies into new or improved process, system or ways of doing things. Clean technology adoption promotes sustainable development as it requires developing new technologies, production techniques, industries, energy sources and relying on other eco-friendly sources of economic growth (Ghisetti & Quatraro, 2017).

Global warming and climate change challenges are not as other environmental issues in terms of magnitude of impact currently and relative to the future. However, when it comes to climate change adaption and mitigation of GHG emissions, clean technology is one of the key favourable factors. What is more, from the perspectives of modern ecological-energy-technology viewpoints, transition to clean technologies plays a critical role in terms of stabilizing and decarbonizing the environment, (Gibbs, 2000). Environmental technologies often come in two forms: pollution prevention and pollution treatment (control) technologies. Clean technologies are simply eco-friendly or pollution avoiding technologies.

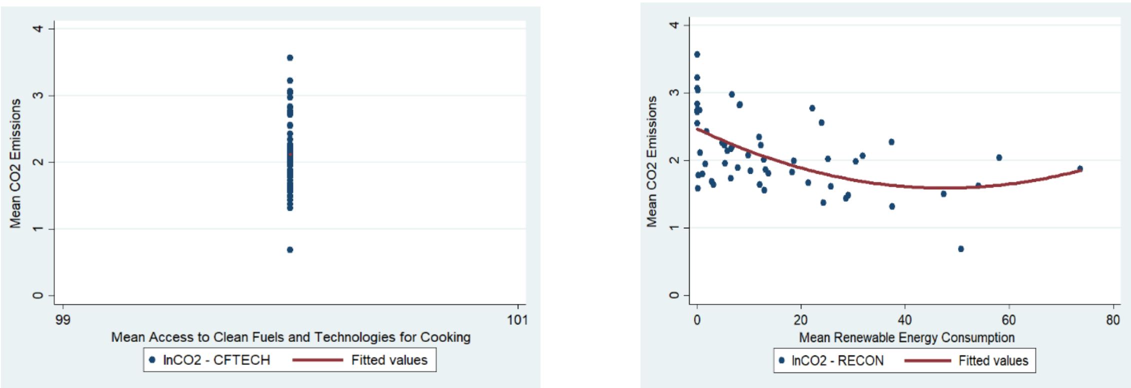
According to Dincbas et al. (2020), to date, major developments in the environmental technologies are in the area of treatment technologies. Argument has it that, clean technologies could mitigate about 70% of carbon emissions (WBCSD, 2009). Besides, with energy still being the major source of carbon emissions and inputs of industrial production processes, the importance of clean technologies cannot be ignored as their adoption could ensure efficiency improvement, clean energy production and use, consumption of sustainable goods and services as well as reduce environmental impact of production processes (Dincbas et al., 2020).

Figures (4 – 6) below are a scatter plots of the average values of indicator measures of clean technology adoption (i.e., access to clean fuels and technologies for cooking, and renewable energy consumption), and CO_2 emissions for the global economy, developed countries and emerging-developing countries, respectively. They show the relationship and distributional trends between clean technology and carbon dioxide emissions. The distributions show correlations between the indicators of clean technology and CO_2 emissions giving evidence for further investigation of these relationships.



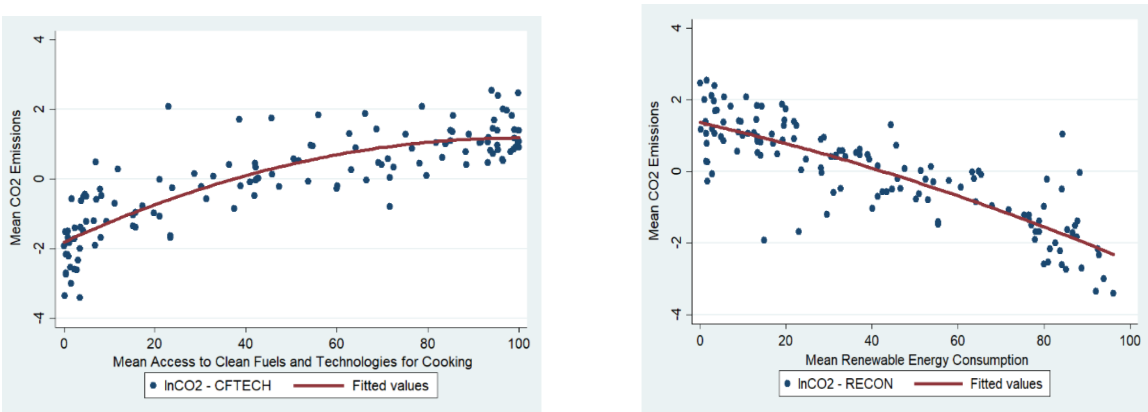
Global economy

Figure 4. Scatter plot of average CO_2 emissions, access to clean fuels and technologies for cooking; and renewable energy consumption for the global economy. Source: Author's computation using data from WDI.



Developed countries

Figure 5. Scatter plot of average CO_2 emissions, access to clean fuels and technologies for cooking; and renewable energy consumption for developed countries. Source: Author's computation using data from WDI.



Emerging-developing countries

Figure 6. Scatter plot of average CO_2 emissions, access to clean fuels and technologies for cooking; and renewable energy consumption for emerging-developing countries. . Source: Author's computation using data from WDI

2.3 Sustainability and Sustainable Development

Sustainability and the need to ensure global sustainable development is a critical challenge facing the present global environment due to the ever-growing demand for the earth's resources in addition to population growth, increasing demand for energy and industrialization, resulting in serious adverse impacts on the global environment, straining it optimum capacity (Fayomi et al., 2021). Actionable measures need to be taken, and this study seeks to investigate the role of broadband and clean technologies on sustainability of the global environment. The term sustainability and sustainable development are often used interchangeably, although both are often considered as similar.

Distinctively, sustainability is concerned with the development of ecological balance between economic growth and the environment, while emphasizing ecological balance. Sustainable development on the other hand deals with ensuring economic growth and development relative to human and environmental welfare (Waas et al., 2011; Wang et al., 2018). Although sustainability has diverse meaning and interpretations across many fields such as ethical, political science, sociology, ecology, economics among others, the universally accepted definition is the one by the Brundtland commission's report (Rogers et al., 2008; Pawłowski, 2007). The Bruntland Commission (Brundtland, 1987) defined sustainable development as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs''. Sustainability can, therefore, be viewed as the management and continuity of global economic, social, and environmental resources and their qualities (Dodd, 2007).

2.3.1 Concepts of Sustainability

Three components form the concept of sustainable development: economic, environmental and social development, and these elements are not usually mutually exclusive nor are they an option between economic growth and environmental preservation. This implies that these elements are rather interrelated and should not be viewed in isolation, but as a compromised relationship between forming sustainable development definition. However, in the context of this study, sustainability is focused on environmental sustainability (Ceigi & Streimikiene, 2005; Fayomi et al., 2021).

2.3.2 Environmental Sustainability

In terms of the environment, sustainability is geared towards the quality and stability of the global ecosystems in terms of biological, physical systems, and a stable level of resource utilization in terms of natural resources so as to forestall incidences of natural and renewable resources over exploitation. This, therefore, implies not only preservation of natural resources for future generation, but also conservation of nature (Fayomi et al., 2021).

2.3.3 Why the Need for Global Sustainability?

Since the 20th century around which time, industrialization was ushered in and propelled by human scientific and technological innovations, the global ecosystem has been deteriorating and very rapidly into the 21st century and there is no denying the fact that, the burning of fossil fuels has been the leading cause of climate change and global warming. Since the industrial revolution, the global economy has evolved and still evolving at a faster pace, resulting in rapid increase in economic growth and global energy demand that are associated with severe degradation of the environment. In 2017, the New Policies Scenario of the World Energy Outlook 2017 advised that global energy-related CO_2 emissions are increasing toward 2040 (IEA, 2013). The Panel on Climate Change (IPCC) indicates that increasing greenhouse gas emissions from anthropogenic activities are adversely impacting the global environment (IPCC, 2007a). Statistics indicate that, over the last century, global temperatures have increased by 0.70 ^{0}C averagely, and is projected to rise by between 1.8 and 40 ^{0}C by the year 2100 (IPCC, 2007a). This will have devastating consequences such as rising sea levels, changing rainfall patterns, reduction in biodiversity of organism, threat to coastal settlements, and economic impact on agrarian economies (Brahic et al., 2007; IPCC, 2007b).

What is more, in as much as industrialised countries continue to consume energy and developing economies are also increasing their demand for fossil fuel consumption the concentration of greenhouse gases in the atmosphere will continue to rise. Climate change and global warming have therefore become crucial challenges undermining the achievement of the Sustainable Development Goals (SDGs) of the United Nations. This has made achievement of sustainable growth and development serious challenges in economies of the world. These developments have therefore, raised awareness about the need for mitigation and preservation actions to ensure environmental sustainability of the world.

CHAPTER THREE

LITERATURE REVIEW

3.1 Introduction

Though many scholastic studies have analysed and provided empirical evidence on the relationship between the use of ICT, technological innovation, economic growth and carbon emissions using different models, samples, and periods of study. When it comes to the relationship among these variables, the literature is very vast; and a review of the related literature identifies three main strands of arguments: (1) general ICT and technological innovation promote environmental quality, (2) they have negative effects on the environment, and (3) the third arguments border on other perspectives of the relationship between these technologies and the environment. However, in these arguments, specific studies capturing and focusing on the linkage between broadband, clean green technologies and carbon dioxide emissions in a global perspective are limited and still evolving. Table 1 presents a summary of studies categorized into those: (i) linking ICT, broadband technology and carbon emissions, (ii) linking technological innovation, clean technology and carbon emissions, (iii) linking economic growth and carbon emissions (the EKC hypothesis). As the summary of these studies and their empirical findings in table 1 demonstrates, a general consensus is still lacking, reflected by the conflicting and inconclusive range of results obtained.

3.2 ICT, Broadband Technology and Carbon emissions

Although, numerous contemporary works have advanced arguments on the roles of broadband and ICT promoting energy efficiencies and mitigating carbon emissions, several other studies have also highlighted findings respecting the rebound effects associated with broadband and ICT development and utilization (Walzberg et al., 2020). For instance, Collard et al. (2005) postulate that the use of broadband and ICT goods and services increase electricity consumption intensity which leads to loss of efficiency in energy use in six French service industries. Bernstein and Madlener (2010) arrive at similar conclusion regarding some industries across 8 European countries. Zhou et al. (2018) argue that about 4.5% higher energy intensity associated with energy use is accounted for by the use of ICT.

However, these arguments and findings sharply conflict with others that indicate that general development of ICT can mitigate GHG emissions and promote environmental quality. For instance, Malmodin and Bergmark (2015) in a report state that integrating ICT enabled by broadband usage in critical macroeconomic sectors such as the energy sector could contribute to about 15% reduction of carbon emissions by the year 2030. According to IEA (2017a, 2017b) broadband technology and ICT applications can facilitate transition from non-renewable energy use to renewable energy use which can help in mitigation of global carbon emissions. Relatedly, prediction has been made by The International Renewable Energy Agency which indicates that the use of broadband and ICT application systems in the transportation sector can facilitate transition from the use of fossil fuel-powered automobiles engines to state-of-the-art engines powered by clean fuels and renewable sources and this will facilitate reduction of carbon emissions from the transportation sector (IRENA, 2018).

ICT and Broadband Technology Reduce Carbon Emissions

Studies abound that link the application of broadband and ICT to energy efficiency which add to carbon emissions mitigation. It is in this perspective, Laitner (2015) argues that broadband

and ICT deployment could potentially reduce energy wastages by improving both economic and energy consumption efficiencies. Goldbach et al. (2018) equally claim broadband enabled digital ICT-centred energy services reduce energy consumption intensity. Study by Bastida et al. (2019) also indicates that the use of broadband and ICT can influence the behaviours of households and improve efficiency of electricity consumption by about 5% in the EU countries.

Mathiesen et al. (2015) support the use of ICT to consolidate energy infrastructure so as to be able to promote the use, storage and power production activities from cleaner sources. They further assert that the integration of broadband enabled ICT can serve as a viable solution to bottlenecks associated with production and consumption of cleaner energy through smartening electricity grids, thermal grids, and gas grids to ensure 100% renewable energy shares in the total energy consumption mix of Denmark.

The use of broadband and ICT are also viewed as solution to limited electrification rates in developing countries in which the use of renewable sources can ensure off-grid electric power access in the hinterlands and other remote places (Murshed, 2020a). For example, in their study of rural areas in emerging developing countries, Uhomoibhi and Paul (2012) discover that the use of ICT often enabled by broadband is effective in promoting off-grid solar electric power access in rural areas. Additionally, in their investigation of 27 industries across 13 OECD countries, Schulte et al. (2016) discover evidence of ICT optimizing energy efficiency and reducing electric power demand by these industries. Voigt et al. (2014) state that ICT development is important to ensure energy efficiencies in industries across 40 major economies of the world.

Empirically, Claussen et al. (2009) also explored the direct and indirect ways of how advances in broadband technology can help to improve environmental sustainability. They focused on how telecommunication network typology (joint macro and picocell deployment) enabled by wide broadband accessibility influence energy efficiency. Their results showed that a joint deployment of macrocells for area coverage and publicly accessible user-deployed residential picocells can reduce the total network energy consumption by up to 70%. However, they focused on only residential urban areas and did not employ any econometric technique but rather relied on exploration and comparison techniques.

In a similar vein, Vergara et al. (2014) also argue that reduction of energy consumption of wireless transmissions is possible through awareness of the energy consumption characteristics of broadband technologies like 3G and Wi-Fi. This observation was reached after their investigation of energy consumption of data transmission of broadband technologies like 3G and Wi-Fi. They used EnergyBox as an estimation tool, not an econometric technique. Besides, the study was carried out on a single major mobile operator in Sweden, not worldwide.

Haseeb et al. (2019) examined the impact of ICTs (i.e., internet usage and mobile cellular subscriptions), globalization, electricity consumption, financial development, and economic growth on environmental quality by using panel data of BRICS economies for the period 1994-2014. They used estimation techniques such as second-generation panel unit root test, Westerlund panel co-integration test, dynamic seemingly unrelated regression (DSUR). Their results indicated that internet usage and mobile cellular subscriptions (ICTs) have significant, adverse impact on carbon dioxide emissions.

Similarly, Ozcan and Apergis (2017) analysed the impact of the Internet users (internet use proxied ICT) on CO_2 emissions for a panel of 20 emerging economies using a panel data framework over the period 1990 - 2015. Their results showed that the more Internet users a country has, the lower emissions it will emit. The results further showed that, while economic growth, energy consumption and trade raise emissions, financial development does not significantly in the 20 emerging countries investigated.

Zhang and Liu (2015) also in their study, Investigated the impact of the general ICT industry on CO_2 emissions at the national and regional levels in China using a provincial panel data for the period 2000 - 2010. They used STIRPAT model, and their results showed that the ICT industry reduces emissions in China. It was further discovered that at the regional level, while the impact was very significant in the central region, it was insignificant in the western region. Relatedly, Khan et al. (2020) analysed the impact of ICT on carbon dioxide emissions for a panel of 91 countries for the period 1990 - 2017. They employed pooled ordinary least squares, fixed-effects model, and system-generalized method of moments estimation techniques, and their results showed that ICT mitigates CO_2 emissions for the full sample and in developed countries but not in developing countries. The study constructed an ICT index through principal component analysis.

Danish (2019) investigated the relationship between ICT, real income, and CO_2 emissions while controlling for foreign direct investment and international trade for 59 countries along the BRI from 1990 - 2016. GLS estimation method was used. The results indicated that ICT mitigates the level of CO_2 emissions in countries along the BRI. Also, Al-Mulali et al. (2015b) analysed the influence of internet retailing on emissions in 77 countries grouped into developed countries and developing countries for the period 2000 - 2013. Using a panel two-stage least square (TSLS) and GMM, the results showed that internet retailing had significant negative effect on CO_2 emissions in developed countries, and in general but had no significant effect in developing countries.

Lastly, Higón et al. (2017), investigated the non-linear relationship (EKC) between ICT and CO_2 emissions on a global scale (142 countries) over the period 1995 - 2010. They further analysed this relationship in countries divided into developed (24 countries) and developing countries (116 countries) based on levels of development. Employing Pooled OLS, Driscoll-Kraay Fixed Effects (DK_FE) model, instrumental variable Fixed Effect among others, their empirical results showed that ICT could positively contribute to the reduction of CO_2 emissions once a threshold level of ICT development has been achieved. Both for the samples of developed and developing countries, as well as for the total sample, they found that the relationship between ICT and CO_2 emissions had an inverted U-shape form.

ICT and Broadband Technology Increase Carbon Emissions

However, much as the above studies highlight the inherent benefits of how broadband and ICT can ensure energy efficiencies, facilitate the use of renewable sources and cleaner technologies, which can reduce carbon emissions and improve environmental quality, there are several other studies that also indicate that broadband and ICT development can lead to greater increase in general energy demand which can be met by power generation from conventional non-renewable resources (Murshed, 2020b). For instance, Røpke and Christensen (2012) argue that the use of broadband and ICT facilities and services lead to increased energy consumption. Moyer and Hughes (2012), also make the argument that the use of ICT can deepen the use of electricity power which can result in greater CO_2 emissions. Similarly, Khayyat et al. (2016), indicate that the deployment of broadband-enabled ICT application in industries of Japan and South Korea tend to substitute labour with energy inputs and this increases industrial demand for energy generated from non-renewable resources.

Heddeghem et al. (2014) studied the global electricity uses of communication networks, data centres and personal computers dimensions of general ICT from the period 2007 - 2012. Their findings showed increased energy use of these three dimensions of ICT for the study period. They concluded by highlighting the need for energy-efficiency research across all these domains, rather than focusing on a single one. Park et al. (2018) analysed the impact of Internet use, financial development, economic growth, and trade openness on CO_2 emissions in selected EU countries. They used, pooled mean group (PMG) estimator for panel data from 2001 - 2014. Their empirical findings indicated that, internet use has a long-run relationship with CO_2 emissions, as well as reduces environmental quality in EU countries. They further discovered that electricity consumption has significant positive impact on CO_2 emissions.

Wan Lee et al. (2014) also examined relationships among ICT, CO_2 emissions and economic growth. Using annual panel data from 1991 - 2009 for a group of nine ASEAN countries. Using cointegrating regression techniques and estimation methods, the results showed that ICT and growth had significant positive effect on CO_2 emissions. The study was on only 9 ASEAN economies. Using China as a case study in a sectorized level investigation, Zhou et al. (2019), developed an embodied carbon analysis framework by integrating input-output approaches to explore the extent to which and how ICT drives carbon emissions at the sectoral level. The results showed that the ICT sector was not environment-friendly and impacted carbon emissions.

Additionally, Asongu (2018a) investigated how the complementary roles of ICT and globalization could influence CO_2 emissions in 44 SSA countries over the period 2000 - 2012 using GMM. ICT was proxied by internet and mobile phones penetration, and globalization by trade and financial openness. The results showed the adoption of ICT could be used to mitigate the potentially negative effect of globalisation on environmental deterioration like CO_2 emissions.

Other Perspectives of the Impact of ICT and Broadband Technology on Carbon Emissions

Others have also averted to the influence of time lags when it comes to the impact of ICT development and environmental quality (Faisal et al., 2020). Avom et al. (2020) argue that much as the use of broadband enabled-ICT goods and services could directly increase energy consumption and carbon emissions, this could also be reversed by efficiency of energy use and greening impact of the ICT sector.

Investigating the role of technology innovation and adoption on CO_2 emissions in BRICS economies for the period 1990 - 2018, Su et al. (2021) use fixed telephone, fixed broadband and mobile cellular subscriptions as technology innovation instruments, and high-technology exports and electric power consumption as technology adoption indicators in the investigation, and their empirical results show that, while mobile cellular subscription reduces CO_2 emissions, fixed broadband subscription, fixed telephone subscriptions, high-technology exports, and electric power consumption increase CO_2 emissions in BRICS economies.

Dehghan and Shahnazi (2019) studied the short-run and long-run causality between energy consumption, gross domestic product (GDP), CO_2 emissions, and ICT in Iranian economic sectors over the period 2002 - 2013. Using Dynamic ordinary least squares (DOLS) estimator and panel error correction model, the empirical results validated the presence of the environmental Kuznets curve in all the sectors. In addition, while ICT had positive impact on industrial sector CO_2 emissions, it had a negative impact on CO_2 emission in the transportation and services sectors.

3.3 Technological Innovation, Clean Technology and Carbon Emissions

Green technology innovations have been touted as one of the important alternative paths to reducing carbon emissions (Weina et al., 2016; Nikzad & Sedigh, 2017). Theoretically, the more the availability of environmental-related clean technologies, the better for combating global warming and climate change. There are empirical works that support this assertion (Su & Moaniba, 2017). This notwithstanding, previous studies show that the impact of green technology innovations on carbon emissions could be positive or negative under different conditions and various influential factors such as time and income (Acemoglu et al., 2012; Jaffe et al., 2002; Du et al., 2019a). Braungardt et al. (2016) argue that even though green innovations (technologies) are generally considered as an essential element towards a green growth path, the effect on climate goals has been subjected to on-going debate due to the existence of the rebound effects. Wang et al. (2012) also state that energy technology patents do not have a significant impact in reducing China's CO_2 emissions and that, energy patents with free-carbon technologies contribute to reduction of CO_2 emissions only in the eastern province of China. Weina et al. (2016) also claim that green innovation in Italy only improves environmental productivity (performance) but do not significantly reduce CO_2 emissions.

Technological Innovation and Clean Technology Reduce Carbon Emissions

Xiaosan et al. (2021), analysed the role of green innovation, renewable energy production and hydroelectric power generation in promoting environmental quality during the period 1990 - 2018. Results of their ARDL estimates indicated that green innovation improved environmental quality. Anwar et al. (2021) evaluated the link between renewable energy consumption, forest area and CO_2 emissions among 33 partner economies of BRI for the period 1986 - 2018. Using cointegration and heterogeneous Granger causality framework to explore the long-run and causal linkage among the variables. Their empirical evidence did not only show significant negative relationship between renewable energy consumption and CO_2 emissions, but also reveal that expansion in renewable energy consumption and increase in forestation can help to reduce CO_2 emissions.

In their study, Acharya and Marhold (2019) also argue that the use of ICT applications can influence transition from the use of unhealthy cooking fuels such as firewood and kerosene fuels for cooking to a cleaner source of energy such as liquefied petroleum gas (LPG) and electricity which can help to avoid and mitigate pollution, particularly in developing economies. Yasmin and Grundmann (2019) also state that linking ICT and media communication can influence and facilitate the adoption of cleaner options such as the use of biogas for cooking in the state of Punjab in Pakistan.

Similarly, Ghisetti and Quatraro (2017) also studied the effects of environmental innovations on environmental performances proxied by environmental productivity measure. Concentrating on sectoral environmental productivity of Italian Regions by exploiting Regional Accounting Matrix, their econometric results indicated that regional sectors characterized by higher levels of green technologies had better environmental performance. Jin et al. (2017), studied the relationship between technological progress in the energy sector and carbon emissions based on the Environment Kuznets Curve (EKC) and data from China from the period 1983 - 2014. The empirical findings confirmed the EKC hypothesis and inverted U-shaped relationship between per capita income and carbon emissions. Their results further showed that technological progress in the energy sector contributes to a reduction in carbon emissions.

Carrion-Flores and Innes (2010) studied a panel of 127 manufacturing industries from the period 1989 to 2004 in the United States. Having estimated a simultaneous panel data model of environmental innovation and toxic air pollution, they did not only identify bi-directional causal links between the two; but also discovered that environmental innovation was a crucial driver of reductions of toxic emissions in US. It has also been argued by Noorpoor and Kudahi (2015) that GDP per capita, population size, electricity intensity and the use of fossil fuels for electricity generation positively impact carbon dioxide emissions, while electricity generation by hydropower, renewable energies and nuclear energy negatively mitigate CO_2 emissions. They applied a STIRPAT model.

Besides, IEA (2012) analyses technological options necessary to ensure sustainable supply of energy and carbon emissions reduction. Their conclusions indicate that although, clean technology can potentially contribute to reduction of carbon emissions from generation of electricity, industrial and building sectors, improve energy efficiency as well as reduce over dependence on fossil fuels, but this would not be realized if advance technologies are not adopted. Their findings further identify progress in the use of clean and renewable technologies such as hydro, solar photovoltaic (PV), wind, and biomass. They also conclude that carbon capture can cumulatively reduce about 20% of carbon emission by 2050.

More to the above, in estimating the cost of carbon emissions avoidance from India's thermal and renewable industries, Prakash et al. (2020) conclude that while ultra-supercritical power plants are the most cost-effective strategies of mitigating carbon emissions, solar and wind are also innovative way of helping coal-powered plants operators cut coal consumption. Sensitivity analysis and scenario building exercises are employed.

Technological Innovation and Clean Technology Increase Carbon Emissions

Although, it is widely recognised that technological innovation and clean technologies could reduce carbon emissions; many studies have shown that they could also lead to increased energy consumption and carbon emissions. For instance, Xu et al. (2021) find a positive impact between heterogeneous green technologies and carbon emission performance in Chinese cities over the study period 2007 to 2013, using two-way fixed effect model, instrumental variable method, and spatial econometric model. Also, in analysing the relationship between green technological change and both emission efficiency and CO_2 emissions using a panel of 95 Italian provinces from 1990 to 2010, Weina et al. (2016) discover that green innovations do not significantly impact CO_2 emission reduction, although it significantly improves environmental productivity. Consolidated IPAT/STIRPAT framework is used in the study.

Alatas (2021) also analysed the linkage between CO_2 emissions from the transport sector and environmental technologies in the EU-15 member countries over the period spanning from 1977 to 2015. Proxying carbon emissions with transport sector per capita CO_2 emissions and environmental technologies with environmental-related patent applications, he discovered that environmental technologies had a statistically insignificant positive effect on CO_2 emissions from the transport sector. Mean Group, Common Correlated Effects Mean Group, and the Augmented Mean Group estimators were employed.

That is not all, using a panel data of 287 cities in China over the period 2003 to 2016, Yuan et al. (2020) investigated the nonlinear effect and action path of manufacturing agglomeration on green economic efficiency. They employed dynamic spatial panel Durbin model and mediating effect model. Their results showed a strong positive U-shaped relationship between manufacturing agglomeration and green economic efficiency irrespective of time period (short or long run). This shows that green technological progress does not only induce production and growth but also generates negative environmental impacts.

Other Perspectives of the impact of Technological Innovation and Clean Technology on Carbon Emissions.

The empirical findings of a study by Du et al. (2019) on 71 countries from 1996 to 2012 indicate that CO_2 emissions mitigation impact of green technology varies significantly across different countries. Specifically, the results showed that, while in advance countries, green technological innovation can significantly contribute to CO_2 emissions reduction, they cannot in countries with income levels below certain thresholds. The results also validate the inverted U-shaped relationship between per capita CO_2 emissions and per capita GDP.

Additionally, using a panel data on 264 cities in China over the period 2006 to 2017, Lin and Ma (2021) explore the impact of urban innovation environment on the effect of green technological innovations on CO_2 emissions. Panel two-way fixed effect and partially linear functional-coefficient panel models are used. Their empirical results show green technology innovations has heterogeneous impacts in the different cities. The results further indicate that green technological innovations could contribute to CO_2 emission mitigation after 2010, while the effect is not significant in Chinese cities before 2010.

Similarly, Chen et al. (2020) studied the impacts of technological changes and progress on carbon emissions using data from China's 30 provinces from 2005 to 2015. By incorporating Solow residual model into a logarithmic mean Divisia index model, their results indicated the following conclusions: (i) overall domestic technological progress of China in the study period reduced carbon emissions; (ii) while technological progress in Central and West China strongly reduces carbon emissions, it slightly increased emissions in Eastern China; and (iii) the linkage between technological progress and carbon emissions is complex and depends on both environmental technological changes and production technological changes.

Töbelmann and Wendler (2020), also examined the impacts of environmental innovation on carbon dioxide emissions in the EU-27 countries from 1992 to 2014. They used GMM in a dynamic panel setting and proxied environmental innovation with environmental patent applications. They discovered that neither environmental innovation nor general innovative activity cause a reduction in carbon dioxide emissions. The results further showed that the impact of innovation differs across countries.

Coupled with the above studies, Wang et al. (2019) studied the effect of technological progress on carbon emissions in Chinese economic sectors (i.e., construction, heavy, light, and services). A panel quantile regression technique and a balanced city panel data model were applied over the period 2001 - 2013. Having decomposed the impact of technological progress relative to the heavy industry, light industry, construction industry, and the service industry, their results confirmed that technological progress increases CO_2 emissions in the light and heavy industries in spite of its energy efficiency in these industries. But in the case of the service and construction industries it had a negative impact on CO_2 emissions.

Lastly, Erdogan et al. (2020) also analysed the impact of innovation on sectoral carbon emissions for a group of 14 G20 economies for the period spanning from 1991 to 2017. Their findings did not indicate significant relation between innovation and emissions in the energy and other sectors. Meanwhile it had a negative and positive impacts on carbon emissions from industrial and construction sectors respectively. The results additionally did not confirm the EKC hypothesis.

3.4 Economic Growth and Carbon Emissions (The EKC Hypothesis)

Since the EKC was proposed in 1991, many scholars have used it to analyse the relationship between environmental degradation and economic growth and development. Many of these studies are different in terms of settings, periods of study, methods used, measurement variables and samples used. Besides, findings of most of these studies show inconsistencies about the validity of the EKC hypothesis and its shape (Jin et al., 2017).

Many prior studies give evidence that increasing economic growth (GDP) leads to increasing CO_2 emissions. For instance, Omri (2013) discovers a monotonic relationship between CO_2 emissions and economic growth in 14 MENA countries. Similarly, Sohag et al. (2017) document a linear relationship between economic growth and CO_2 emissions for middle-income economies.

This notwithstanding, several existing studies have also arrived at inverted U-shaped relationship between CO_2 emissions and economic growth, validating the EKC hypothesis for the global economy (Caviglia-Harris et al., 2009), and EU countries (Ahmed et al., 2016). Yet still, there are other studies too that invalidate or contradict occurrence of the EKC hypothesis by evidencing a U-shape relationship between carbon emissions and economic growth for OECD countries (Sohag et al., 2019; Ekins, 1997); Asia, Africa, and Central America (Dietz & Adger, 2003). In addition, findings by Ahmed et al. (2019), Inglesi-Lotz (2016), and Apergis and Payne (2010) indicate that adoption of renewable energy can complement economic growth by reducing economic externalities. Some empirical studies have also discovered other perspectives. For example, Saboori et al. (2014) find a bi-directional relationship between CO_2 emissions and growth for OECD countries, whiles no causal link is established between CO_2 emissions and growth by Ozturk and Acaravci (2010) for the Turkish economy.

However, despite the large volume of empirical studies carried out on the EKC, little is known on whether the EKC hypothesis is holding in the context of the global economy, developed countries and emerging-developing countries given the augmenting role of broadband and clean technology adoption in influencing carbon emissions .

Table 1. Summary of review of selected studies on ICT - broadband technology, technological innovation - clean technology, and economic growth - CO_2 emissions.

Author(s) and Year	Scope/ Setting/country	Period	Methodology	Findings
Economic Growth - CO2 Emissions (The EKC Hypothesis)				
Omri (2013)	14 MENA countries.	1990 - 2011	Simultaneous-equations models.	Discovers a monotonic relationship between economic growth and CO_2 emissions.
Sohag et al. (2017)	Middle-income countries.	1980 - 2012	Panel methods, panel unit root and cross-sectional dependence tests.	Confirms that GDP per capita is a positive factor in CO_2 emissions for all middle-income countries.
Caviglia-Harris et al. (2009)	Worldwide.	1961 - 2000	EKC model, OLS, two stage least squares, dynamic panel model using Arellano and Bond (1991) estimation procedure.	No empirical evidence of an EKC relationship between ecological footprint and economic development.
Ahmed et al. (2016)	24 European countries.	1980 - 2010	Pooled mean group estimations in a dynamic heterogeneous panel setting.	Confirm inverted U-shaped relationship in the long run but not in short run.
Sohag et al. (2019)	OECD countries.	1980 - 2017	cross-sectional-autoregressive distributed lags (CS-ARDL).	Economic growth and carbon emissions follow a U-shaped relationship.
Saboori et al. (2014)	OECD countries.	1960 - 2008	Fully Modified Ordinary Least Squares cointegration approach.	Bi-directional relationship between CO_2 emissions and growth for OECD countries.
ICT and Broadband Technology Reduce Carbon Emissions				
Mathiesen et al. (2015)	Denmark.	n. d	Smart energy system approach.	Smart Energy Systems also enable a more sustainable and feasible use of bioenergy, It can potentially pave the way to a bioenergy-free 100% renewable energy and transport.
Schulte et al. (2016)	10 OECD countries and 27 industries.	1995 - 2007	cross-country cross-industry panel data set.	ICT is associated with a significant reduction in total energy demand.
Voigt et al. (2014)	40 major economies.	1995 - 2007	logarithmic mean Divisia index decomposition.	Technological change influence energy intensity at country level, at global level, energy efficiency improved due to technological change.
Claussen et al. (2009)	Residential urban areas.	n. d	Exploration, comparison, assumptions and scenarios.	Joint macro and picocells of broadband technology reduce total network energy consumption by 70%.
Vergara et al. (2014)	Mobile Network operator in Sweden.	n. d	EnergyBox estimation tool.	3G and Wifi of broadband technology usage can reduces energy consumption.
Haseeb et al. (2019)	BRICS economies.	1994 - 2014	Panel unit root test, Westerlund panel co-integration test, and dynamic seemingly unrelated regression (DSUR).	Internet and mobile cellular usage reduce CO_2 emissions significantly.
Zhang and Liu (2015)	China (national and regional levels).	2000 - 2010	STIRPAT model.	ICT industry reduces CO_2 emissions in China, but not significantly in Western province.
Khan et al. (2020)	91 Countries (developed and developing).	1990 - 2017	GMM, Pooled OLS, FE,	ICT reduces CO_2 emissions, but not in developing countries.
Danish (2019)	59 Belt and road countries.	1990 - 2016	Generalized least square	ICT mitigated CO_2 emissions in countries along the BRI.
Al-Mulali et al. (2015b)	77 countries (developed and developing).	2000 - 2013	GMM, two-stage least square (TSLS)	Internet retailing reduces CO_2 emissions, but not in developing countries.
Higón et al. (2017)	142 countries (developed and developing).	1995 - 2010	Pooled OLS, Driscoll-Kraay Fixed Effects, instrumental variable fixed effects.	Confirms Inverted U-shaped relation between ICT and CO_2 emissions, ICT reduces CO_2 emissions in developed and developing countries.
Shahnazi and Shabani (2019)	Iran.	2001 - 2015	Dynamic spatial Durbin model.	Inverted U-shaped relationship between spatial spill over effects of ICT and CO_2 emissions.
Ozcan and Apergis (2017)	20 emerging economies.	1990 - 2015	Panel data framework, Westerlund and Edgerton cointegration test.	Increased Internet access results in lower levels of air pollution.

Asongu (2018a)	44 SSA countries.	2000 - 2012	GMM.	Complementary role of ICT can mitigate the negative environmental effect of globalization.
Murshed (2020a)	Selected South Asian economies.	2000 - 2016	Panel data estimation techniques.	ICT trade directly increases renewable energy consumption, enhances renewable energy shares, reduces intensity of energy use, facilitates adoption of cleaner cooking fuels, and reduces CO_2 emissions.
ICT and Broadband Technology Increase Carbon Emissions				
Moyer and Hughes (2012)	Worldwide.	2007 - 2050	International Futures (IFs) integrated assessment system.	ICT can have a downward impact on overall carbon emissions across a 50-year time horizon.
Khayyat et al. (2016)	South Korea and Japan.	1973 - 2006 1980 - 2009	Dynamic factor demand model.	ICT and non-ICT capital investment substitute labour with energy inputs which increase demand for energy generated from non-renewables.
Heddeghem et al. (2014)	Worldwide.	2007 - 2012	Trend, comparison and descriptive analysis.	Communication network, data centres and Personal computers increase energy use.
Park et al. (2018)	Selected EU countries.	2001 - 2014	Pooled mean group (PMG).	Internet use reduces EU's environmental quality.
Wan Lee et al. (2014)	9 ASEAN countries.	1991 - 2009	Cointegrating regression techniques and estimation methods.	ICT and growth increase CO_2 emissions.
Zhou et al. (2019)	China (sectoral level).		Input-output approach.	ICT sector is not environment-friendly and impacts carbon emissions.
Other Perspectives of the Impact of ICT and Broadband Technology on Carbon Emissions				
Su et al. (2021)	BRICS economies.	1990 - 2018	Driscoll-Kraay panel regression, Newy- West and DK standard error methods.	Except mobile subscription, fixed broadband, telephone, electric power increase CO_2 emissions in BRICS, confirms the EKC hypothesis.
Faisal et al. (2020).	Fast-emerging countries.	1993 - 2014	FMOLS, DOLS, second-generation panel cointegration techniques, second-generation panel unit root test	Pollution declines after attaining a threshold point as the ICT usage increases, a unidirectional causal relationship between electricity consumption and CO_2 emissions, CO_2 emissions and ICT, gross domestic product and CO_2 emissions.
Avom et al. (2020)	21 SSA countries.	1996 - 2014	Stochastic Impact by Regression on Population, Affluence and Technology model (STIRPAT model)	ICT use - measured by mobile phone and internet penetrations - significantly stimulates CO_2 emissions
Dehghan and Shahnazi (2019)	Iranian economic sectors.	2002 - 2013	Dynamic ordinary least squares (DOLS), panel error correction model.	ICT has positive impact on industrial CO_2 emission, negative impact on transportation and service sectors, confirms the EKC hypothesis.
Technological Innovation and Clean Technology Reduce Carbon Emissions				
Ghisetti and Quatraro (2017)	Italian Regions.		Regional Accounting Matrix.	Regions with higher green technologies have better environmental performance.
Jin et al. (2017)	China.	1983 - 2014	EKC model, annual data.	Technological progress in the energy sector reduces CO_2 emissions, confirmed the EKC hypothesis.
Anwar et al. (2021)	33 Belt and Road Initiative economies.	1986 - 2018	Cointegration and heterogeneous Granger causality framework.	Significant negative relationship between renewable energy use and CO_2 emission, increased renewable energy use and forestation reduce CO_2.
Acharya and Marhold (2019)	Nepalese households.	n. d	Multiple discrete continuous extreme value (MDCEV) model, annual household survey data.	lower education levels of the household and private house ownership are linked to the use of fuels such as firewood and kerosene, whereas ownership of (ICT) devices and access to renewable energy led to use of modern cleaner fuels.
Yasmin and Grundmann (2019)	Rural Pakistan.	n. d	A multistage sampling procedure, logit model and propensity score matching approach.	Older and wealthy farmers are more likely to adopt biogas technology.
Khan et al (2020b)	Pakistan.	1991 - 2017	quantile regression method.	Agriculture and services sectors have a negative effect on CO_2 emissions, but the construction, manufacturing,

				transportation sectors significantly add to emissions.
Carrion-Flores and Innes (2010)	USA.	1989 - 2004	Simultaneous panel data model.	Environmental innovation is a crucial driver of reduction of toxic emissions in US.
Noorpoor and Kudahi (2015)	Iran.	2003 - 2013	STIRPAT model.	Electricity generation from fossil fuel raises CO_2 emissions, while generation from hydro, renewable and nuclear energies mitigate CO_2 emissions.
IEA (2012)	Worldwide.	2012 - 2050	Detailed scenarios and strategies.	Clean and advance technologies adoption can reduce CO_2 emissions and improve energy efficiency.
Prakash et al. (2020)	India.	2009 - 2018	Sensitivity analysis.	Solar and wind are innovative ways of cutting coal consumption, super and ultra-supercritical power plants are economic option for reducing CO_2 in India.
Technological Innovation and Clean Technology Increase Carbon Emissions				
Alatas (2021)	EU-15 countries.	1977 - 2015	Mean Group, common correlated effect mean group, augmented mean group estimators.	Environmental technologies have insignificant positive impact on CO_2 emissions from the transport sector.
Yuan et al. (2020)	China.	2003 - 2016	Dynamic spatial panel Durbin model and mediating effect. model.	Strong positive U-shaped relationship between manufacturing agglomeration and green economic efficiency.
Xu et al. (2021)	Chinese cities.	2007 - 2013	Two-way fixed effect model, instrumental variable method, and spatial econometric model.	Positive heterogenous impacts of green innovations on CO_2 emissions in chines cities.
Weina et al. (2016)	Italian provinces.	1990 - 2010	Consolidated IPAT/STIRPAT framework.	Green innovation did not significantly impact CO_2 emissions but improves environmental productivity.
Other Perspectives of the Impact of Technological Innovation and Clean Technology on Carbon Emissions				
Du et al. (2019)	71 countries.	1996 - 2012	Panel threshold model.	Green technology impact on CO_2 emissions varies among countries (developed and developing countries).
Lin and Ma (2021)	264 Chinese cities.	2006 - 2017	Panel two-way fixed effect and partially linear functional-coefficient panel models.	Green technology innovations have heterogeneous impacts in different cities.
Chen et al. (2020)	30 Chinese provinces.	2005 - 2015	Solow residual in logarithmic mean divisia index model.	Technological progress reduces emissions in Central and Western China, but increases emissions in Eastern, impact is heterogenous and complex on emissions.
Töbelmann and Wendler (2020)	EU-27 countries.	1992 - 2014	GMM in a dynamic panel setting.	Impact of innovation differs across countries; environmental and general innovative activity do not reduce CO_2 emissions.
Wang et al. (2019)	Chinese economic sectors.	2001 - 2013	Panel quantile regression technique, balanced city panel data model	Technological progress increases CO_2 emissions in the light and heavy industries but reduces emission in service and construction industries.
Erdogan et al. (2020)	14 G20 economies.	1991 - 2017	Westerlund and Egerton 2008 panel LM cointegration test, Pesaran CD test common correlated effects Mean augmented mean group.	No significant relation between innovation and emissions in energy and other sectors, the EKC was not confirmed.

Notes: n .d indicates study did not have specific time span.

CHAPTER FOUR

METHODOLOGY AND DATA PRESENTATION

4.1 Introduction

This chapter presents the methodology employed in the study. The chapter consists of three main sections. The first section gives the empirical model specification. The second section presents the econometric estimation techniques and empirical framework used in the study, and the third section provides the data, source and description.

4.2 Empirical Model Specification

Primarily, the research study aims to test the impacts of income, broadband technology, and clean technology on environmental sustainability (CO_2 emissions) within the classical empirical environmental Kuznets curve hypothesis for the global economy, developed countries and emerging developing countries. In empirical studies of the EKC, scholars usually tend to model environmental degradation (END) as the dependent variable and income (GDPPC) as the explanatory or independent variable. According to the postulation of the EKC hypothesis, there is a non-linear relationship between environmental degradation and income. Thus, existing studies have modelled environmental degradation as a function of income (GDPPC) and its square as shown below:

$$END_{it} = f(GDPPC_{it,} \, GDPPC_{it}^2) \tag{1}$$

However, to control for variable omission bias, other important factors or variables that could potentially affect environmental degradation are often added or incorporated into the model in empirical studies (Kwakwa, 2021). In their studies, Soytas et al. (2007), Pao and Tsai (2011), Apergis and Payne (2009), and Yavuz (2014), regressed CO_2 emissions on income, income square and energy consumption. The conventional EKC empirical model below was used:

$$lnCO_{2it} = \beta_0 + \beta_1 ln\, Y_{it} + \beta_2 Y_{it}^2 + \beta_5 lnEGY_{it} + \varepsilon_{it} \qquad [i]$$

Dogan and Seker (2016), Tang and Tan (2015), Pao and Tsai (2011), and Seker et al. (2015) also applied the EKC model below in their study:

$$lnCO_{2it} = \beta_0 + \beta_1 ln\, Y_{it} + \beta_2 Y_{it}^2 + \beta_3 lnEGY_{it} + \beta_4 lnFD_{it} + \varepsilon_{it} \qquad [ii]$$

Additionally, Shahbaz et al. (2014), Nasir and Rehman (2011), Jalil and Mahmud (2009), Atici (2009), Farhani et al. (2014), and Dogan and Seker (2016) also proposed and used the EKC model below:

$$lnCO_{2it} = \beta_0 + \beta_1 ln\, Y_{it} + \beta_2 Y_{it}^2 + \beta_3 lnEGY_{it} + \beta_4 lnFD_{it} + \beta_5 lnTO_{it} + \varepsilon_{it} \qquad [iii]$$

Where CO_2, carbon dioxide emissions, Y, income (economic growth), EGY, energy use, FD, financial development, TO, trade openness, i, individual country, t, time period, and ε_{it} error term.

As argued in the preceding chapters of the study, broadband technology diffusion and clean technology utilization influence the global environment; and following existing literature (Grossman & Krueger, 1995; Higón et al., 2017; Brock & Taylor, 2010; Dinda, 2004; Kwakwa, 2021; Sohag et al. 2019) and the above authors, this study, also uses the below modified EKC model specifications logarithmically, to regress CO_2 emissions on income, broadband technology, and clean technology adoption among other controlling variables.

Broadband Technology and Carbon Dioxide Emissions Specification:

$$lnCO_{2it} = \beta_0 + \beta_1 ln\, GDPPC_{it} + \beta_2 lnGDPPC_{it}^2 + \beta_3 lnBBT_{it} + \beta_4 lnEU_{it} + \beta_6 lnTRADE_{it} + \beta_5 lnFDI_{it} + \beta_6 lnPOPG_{it} + \beta_6 lnFTS_{it} + \beta_7 lnEDUCS_{it} + \varepsilon_{it} \qquad (2)$$

Clean Technology and Carbon Dioxide Emissions Specification:

$$lnCO_{2it} = \beta_0 + \beta_1 ln\, GDPPC_{it} + \beta_2 lnGDPPC_{it}^2 + \beta_3 lnCTA_{it} + \beta_4 lnRDEXP_{it} + \beta_5 lnEU_{it} + \beta_6 lnFDI_{it} + \beta_7 lnPOPG_{it} + \beta_8 lnFOREST_{it} + \varepsilon_{it} \qquad (3)$$

For validity of the EKC hypothesis, the study expects a priori, that $\beta_1 > 0$, and $\beta_2 < 0$ and significant in both models.

4.3 Econometric Methodology

The research study uses panel data and estimation techniques that are robust in handling cross-sectional and panel time series. However, compared to country-specific time series econometric techniques, panel data provides methodological technique which gives better estimates of dynamic changes of variables of study over time with the estimation techniques involving cross-sectional and or common characteristics (Baltagi, 2008). Besides, panel data analysis minimizes collinearity issues of variables (Gujarati, 2005), allows for higher degrees of freedom (Hsiao, 2005) and generates more credible and efficient estimates (Baltagi, 2013). In addition, it is suitable for controlling and handling possible omitted variables biases (Hsiao, 2005).

Panel Data Models

Panel data models are usually classified into Static Panel data models and Dynamic Panel Models; and the main difference between them is the addition of lagged of the dependent variable as explanatory variable in dynamic panel model. Below are typical standard representations of static and dynamic panel data models.

$$y_{it} = \alpha + x'_{it}\beta + \mu_{it} \tag{4}$$

$$y_{it} = \delta y_{it-1} + x'_{it}\beta + \mu_{it} \qquad ; \; i = 1, \dots, N; \qquad t = 1, \dots, T \tag{5}$$

Where y is the dependent variable, x are the independent variables or regressors, with subscripts i and t being the cross-sectional (individual observations) and time series dimensions (time periods) respectively. μ_{it} is the composite error term which is made up of specific effects and the disturbance term. The specific effects can be decomposed into individual-specific effects and time-specific effects, as shown in the composite error equation below.

$$\mu_{it} = \varphi_{it} + \gamma_{it} + \varepsilon_{it} \tag{6}$$

Where μ_{it} is composite error, φ_{it} individual-specific effects, γ_{it} time-specific effects, and ε_{it} is the disturbance term.

However, to avoid spurious results and ensure that the study's results are robust, preliminary regressions analysis (traditional static panel data model estimations) in addition to descriptive statistical analysis were first carried out before the application of the study's dynamic panel data model estimator (system GMM) and the results and discussions for broadband technology use and clean technology are presented in chapter 5 and chapter 6 respectively. Pooled OLS (POLS), fixed-effects (FE) and random-effects (RE) estimators were carried out as preliminary investigation.

4.3.1 Static Panel Estimation Approach (Static Models)

The study begins by presenting the different static panel data model estimators including summary of their characteristics and possible weaknesses that will be used in the study comparatively to the application of dynamic panel model estimators.

Pooled OLS model:

Theoretically speaking, when the conditions for pooling are fulfilled, pooled model estimators are efficient. Estimators from pooled model are consistent provided all the regressors are strictly exogenous and all the model parameters are random and distributed independently of the regressors. The Pooled OLS is applicable, given the assumption that the regressors can capture all the relevant characteristics of the individual units making the unobserved specific effects in the model redundant. That is, the unobserved individual and time specific effects get dropped in which case, pooled regression could be used to fit the model. Using this model to fit the data treats all the observations for all the time periods as single sample. But the limitation of using this kind of model to fit the data is the fact that when dropped effects are significant, the estimates and standard errors of the model become inefficient and biased respectively. Besides, in practice, these assumptions and particularly the assumption of common slopes might be violated, as countries vary and behave differently.

However, in the event where the unobserved specific effects are significant (and cannot be ignored) in a panel data model, the two most common approaches to consider are fixed effects and the random effects models.

Fixed Effects Model:

Fixed effects model is one of the standard panel data models which could be used to analyse macroeconomic panel dataset and takes into account individual country effects. The fixed effects estimator is only efficient if the errors are homoscedastic and serially uncorrelated. Practically, these assumptions are predisposed to violation in panel data context. This is because countries differ remarkably in their absolute level of environmental degradation, technological innovation, development, adoption and accessibility. They may also show different variation in GHG emissions, clean technology and broadband penetration that maybe subjected to country specific heteroscedasticity. What is more, serial correlation (temporal dependence) of the error terms is probable since unobserved shocks may affect the relationship over time. However, in such an instance, Arellano (1987) recommends a robust variance matrix be estimated to allow for general serial correlation and heteroscedasticity, (Steiner, 2009).

Random Effects Model (Random Coefficient Model):

With this regression model, additional parameter heterogeneity is allowed in the model. That is, with random coefficient regression, all coefficients and the model intercept randomly vary across groups but have a common mean and variance-covariance matrix, instead of only the model intercept varying across the groups. However, given the fact that, the differences among this study's sampled countries of investigation are not random, but systematic, the random model is inappropriate, (Steiner, 2009).

In a nutshell, in a dynamic setting, pooling and static models (pooled OLS, FE and RE) estimates might be affected by endogenous problems (effects) in the presence of lagged regressor in the model. The solution to this limitation is a GMM based approach (Arellano &

Bond, 1991; Arellano & Bover, 1995). The application of GMM based approach requires that, first, the model (equations 7 and 8 below) be expressed in first differences, followed by using the levels of the explanatory variables (in the absence of suitable external instruments), using lag two or more as natural instruments. This is known as first difference GMM estimator (Arellano & Bond, 1991). However, according to Blundell and Bond (1998), using the model in first difference form only, might results in finite sample bias especially when the variables are persistent as is the case with variables as CO_2 emissions per capita. Thus, system GMM is often used as an alternative to difference GMM. The basic idea of system GMM is to estimate a system of equations in both first differences and levels in which instruments of the level equation are lags of the first difference variables.

4.3.2 Dynamic Panel Estimation Approach (Dynamic Models)

In dynamic model specification, lagged of the dependent variable of the model is included as a regressor or explanatory variable. However, when this becomes the case, the exogeneity assumption of the model is violated. This is because the lagged dependent variable would be correlated with the error term of the model. When fixed effects model is for instance applied, the estimators become biased and inconsistent for $N \rightarrow \infty$, and T fixed, (Steiner, 2009).

The study, therefore, applies GMM approach (system GMM) as better alternative to the static model to ensure more robust results could be obtained compared to those of the pooled OLS, fixed effects and random effects models. This is because system GMM estimators are more suitable for unbalanced panel data and better in producing consistent and efficient parameter estimates in the presence of omitted variables, large sample size, limited time periods, endogeneity issue, heteroskedasticity issue, serial autocorrelation, and individual specific distributed effects. This makes estimated results of system GMM preferable and more credible.

To analyse the impact of broadband and clean technologies on environmental sustainability, two separate model specifications were considered, informed by the objectives of the research study. In the first model (equation 2), broadband technology *($lnBBT_{it}$)* was explanatory variable of interest, while in the second model (equation 3) clean technology adoption *($lnCTA_{it}$)* was the explanatory variable of interest in addition to other controlling factors that influence CO_2 emissions. Thus, given the nature of the research data, a dynamic panel data model approach is used and specified as follows:

For Broadband Technology and Carbon Dioxide Emissions Specification:

$$lnCO_{2,it} = \beta_0 + \beta_1 lnCO_{2,it-1} + \beta_2 lnGDPPC_{it} + \beta_3 lnGDPPC_{it}^2 + \beta_4 BBT_{it} + \beta_5 lnEU_{it} + \beta_6 TRADE_{it} + \beta_7 FDI_{it} + \beta_8 POPG_{it} + \beta_9 FTS_{it} + \beta_{10} EDUCS_{it} + yr_i + \delta_i + \varepsilon_{it} \quad (7)$$

For Clean Technology and Carbon Dioxide Emissions Specification:

$$lnCO_{2,it} = \beta_0 + \beta_1 lnCO_{2,it-1} + \beta_2 lnGDPPC_{it} + \beta_3 lnGDPPC_{it}^2 + \beta_4 CTA_{it} + \beta_5 RDEXP_{it} + \beta_6 lnEU_{it} + \beta_7 FDI_{it} + \beta_8 POPG_{it} + \beta_9 FOREST_{it} + yr_i + \delta_i + \varepsilon_{it} \quad (8)$$

$|\beta_1| < 1$

$$i = 1,2 \ldots N. \qquad t = 1,2 \ldots T$$

where i is country identifier, t is time identifier, β_0 is a constant term, β_1, β_2, β_3,…β_{10} are the respective slope coefficients. Specifically, β_1 is a measure of the mean reversion speed of

CO_2 emissions to its long-run equilibrium level following a shock and is expected to be negatively related to $lnCO_{2,it}$.

However, it is expected a priori, that $\beta_2 > 0$ and $\beta_3 < 0$ to reflect the non-linear (inverted U-shape) relationship of the EKC hypothesis. Regarding the data selected and used in the models, $lnCO_{2,it}$ is the logarithm of carbon dioxide emissions per capita, while $lnCO_{2,it-1}$ denotes one period lagged logarithm of carbon dioxide emissions per capita of the individual countries, for this reason, lags 2 or more and lag 1 could be used as instruments for the differenced and level equations, respectively. $lnGDPPC_{it}$ is logarithm of real GDP per capita, $lnGDPPC_{it}^2$ is square of $lnGDPPC_{it}$, BBT_{it} and CTA_{it} in equation (7) and (8) are broadband and clean technology activities (the research variables of interest) respectively and are assumed to be endogenous, thus for the level equations lag 1 is used whereas 2 and above is used for the differenced equations.

$lnEU_{it}$ is logarithm of energy use in kg of oil equivalent per capita, $TRADE_{it}$ is trade openness (total import and export share of GDP), FDI_{it} is foreign direct investment, net inflows (share of GDP), $POPG_{it}$, is population growth (annual %), FTS_{it} is fixed telephone subscription (per 100 people), $RDEXP$ is R&D expenditure (share of GDP), and $FOREST,$ is forest area (% of land area) are a set of other control variables in addition to the explanatory research variables of interest in both equations. Besides, δ_i is unobserved individual country specific effects which is time-invariant and reflects the heterogeneity of the individual countries such as level of economic development, technological advancement, geographical location, environmental policy, among others. yr_i are year specific dummy variables for individual countries added to control for possible cross-sectional correlation which may result from temporal shock affecting all the countries such as signing of the Kyoto protocol and Paris Agreement. It also reflects environmental protection awareness and carbon-saving technology exogeneity common to all the countries (Haftu, 2018; Higón et al., 2017; Iwata et al., 2014). ε_{it} represents the stochastic error term.

Therefore, to investigate the relationship between broadband technology, clean technology and environmental quality, the research study employs the Windmeijer corrected two-step system GMM estimation technique which according to Roodman (2006) reduces finite sample problems of weak instruments and improves efficiency of estimators. He further demonstrates that for studies characterized by the following instances: large sample size, limited time periods, endogeneity issue, heteroskedasticity issue, serial autocorrelation and individual specific distributed effects, system GMM is the most robust panel data estimation method, because the system estimator uses lagged first differences as instruments for the level equations in addition to lagged levels as instruments for the differenced equation as shown below, (Haftu, 2018).

For Broadband Technology:

$$lnCO_{2,it} = \beta_0 + \beta_1 lnCO_{2,it-1} + \beta_2 lnGDPPC_{it} + \beta_3 lnGDPPC_{it}^2 + \beta_4 BBT_{it} + \beta_5 lnEU_{it} + \beta_6 TRADE_{it} + \beta_7 FDI_{it} + \beta_8 POPG_{it} + \beta_9 FTS_{it} + \beta_{10} EDUCS_{it} + yr_i + \delta_i + \varepsilon_{it} \quad (9)$$

$$\Delta lnCO_{2,it} = \beta_0 + \beta_1 \Delta lnCO_{2,it-1} + \beta_2 \Delta lnGDPPC_{it} + \beta_3 \Delta lnGDPPC_{it}^2 + \beta_4 \Delta(BBT)_{it} + \beta_5 \Delta lnEU_{it} + \beta_6 \Delta TRADE_{it} + \beta_7 \Delta FDI_{it} + \beta_8 \Delta POPG_{it} + \beta_9 \Delta FTS_{it} + \beta_{10} \Delta EDUCS_{it} + \Delta\varepsilon_{it} \quad (10)$$

For Clean Technology Adoption:

$$lnCO_{2,it} = \beta_0 + \beta_1 lnCO_{2,it-1} + \beta_2 lnGDPPC_{it} + ln\beta_3 lnGDPPC_{it}^2 + \beta_4 CTA_{it} + \beta_5 RDEXP_{it} + \beta_6 lnEU_{it} + \beta_7 FDI_{it} + \beta_8 POPG_{it} + \beta_9 FOREST_{it} + yr_i + \delta_i + \varepsilon_{it} \quad (11)$$

$$\Delta lnCO_{2,it} = \beta_0 + \beta_1 \Delta lnCO_{2,it-1} + \beta_2 \Delta lnGDPPC_{it} + \beta_3 \Delta lnGDPPC_{it}^2 + \beta_4 \Delta CTA_{it} + \beta_5 \Delta RDEXP_{it} + \beta_6 \Delta lnEU_{it} + \beta_7 \Delta FDI_{it} + \beta_8 \Delta POPG_{it} + \beta_9 \Delta lnFOREST_{it} + \Delta\varepsilon_{it} \quad (12)$$

Most of the relationships among economic variables are dynamic in nature; and one of the benefits of using panel data (models) is that they help researchers to get more informed understanding of the dynamic adjustment of these relationships. This explains why many studies (Baltagi & Levin, 1986; Balestra & Nerlove, 1966; Arellano & Bond, 1991; Holtz-Eakin, 1988) among other reasons, consider panel data and dynamic relationships characterized by inclusion of a lagged dependent variable among other explanatory variables (Baltagi, 2005). As has been amply demonstrated in studies, macroeconomic variables usually behave persistently resulting in a dynamic process. Thus, in this study too, current carbon emissions of individual countries is assumed to depend on its past value (as expressed in the above models).

The lag-term of carbon emissions is therefore included as explanatory variable to indicate the dynamic process of CO_2 emissions. Aside reflecting the dynamic nature of CO_2, inclusion of it would help to cater for the effect of uncontrollable factors which could affect the robustness and credibility of the model estimation results. In addition, because the model is a dynamic one, the use of the conventional panel data estimation techniques for panel data namely, fixed effect and random effect would not produce the most robust estimates as stated earlier. This is so because the application of such estimation methods cannot control for endogenous effect which could affect efficiency of the model parameters. To address the issue of endogeneity, system generalized method of moments (system GMM) is used, (Jiang & Ma, 2019).

According to Blundell and Bond (1998), system GMM estimators perform better in terms of asymptotic efficiency for AR (1) model than first-differenced GMM estimators. This conclusion was reached after their simulation results showed that linear generalized method of moments (GMM) estimator of Arellano and Bond (1991) give large finite sample bias and poor precision.

Windmeijer (2005) also used data of Arellano and Bond (1991) and Blundell and Bond to demonstrate that two step GMM estimator standard errors, particularly in small samples are downward biased and could lead to poor Wald test performance. His argument further showed that the standard errors of two step GMM estimator are more robust (smaller) than those of the one step GMM estimator. His Monte Carlo panel data study showed that corrected variance improves precision of inference (Haftu, 2018).

Although system GMM is a good estimation technique for situation where a study has large sample size, limited time periods, endogeneity issue, heteroskedasticity issue, serial autocorrelation and individual specific distributed effects and omission, it comes with certain drawbacks. Instrument proliferation is one of its weaknesses which leads to poor performance of the Hansen test, Roodman (2006). Secondly, the required number of instruments for efficient estimates is still a debate in literature. Thirdly, the increasing instrumentation may increase biasedness of estimates, and this may not reduce the issue of endogeneity.

The study therefore uses the two-step system GMM for estimation of the models. The statistical software Stata (StataCorp, College Station, Texas, USA) and the command "xtabond2" developed by Roodman (2009) are used for estimation of the models. Results of the system GMM estimations are reported in the next chapters.

4.4 Data Presentation

To achieve the objectives of the study, an unbalanced panel dataset from the period 2005 to 2020 for 216 countries representing the global economy was used. These countries were further classified into 79 developed countries and 137 emerging-developing countries based on the World Bank classification of countries (Higón et al., 2017; WDI, 2021) for comparative analysis. This was relevant because studies showed that heterogeneity in environmental policies, economic structures, technological advancement, resource endowment, education, population, among others exist between developed economies and emerging-developing economies (Jian g & Ma, 2019). However, due to missing data values for some countries in the dataset, the original sample of the global economy and the two country groups dropped after estimation from 216 countries, 79 countries and 137 countries to 190 countries; 56 countries and 134 countries for the global economy, developed countries and emerging-developing countries respectively (see appendix B for the list of countries).

The choice of the study period, countries and data selection source were informed by data availability and the objectives of the study. The study used macroeconomic data, which were all collected from the World Development Indicators (http://data.worldbank.org), a databank of the World Bank. The data variables except for those already dimensionless or in ratio index were transformed into natural logarithmic form for ease of results interpretation in elasticities and to minimize the issue of heteroscedasticity and nonnormality.

However just as there are no perfect indicator measures of variables of interest of most empirical studies, but researchers have often rely on different universally accepted indicators, consistent with data availability and study objectives, the study, guided by the objectives, literature, and practice on environmental studies (Jiang & Ma, 2019, Higón et al., 2017; Ozcan & Apergis, 2017; Haftu, 2018) proxied environmental degradation with carbon dioxide emissions (CO_2), broadband technology (BBT) with mobile cellular (MOBS) and fixed-broadband subscriptions (FBS), clean technology adoption with access to clean fuels and technologies for cooking (CFTECH), and renewable energy consumption (RECON), while controlling for other explanatory variables. Table 2 below gives description and source of the data variables used in the study.

Table 2. Variable description and sources

Variable acronym	Description	Source
	Dependent research variable	
CO_2	Carbon dioxide emissions (metric tons per capita)	WDI
	Independent research variables	
GDPPC	GDP per capita (constant 2015 US$)	WDI
BBT	Broadband technology proxied by:	
MOBS	*Mobile cellular subscribers (per 100 people)*	WDI
FBS	*Fixed broadband subscribers (per 100 people)*	WDI
CTA	Clean technology adoption proxied by:	
CFTECH	*Access to clean fuels and technologies for cooking (% of population)*	WDI
RECON	*Renewable energy consumption (% of total final energy consumption)*	WDI
	Control variables	
RDEXP	R&D expenditure (% of GDP)	WDI
EU	Energy use (kg of oil equivalent per capita)	WDI
TRADE	Total import and export (% of GDP)	WDI
FDI	Foreign direct investment, net inflows (% of GDP)	WDI
POPG	Population growth (annual %)	WDI
FTS	Fixed telephone subscription (per 100 people)	WDI
EDUCS	School enrolment, secondary (% of gross)	WDI
FOREST	Forest area (% of land area)	WDI

Notes: GDP indicates gross domestic product, WDI indicates World Development Indicators

Carbon Dioxide Emissions (CO_2) refers to emissions from the use of fossil fuels and other production and manufacturing processes measured in metric tonnes per capita. It was used as the dependent variable in the study which agrees with many prior studies (Higón et al., 2017;

Ozcan & Apergis, 2017; Haftu, 2018; Jiang & Ma, 2019). Besides, it constitutes the highest share (about three-fourths) in GHG emissions affecting degradation of the ecological environment and has become a burning issue regarding global warming and climate change.

Broadband Technology (BBT) activity is the first research explanatory variable of interest and was proxied by mobile cellular and fixed broadband subscriptions which agrees with existing studies (Su et al., 2021; Danish, 2019). More so, they are regarded as core technologies of the broadband component of general ICT (Kuhndt et al., 2006; Su et al., 2021). From literature, broadband technology usage could positively or negatively impact carbon emissions. Thus, the impact of broadband technology could not be determined a priori. Yasmin and Grundmann (2019) state that linking ICT and media communication can influence and facilitate the adoption of cleaner options such as the use of biogas for cooking in the state of Punjab in Pakistan. This is supported by Acharya et al. (2017) who also argue that ICT-enabled wireless technology such as the use of internet of things could improve the efficiency levels of biogas generation plants.

Mobile Broadband Subscription (MOBS) refers to the number of persons per 100 people using mobile cellular services via cellular technology. Mobile subscription per 100 people is obtained by dividing the number of mobile cellular subscribers by the population and then multiplying by 100.

Fixed Broadband Subscriptions (FBS) refer to the number of persons per 100 people using high-speed fixed broadband internet service with downstream speed of 256 kbps or higher; and comprises cable modem, DSL, fiber-to-the-home or building, other fixed (wired)-broadband subscriptions, satellite broadband and terrestrial fixed wireless broadband. Fixed broadband

Internet subscribers per 100 people is obtained by dividing the number of fixed broadband Internet subscribers by the population and then multiplying by 100.

Clean Technology Adoption (CTA) is the second research explanatory variable of interest and was proxied by access to clean fuels and technologies for cooking and renewable energy consumption which is in line with empirical studies (Acharya & Marhold, 2019; Evans et al., 2017; Song et al., 2018). For example, Song et al. (2018) use afforestation expanse from environmental technology input to proxy green technology in their study. From literature clean technologies have the potential to mitigate or avoid emissions (Hoffert et al., 1998; Omoju, 2015; IEA, 2012; IEA/OECD, 2005). For instance, Fisher et al. (2006), point that application of carbon capture and storage technologies could help United States, Australia, India, China, Republic of Korea and Japan, known as the Asia Pacific 6 (AP 6), to cut global carbon emissions by about 11-23% from 2020 to the year 2050. Thus, the impact of clean technology adoption was expected to have a negative impact on CO_2 emissions.

Access to Clean Fuels and Technologies for Cooking (CFTECH) refers to the proportion of total population of a country, primarily using clean cooking fuels and technologies, excluding kerosene for cooking. In their study, Acharya and Marhold (2019) argue that the use of ICT applications can influence transition from the use of unhealthy cooking fuels such as fire wood and kerosene fuels for cooking to a cleaner source of energy such as liquefied petroleum gas (LPG) and electricity which can help to avoid and mitigate pollution, particularly in developing economies. Similarly, Evans et al. (2017) claim that ICT can be a mechanism for awareness creation, in terms of gains of adopting cleaner options such as cookstove, among households in Kenya, Bangladesh, and Nigeria.

Renewable Energy Consumption (RECON) is the share of renewable energy in total final energy consumption. Literature shows energy diversification through renewable energy production and use can contribute to mitigation of environmental degradation and ensure energy security (Luni & Majeed, 2020). Anwar et al. (2021) conclude that renewable energy consumption and forestation can significantly reduce carbon emissions in 33 partner economies of the Belt and Road Initiative economies. What is more, because renewable energy production and use is environmentally friendly, reliable, and could reduce carbon emissions by about 90% (Luni & Majeed, 2020), both developed and developing countries are making efforts to increase the use of renewable energy.

Real Gross Domestic Product (GDPPC), a measure of economic growth was included to test the validity or observe the presence of the EKC hypothesis. Investigating the nexus between carbon emissions and economic growth with the view to determine whether the EKC holds or not in the presence of broadband and clean technologies usage is relevant and of interest because in the argument of Narayan and Narayan (2010), it would afford environmental policy makers the opportunity to have knowledge of how the environment relates to economic growth. According to literature, increase in economic growth (GDPPC) increases the level of carbon emissions that affect environmental quality (Danish et al., 2018; 2017; Ozcan & Apergis, 2017). For instance, increasing economic growth may lead to increasing quantities of energy use produced usually from high carbon content sources (oil, coal, natural gas) and this could lead to increasing CO_2 emissions. Shahbaz et al. (2013b) in their study discover that increase in energy intensity and economic growth increase CO_2 emissions.

However, to avoid or control for misspecification bias in the models (for broadband and clean technologies) of the research study, other control variables: energy use, trade openness, foreign direct investment, population, fixed telephone use, R&D expenditure, education (secondary school enrolment), and forest area cover that influence environmental sustainability were included as additional explanatory variables in investigating the impact of broadband (mobile and fixed broadband) and clean technologies (access to clean fuels and technologies for cooking and renewable energy consumption) on environmental sustainability.

Energy Use (EU) refers to the use of primary energy before transformation to other end-use fuels (such as electricity and refined petroleum products). Energy use (kg of oil equivalent per capita) was included to measure the impact of energy consumption on carbon emissions and was expected a priori to have a positive impact on carbon emissions. Energy economics literature shows that energy use is one of the main contributory factors or determinants of CO_2 emissions. Kohler (2013) investigates the relationships between CO_2 emissions, energy consumption, income, and foreign trade to test the validity of the EKC hypothesis, for the period 1960 - 2009. The findings show that energy use increase CO_2 emissions while higher levels of trade reduced them. Also, Arouri et al. (2012) and Omri (2013) considered energy use in their investigation of the nexus between CO_2 emissions, energy consumption and economic growth for MENA countries. Others include Paramati et al. (2016) for the United States, and Wang et al. (2011) for China. And the results of these studies show energy use impact CO_2 emissions positively.

Trade Openness (TRADE) is the sum of exports and import of goods and services measured as percentage of gross domestic product. Trade activities such as the production and use of broadband and environmental technology goods and services could positively or negatively affect CO_2 emissions, thus its impact could only be determined posteriori. In their study of the Turkish economy, Ozturk and Acaravci (2013) discover that foreign trade to GDP ratio raises carbon emissions per capita. Similarly, Osabuohien et al. (2014) also find that increasing trade does not add to pollution in Africa. But these findings are not consistent with those of Kaika and Zervas (2013) who discover that trade openness decreases CO_2 emissions.

Foreign Direct Investment (FDI), net inflows percent of GDP was also used as control variable and could impact CO_2 emissions positively or negatively. For instance, FDI may come with the transfer and use of environmentally clean or polluting technologies which can affect energy efficiency and influence CO_2 emissions (Danish, 2019). Paramati et al. (2016) analysed the effects of FDI inflows and stock market development on clean energy use across emerging market economies for the study period 1991–2012. They argued that two-main conflicting FDI hypotheses exist in literature. The first was that FDI increases growth and CO_2 emissions. The second was that FDI comes with improved technologies which increases energy efficiency, promotes the use of renewable energy and could lead to decrease in CO_2 emissions.

Research and Development Expenditure (RDEXP) refers to expenditures on research and development (R&D), expressed as a share of GDP, including both capital and current expenditures in business enterprise, government sector, higher education and private non-profit sectors. R&D covers basic research, applied research, and experimental development.

Education (EDUCS) proxied by secondary school enrollment is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown. Secondary education completes the provision of basic education that began at the primary level and aims at laying the foundation for lifelong learning and human development.

Forest Area (FOREST) is land under natural or planted stands of trees of at least 5 meters in situ, whether productive or not, and excludes tree stands in agricultural production systems (for example, in fruit plantations and agroforestry systems) and trees in urban parks and gardens. It is argued that if forest area is carefully preserved and managed with the necessary investment, it can serve as an economical and cheap source of reducing atmospheric pollution and biomass energy (Waheed et al., 2018; Farooq et al., 2018). On the other hand, when there is too much deforestation and cutting down of trees for industrial and development projects, it could lead to global warming and degradation of the environment (Achard et al., 2004; Brown et al., 2004; Stern, 2006).

Finally, empirical evidence indicates that concentration of carbon emissions is affected by the economic activities of population of countries (Bongaarts, 1992; Sohag et al., 2019). Thus, population growth measured as annual population growth rate and fixed telephone subscription (Su et al., 2021) which influence CO_2 emissions were also included as other additional control variables.

CHAPTER FIVE

DESCRIPTIVE ANALYSIS AND DISCUSSION OF EMPIRICAL RESULTS: BROADBAND TECHNOLOGY AND CARBON DIOXIDE EMISSIONS.

5.1 Introduction

This chapter presents the descriptive analyses and discussions of the empirical results of the study on the role of broadband technology on carbon dioxide emissions. Thus, it begins with presentation of preliminary descriptive analysis, followed by results of static panel model regressions, dynamic panel model regressions and long-run estimates of the dynamic short-run significant estimates.

5.2 Descriptive Statistics and Correlation Matrices for the Global Economy and the Two Country Groups.

Table 3 below gives the summary statistical reports of the study's variables of the impact of broadband technology usage on CO_2 emissions investigation of the global economy, developed countries and emerging-developing countries. They give information in terms of the means, standard deviations, and the number of observations.

Table 3. Descriptive statistical analysis of data used.

	Global economy			Developed countries			Emerging-developing countries		
Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
lnCO2	0.634	1.534	2653	2.110	0.565	784	0.014	1.382	1869
lnGDPPC	8.698	1.463	3254	10.331	0.644	1118	7.844	0.956	2136
MOBS	91.440	45.815	3136	121.066	34.701	1076	75.965	43.231	2,060
FBS	11.528	13.167	2960	24.461	12.223	1069	4.216	6.236	1,891
lnEU	7.261	1.127	1522	8.351	0.611	547	6.650	0.856	975
TRADE	93.264	61.104	2917	121.640	84.367	998	78.506	36.601	1919
FDI	10.560	71.087	3064	23.520	124.477	979	4.474	6.311	2085
POPG	1.351	1.502	3447	0.9678	1,264	1264	1.572	1.225	2183
FTS	19.773	19.469	3164	38.814	18.471	1117	9.382	9.690	2047
EDUCS	83.655	28.069	2113	104.574	15.737	787	71.239	26.357	1326

Source: Author's computation using data from WDI.

From the summary statistical reports in table 3, columns (2 - 4), columns (5 - 7), and columns (8 - 10) present description of the data for the global economy, developed countries and emerging-developing countries respectively. The statistics show that the mean values of carbon dioxide emissions (CO_2) for the global economy, developed countries and emerging-developing countries are 0.634, 2.110, and 0.014, with standard deviations of 1.534, 0.565, and 1.382 respectively. In terms of broadband technology measured by mobile and fixed broadband subscriptions, the mean values of mobile and fixed broadband subscriptions are 91.440 and 11.528 for the global economy, 121.066 and 24.461 for developed countries, 75.965 and 4.216 for emerging-developing economies respectively. Their respective standard deviations are 45.815 and 13.167 for the global economy, 34.701 and 12.223 for developed countries, 43.231and 6.236 for emerging-developing countries. These statistics clearly show that developed countries and emerging-developing countries are different in terms of broadband technology accessibility and CO_2 emissions. CO_2 emissions and all the indicators (mobile and fixed) of broadband technology on average are higher in developed countries compared to emerging-developing countries. These descriptive analysis of the data in effect, shows that developed countries and emerging-developing countries are different in term of environmental deterioration and broadband technology accessibility.

Furthermore, correlation matrices were also carried out in analysing the impact of broadband on CO_2 emissions in the global economy, and the two country groups. According to rule of thumb, when the coefficient of correlation is less than 0.7, we say there is moderate correlation, and from the results of the correlation matrices for the global economy, developed countries and emerging-developing countries in terms of broadband diffusion and CO_2 (see appendix A for the correlation matrix results), almost all coefficients of the variables show moderate correlation, which means there is no serious multicollinearity issue with the study's variables.

Additionally, tables 4, 5 and 6 below present the panel data summary statistics of indicator measures of the research variables of the study for the global economy, developed countries and emerging-developing countries. They provide more statistical evidence on the within and between variations of the research variables of interest in terms of the role of broadband technology on carbon emissions.

Table 4. Overall, between and within variations of CO_2 emissions and broadband technology (mobile and fixed broadband subscriptions) for the global economy.

Variable		Mean	Std. Dev.	Min	Max	Observations
lnCO2	Overall	0.63377	1.534292	-3.8293	3.86493	N = 2653
	Between		1.529828	-3.39621	3.56585	n = 190
	Within		0.190077	-0.45004	2.047477	T = 13.9632
lnGDPPC	Overall	8.698365	1.462788	5.60098	12.11016	N = 3254
	Between		1.484424	5.709105	12.02762	n = 210

	Within		0.132447	8.03067	9.24766	T-bar = 15.4952
GDPPCSQ	Overall	77.80065	25.59487	31.37097	146.6561	N = 3254
	Between		26.06963	32.5968	144.6637	n = 210
	Within		2.218828	63.32007	87.49237	T-bar = 15.4952
MOBS	Overall	91.43952	45.81485	0	345.3245	N = 3136
	Between		38.90225	5.840659	245.5909	n = 209
	Within		26.17546	-43.817	191.1732	T-bar = 15.0048
FBS	Overall	11.52776	13.16674	0	62.28062	N = 2960
	Between		12.16795	0.001039	46.96808	n = 206
	Within		5.023487	-11.477	38.54159	T-bar = 14.3689

Source: Author's computation using data from WDI.

Table 4 shows that for CO_2 emissions, there are 2653 observations for 190 countries for the global economy. On average, a country's CO_2 emissions is observed 13.96 times. The overall mean of CO_2 is 0.63377, and overall standard deviation is 1.534292. The between and within standard deviations of CO_2 emission are 1.5298, and 0.19007 respectively. The within standard deviation of 0.19007 indicates that global CO_2 emissions is time-variant.

When it comes to broadband technology (proxied by mobile (MOBS) and fixed (FBS) broadband subscriptions), for mobile subscriptions there are 3136 observations for 209 countries for the global economy. On average, a country's mobile broadband subscription is observed 15 times. The overall mean and standard deviation are 91.43952, and 45.81485 respectively. The between and within standard deviations are 38.90225 and 26.17546 respectively. For fixed broadband subscriptions there are 2960 observations for 206 countries. On average, a country's fixed broadband subscription is observed 14.36 times. The overall mean and standard deviation are 11.52776, and 13.16674 respectively. The between and within standard deviations are 12.16795 and 5.023487 respectively. The within standard deviations of mobile and fixed broadband subscription, measures of broadband technology indicate that global broadband accessibility is time-variant. Besides, the between variations of CO_2 and broadband technology diffusion are larger than the within variations.

Table 5. Overall, between and within variations of CO_2 emissions and broadband technology (mobile and fixed broadband subscriptions) for developed countries.

Variable		Mean	Std. Dev.	Min	Max	Observations
lnCO2	Overall	2.110214	0.565942	0.487743	3.86493	N = 784
	Between		0.552853	0.690299	3.56585	n = 56
	Within		0.140421	1.554223	3.175511	T = 14
lnGDPPC	Overall	10.33132	0.644507	7.946198	12.11016	N = 1118
	Between		0.654457	8.613892	12.02762	n = 74
	Within		0.107467	9.663627	10.77187	T-bar = 15.1081
GDPPCSQ	Overall	107.1512	13.32982	63.14205	146.6561	N = 1118
	Between		13.62887	74.3598	144.6637	n = 74
	Within		2.15068	92.67065	115.3917	T-bar = 15.1081
MOBS	Overall	121.0658	34.70121	30.58996	345.3245	N = 1076
	Between		29.40108	74.49394	245.5909	n = 73
	Within		21.62422	-14.1908	220.7995	T-bar = 14.7397
FBS	Overall	24.46138	12.22304	0.284672	62.28062	N = 1069
	Between		10.67835	1.692009	46.96808	n = 73
	Within		6.773005	1.456578	51.4752	T-bar = 14.6438

Source: Author's computation using data from WDI.

Table 5 shows that for the CO_2 emissions, there are 784 observations for 56 countries for the developed countries. On average, a country's CO_2 emissions is observed 14 times. The overall mean of CO_2 is 2.110214, and overall standard deviation is 0.565942. The between and within standard deviations of CO_2 emission are 0.552853, and 0.140421 respectively. The within standard deviation of 0.140421 indicates that developed countries CO_2 emissions is time-variant.

When it comes to broadband technology (proxied by mobile (MOBS) and fixed (FBS) broadband subscriptions), for mobile subscriptions there are 1076 observations for 73 countries for the developed countries. On average, a country's mobile broadband subscription is observed 14.7 times. The overall mean and standard deviation are 121.0658, and 34.70121 respectively. The between and within standard deviations are 29.40108 and 21.62422 respectively. For fixed broadband subscriptions there are 1069 observations for 73 countries. On average, a country's fixed broadband subscription is observed 14.6 times. The overall mean and standard deviation are 24.46138, and 12.22304 respectively. The between and within standard deviations are 10.67835 and 5.023487 respectively. The within standard deviations of mobile and fixed broadband subscriptions, measures of broadband technology indicate that broadband technology use is time-variant in developed countries. Besides, the between variations of CO_2 and broadband technology diffusion are larger than the within variations.

Table 6. Overall, between and within variations of CO_2 emissions and broadband technology (mobile and fixed broadband subscriptions) for emerging-developing countries.

Variable		Mean	Std. Dev.	Min	Max	Observations
lnCO2	Overall	0.014437	1.381708	-3.8293	2.711202	N = 1869
	Between		1.373355	-3.39621	2.552308	n = 134
	Within		0.207431	-1.06937	1.428145	T = 13.9478
lnGDPPC	Overall	7.843662	0.956925	5.60098	9.70739	N = 2136
	Between		0.951691	5.709105	9.475001	n = 136
	Within		0.143826	7.192291	8.392957	T-bar = 15.7059

GDPPCSQ	Overall	62.43831	14.76358	31.37097	94.23342	N = 2136
	Between		14.66163	32.5968	89.7806	n = 136
	Within		2.254173	51.30635	72.13003	T-bar = 15.7059
MOBS	Overall	75.96481	43.23128	0	207.7518	N = 2060
	Between		33.30331	5.840659	163.2677	n = 136
	Within		28.2678	-25.3564	157.3944	T-bar = 15.1471
FBS	Overall	4.21627	6.236496	0	34.45275	N = 1891
	Between		4.915464	0.001039	21.40552	n = 133
	Within		3.685996	-17.1729	22.1765	T-bar = 14.218

Source: Author's computation using data from WDI.

Table 6 shows that for the CO_2 emissions, there are 1869 observations for 134 countries for the emerging-developing countries. On average, a country's CO_2 emissions is observed 13.94 times. The overall mean of CO_2 is 0.014437, and overall standard deviation is 1.381708. The between and within standard deviations of CO_2 emission are 1.373355, and 0.207431 respectively. The within standard deviation of 0.207431 indicates that emerging-developing countries CO_2 emissions is time-variant.

When it comes to broadband technology (proxied by mobile (MOBS) and fixed (FBS) broadband subscriptions), for mobile subscriptions there are 2060 observations for 136 countries for the emerging-developing countries. On average, a country's mobile broadband subscription is observed 15.1471 times. The overall mean and standard deviation are 75.96481 , and 43.23128 respectively. The between and within standard deviations are 33.30331 and 28.2678 respectively. For fixed broadband subscriptions there are 1891 observations for 133 countries. On average, a country's fixed broadband subscription is observed 14.218 times. The overall mean and standard deviation are 4.21627, and 6.236496 respectively. The between and within standard deviations are 4.915464 and 3.685996 respectively. The within standard deviations of mobile and fixed broadband subscriptions, measures of broadband technology indicate that broadband technology use is time-variant in emerging-developing countries. Besides, the between variations of CO_2 and broadband technology diffusion are larger than the within variations.

5.3 Preliminary Regression Results

Static Panel Results

In this section, traditional static panel data models, namely pooled OLS (POLS), fixed effects (FE), and random effects (RE) estimation technique were carried out as part of a battery of preliminary investigation of the impact of broadband technology on CO_2 emissions. However, the estimated static panel models (POLS, FE, RE) gave different results for both some of the explanatory variables of interest and the control variables. And since the results of all these models cannot be taken, but only those that appropriately fit or explain the data based on optimal tests of model selection should be selected; therefore, choosing between the FE and RE models, the Hausman test indicated that the FE model was appropriate for representing the data relative to the RE model. Besides, between the pooled OLS and the RE models, the Breusch and Pagan Lagrange Multiplier (ML) test showed the pooled OLS model was more appropriate and better in explaining the data than the RE model. Based on the results of these tests, the study considers only the FE estimates as most appropriate. Table 7 below presents the estimated results of the static panel data models.

Table 7. Static panel regression results of CO_2 emissions and broadband technology for global economy, developed countries and emerging-developing countries.

	Pooled OLS			Fixed Effect		
Variable	**Global economy**	**Developed Countries**	**Emerging-developing countries**	**Global economy**	**Developed countries**	**Emerging-developing countries**
lnCO2						
lnGDPPC	2.742***	5.961***	4.752***	2.554***	0.147	3.842***
	(0.181)	(1.033)	(0.471)	(0.695)	(1.148)	(1.090)
$lnGDPPC^2$	-0.142***	-0.283***	-0.277***	-0.122***	0.007	-0.219***
	(0.010)	(0.049)	(0.030)	(0.037)	(0.059)	(0.067)
MOBS	-0.000	0.000	-0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
FBS	-0.012***	-0.010***	0.001	-0.006***	-0.006***	-0.001
	(0.002)	(0.002)	(0.005)	(0.001)	(0.001)	(0.002)
lnEU	0.729***	0.545***	0.750***	0.730***	0.586***	0.877***
	(0.059)	(0.069)	(0.104)	(0.116)	(0.199)	(0.107)
TRADE	0.003***	0.002***	0.004***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
FDI	-0.001*	-0.000	-0.010***	0.000	0.000	0.001
	(0.000)	0.000	(0.004)	(0.000)	(0.000)	(0.002)
POPG	0.044***	0.039***	0.052*	0.002	0.006	-0.018
	(0.009)	(0.008)	(0.030)	(0.011)	(0.012)	(0.028)
FTS	0.006***	-0.002	0.010***	0.004***	0.006***	0.001
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
EDUCS	0.005***	-0.003	*0.007****	-0.001*	-0.002***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-Sq.	0.905	0.705	0.883			
F-statistic	618.90***	233.97***	349.81***	73.33***	52.41***	30.99***
Obs.	996	428	568	996	428	568
No. groups				136	47	89

Test	H0 & H1	Appropriate Model	Prob of chi2 & chibar2	Decision
Breusch and Pagan	H0	Pooled OLS	0.000	Reject Ho
LM Test	H1	Random Effects		
	H0	Random Effects		
Hausman Test			0.000	Reject Ho
	H1	Fixed Effects		

Notes: This is the report of pooled OLS (POLS) and fixed effects (FE) estimates. $lnCO_2$ (CO_2 emissions) is dependent variable. Figures in parenthesis denote robust standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, indicate significance at 1%, 5%, and 10% levels, respectively.

Table 7. continued

	Random Effects		
Variable	**Global economy**	**Developed Countries**	**Emerging-developing countries**
lnCO2			
lnGDPPC	2.684***	0.838	3.913***
	(0.555)	(0.919)	(0.988)
$GDPPC^2$	-0.131***	-0.030	-0.216***
	(0.030)	(0.046)	(0.061)
MOBS	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
FBS	-0.006***	-0.006***	-0.001
	(0.001)	(0.002)	(0.002)
lnEU	0.676***	0.611***	0.753***
	(0.107)	(0.195)	(0.119)
TRADE	0.000*	0.000	0.001
	(0.000)	(0.000)	(0.001)
FDI	0.000	0.000*	0.001
	(0.000)	0.000	(0.002)
POPG	0.004	0.009	-0.019
	(0.011)	(0.013)	(0.029)
FTS	0.005***	0.005***	0.002
	(0.001)	(0.002)	(0.002)
EDUCS	-0.000	-0.002***	-0.000
	(0.000)	(000)	(0.001)
Wald-test	1044.19***	551.87***	338.10***
Obs.	996	428	568
No. groups	136	47	89

Test	H0 & H1	Appropriate Model	Prob of chi2 & chibar2	Decision
Breusch and Pagan	H0	Pooled OLS	0.000	Reject Ho
LM Test	H1	Random Effects		
	H0	Random Effects		
Hausman Test			0.000	Reject Ho
	H1	Fixed Effects		

Notes: This is the report of pooled OLS (POLS) and fixed effects (FE) estimates. lnCO_2 (CO_2 emissions) is dependent variable. Figures in parenthesis denote robust standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, indicate significance at 1%, 5%, and 10% levels, respectively.

Although the Hausman test indicated that the FE model was appropriate, the estimated results of the pooled OLS, FE, and RE are all reported. Focusing on the estimated results of the FE model as most appropriate, the results show that, the coefficients of mobile broadband are statistically insignificant and positively correlated with carbon dioxide emissions in the global economy and the two country groups; whereas fixed broadband has a statistically significant (at 1% level) negative correlation with CO_2 emissions in the world economy and developed countries but negative insignificant correlation in emerging-developing countries. GDP per capita and its square show significant (at 1% level) and negative relationship with CO_2 emissions respectively in the global economy and emerging developing economies but insignificant relationship in developed countries. For the control variables, energy consumption shows significant (at 1% level) positive relationship with CO_2 emissions for all the country groups, while fixed telephone use has significant positive relationship with CO_2 emissions for only developed countries and the world economy. The estimates of the pooled OLS and random effects are not that remarkably different from those of the fixed effect model.

However, inferences from the descriptive analysis and these battery of static preliminary regressions results show somewhat evidence of prior expectation of some statistical relationship between CO_2 emissions and broadband technology diffusion. This means that, further investigation and explanation cannot be rule out, especially since static panel model estimates might be potentially affected by endogenous effects and particularly so since the study uses unbalanced panel dataset with short time series dimensions and very wide cross-sectional dimensions. The study, therefore, proposed to use a more appropriate alternative model of analysis and estimation in investigating the role of broadband technology on CO_2

emission further which could cope with or eliminate endogenous problems or effects and weaknesses of static panel data models.

Additionally, static models are always possibly affected by misspecification issues due to the within-group error terms being serially correlated, often invalidating their point estimates and statistical inferences, whereas dynamic models rather turn to be more correctly specified because the dynamics are in the estimated part of the model rather than displaced into the error terms, which invalidates static models (FE, RE) estimations, (Pugh, 2018). To address and avoid these possible issues associated with the static model estimates, the study uses the dynamic model, System Generalized Method of Moments (System GMM).

5.4 Dynamic Panel Estimation Results

Given the nature of the research data and time span, a dynamic panel approach was more appropriate. Thus, to avoid spurious results and account for robustness of the study results in analysing the impacts of broadband technology on global carbon emissions, the study employed a dynamic econometric approach (system GMM) as a better alternative to the static panel model estimators. Dynamic models are more sophisticated in terms of economic content because of the fact that, they are able to distinguish between short and long-run impacts of independent variables on dependent variables (Pugh, 2018). Besides, system GMM estimators are more suitable for unbalanced panel data and better in producing consistent and efficient parameter estimates in the presence of omitted variables, large sample size, limited time periods, endogeneity issue, heteroskedasticity issue, serial autocorrelation, and individual specific distributed effects. This makes estimated results of system GMM more preferable and credible. Table 8 below, present the dynamic panel model estimated results of system GMM for the global economy, developed and emerging-developing countries. Unlike the static panel models, system GMM model estimation uses lag of the dependent variable in addition to the other control variables.

Table 8. System GMM results of CO_2 and broadband technology for global economy, developed countries and emerging-developing countries.

	with full instruments			with collapsed instruments		
	Global economy	Developed countries	Emerging-developing countries	Global economy	Developed countries	Emerging-developing countries
lnCO2						
L1.lnCO2	0.877***	0.727***	0.894***	0.432***	0.716***	0.565***
	(0.039)	(0.163)	(0.044)	(0.157)	(0.126)	(0.105)
lnGDPPC	0.218*	-0.298	0.100	1.254**	0.260	3.590***
	(0.131)	(0.813)	(0.349)	(0.530)	(01.291)	(1.242)
$GDPPC^2$	-0.011	0.011	-0.005	-0.060**	-0.012	-0.213***
	(0.007)	(0.037)	(0.0213)	(0.026)	(0.064)	(0.078)
MOBS	0.000	-0.001	-0.000	-0.001	0.001	-0.002*
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
FBS	-0.003**	-0.002	-0.005**	-0.012***	-0.006*	-0.006
	(0.001)	(0.003)	(0.002)	(0.004)	(0.003)	(0.007)
lnEU	0.099***	0.183*	0.075**	0.465***	0.234*	0.357***
	(0.035)	(0.103)	(0.034)	(0.117)	(0.132)	(0.102)
TRADE	0.000	0.000	0.001	0.001*	0.000	0.003
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)
FDI	0.000	0.000	-0.002	0.000	0.000	-0.002
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.005)
POPG	-0.000	0.025	-0.007	-0.002	-0.000	0.018
	(0.003)	(0.027)	(0.008)	(0.009)	(0.007)	(0.016)
FTS	0.000	0.001	0.002	0.002	0.002	0.005
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.004)
EDUCS	0.001	-0.000	0.000	0.001	-0.001	0.001
	(0.000)	(0.000)	(0.001)	(001)	(001)	(0.001)
Year dummies	YR	YR	YR	YR	YR	YR

F-test	3396.29***	347.50***	4069.42***	191.81***	676.28***	139.57***
AR (2)	0.995	0.085	0.307	0.979	0.099	0.277
Hansen test	0.198	1.000	0.991	0.104	0.243	0.179
No. of obs.	894	383	511	894	383	511
No. of groups	132	47	85	132	47	85
No. of instru.	126	173	117	32	38	32

Notes: This is the report of system GMM estimates. lnCO_2 (CO_2 emissions) is dependent variable. Figures in parenthesis denote robust standard errors. ***p < 0.01, **p < 0.05, *p < 0.1, indicate significance at 1%, 5%, and 10% levels, respectively. AR(2) and Hansen statistics p-values are reported

The estimation was first done with full instruments for all the country groups. The results are reported in column 2, 3 and 4 in table 8. These results are affected by the issue of instrument proliferation as indicated by the higher p-values of the Hansen tests of 0.198, 1.000 and 0.991 for the global economy, developed countries and emerging-developing countries respectively. This was not a good development for the model because according to Roodman (2009), increasing instrumentation increases the estimates' bias which does not eliminates endogenous effects of the endogenous variables. Thus, following literature, re-estimation was done with collapsed instruments for all the country groups, and the results are reported in columns (5 - 7) in table 8.

Focusing on the results in columns (5 - 7) with collapsed instruments across all the levels of economic development, the null hypothesis of all the explanatory variables being insignificant against the alternative hypothesis of being significant is rejected at all commonly accepted levels of significance (1%, 5% and 10%), confirmed by the p-values of the F-statistic being less than 1%. This means that, aside the fact that the selected independent variables are jointly valid in explaining the CO_2 emission, the model does not suffer from misspecification problem (i.e., correctly specified). Besides, the Arellano-Bond test of no serial autocorrelation in first difference errors of order 2 indicates that, there is no second order serial autocorrelations for the country groups, which means that the parameter estimates are consistent. This further implies validity of the instruments used for all the groups. The Hansen test of overidentifying restriction with p-values of 0.104, 0.243, and 0.179 for the global economy, developed countries and emerging-developing countries respectively at 1% significant level, show that the study cannot reject the null hypothesis that the instruments used were valid.

The estimated results further show that mobile subscription measure of broadband technology has a negative effect on CO_2 emissions in the global economy and in emerging-developing countries but positive effect on emissions in developed countries. But its impact (-0.002) is only significant in emerging-developing countries at 10% significant level. This means that a percentage change in mobile broadband subscription is associated with -0.00.2% reduction in CO_2 emissions at 10% significant level on average, which implies mobile broadband subscription has an inelastic relationship with CO_2 emissions in emerging-developing countries. This result is consistent and agrees with Su et al. (2021), Asongu (2018a), and Haseeb et al. (2019) who discovered that mobile subscription reduces CO_2 emissions but disagrees with Moyer and Hughes (2012), Heddeghem et al. (2014) and, Khayyat et al. (2016). Fixed broadband subscription measure of broadband technology on the other hand has a negative impact on CO_2 emissions for the global economy and the two country groups. But whereas its impact in mitigating CO_2 emissions is insignificant in emerging-developing countries, it is significant in developed countries and strongly significant in the global economy. This means that a percentage change in fixed broadband subscription leads on average, to -0.00.6% and -0.01.2% reductions in CO_2 emissions in developed countries and in the global economy at 10% and 1% significant levels respectively. This result is in sharp contrast with that of Su et al. (2021) who in their investigation of BRICS countries discovered that fixed broadband subscription increases CO_2 emissions. Besides, these results of the measures of broadband technology having negative impacts show that on average, broadband technology activity in the form of mobile and fixed broadband subscriptions contribute to mitigation of global CO_2 emissions. These findings are consistent and supportive of empirical findings (Vergara et al., 2014; Claussen et al., 2009; Mathiesen et al., 2015; Malmodin & Bergmark, 2015) that argue that broadband and ICT application and services have mitigating impact on carbon emissions but are inconsistent with studies (Collard et al., 2005; Bernstein & Madlener, 2010; Moyer & Hughes, 2012; Røpke & Christensen, 2012) that argue otherwise.

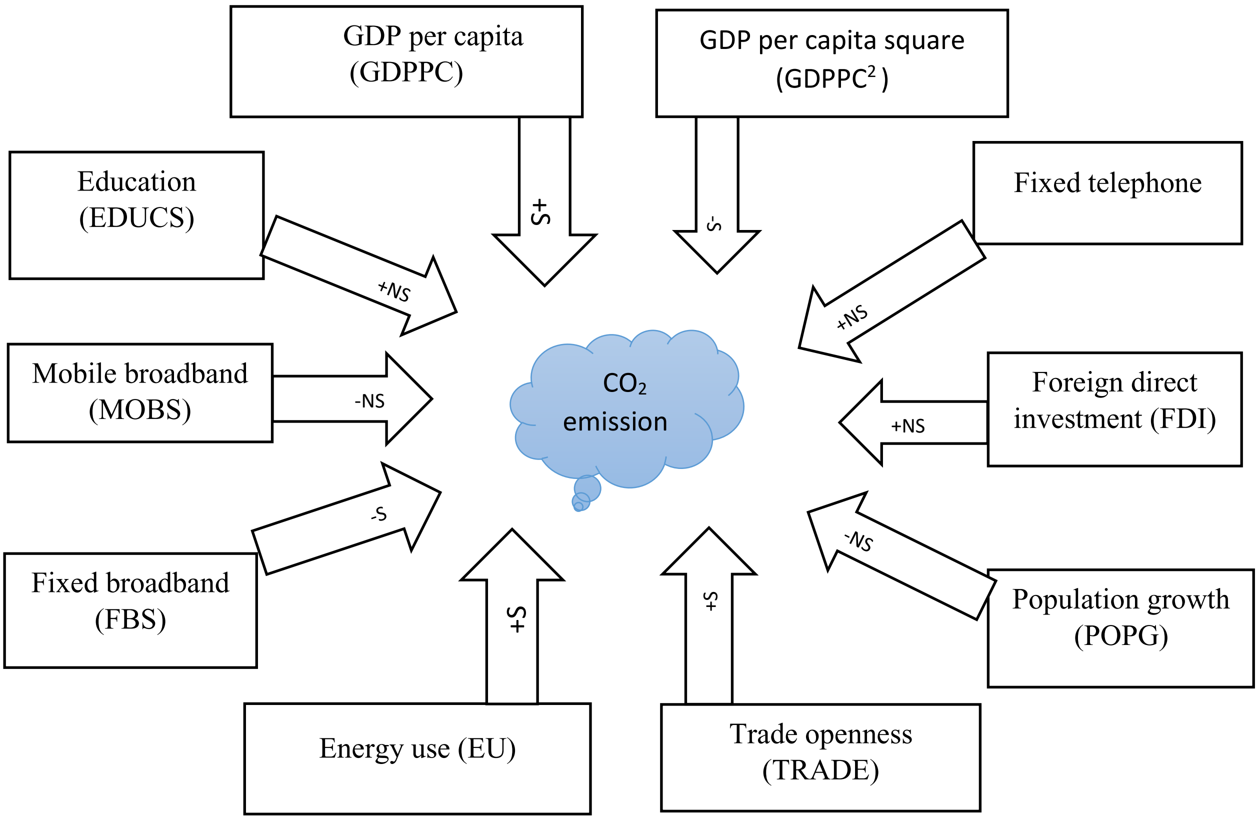
In terms of development levels, while mobile broadband measure of broadband technology activity insignificantly increases CO_2 emissions in developed countries, it significantly reduces CO_2 emissions in emerging-developing countries. Fixed broadband measure of broadband technology activity has mitigating effects on CO_2 emissions in the two country groups but does so significantly in developed countries. These results show that these indicator measures of broadband technology activity have heterogenous outcomes for developed and emerging-developing countries.

The parameter estimates of economic growth variables, GDPPC (1.254) and $GDPPC^2$ (-0.060) for the global economy; GDPPC (0.260) and $GDPPC^2$ (-0.012) for developed country; GDPPC (3.590) and $GDPPC^2$ (-0.213) for emerging-developing countries have negative and positive effects respectively for the global economy and the two country groups in the presence of broadband technology. But they are only significant at 5% level for the global economy and 1% level for emerging-developing countries. These findings relative to the world economy and emerging-developing countries however, confirm the EKC hypothesis and are consistent with empirical studies (Grossman & Krueger, 1995; Panayotou, 1997; Dinda, 2004; Caviglia-Harris et al., 2009; Ahmed et al., 2016) that arrived at similar results but are inconsistent with studies

(Sohag et al., 2019; Ekins, 1997; Dietz & Adger, 2003; Amri, 2018; Belloumi et al., 2017) that contradicted the EKC hypothesis or showed no causal link (Ozturk & Acaravci, 2010) between economic growth and CO_2 emissions. For instance, while Caviglia-Harris et al. (2009) and Ahmed et al. (2016) confirmed the EKC hypothesis for the world economy and EU countries respectively, Sohag et al. (2019), and Dietz & Adger (2003) discovered U-shape relationship between CO_2 emissions and economic growth for OECD countries, Asia, Africa, and Central America respectively.

The results further show that for the control variables, energy use has significant negative effect on environmental quality in all the country groups, and this development concurs with empirical findings on the impact of energy consumption on environmental quality (Ozcan & Apergis, 2017; Kohler, 2013; Arouri et al., 2012; Omri, 2013). The negative impact of energy use on the quality of the environment for the world economy and the two country groups is not surprising because most economies of the world are still powered by energy from fossil fuel consumption and other non-renewable sources which increases global air pollution (Khan et al., 2020; Ozcan & Apergis, 2017). The role of energy use contributing significantly to carbon emissions is expected a priori because in as much as developed economies continue to use energy from non-renewable sources and emerging developing economies are also increasing their demand for fossil fuels consumption couple with the slow pace of diversification of energy production from non-renewables to renewables, energy consumption will continue to significantly affect global climate change. International trade activities also increase emissions in the global environment which deepens degradation of the environment and this in in tandem with findings by Ozturk and Acaravci (2013). Also, the coefficients of the lag of CO_2 emissions for the global economy and the two country groups are statistically significant at 1% level reflecting the fact that past carbon dioxide emissions in all the country groups influence not only current but also future emissions levels. These coefficients indicate that deterioration of the environment is not influenced by development levels of economies of the world. Besides, the coefficients of the lag of CO_2 show that the study's model is a dynamic one much as it does not converge to its long run equilibrium.

Pictogrammic Summary of the Results of Broadband Technology on Global CO_2 Emissions.



Pictogramme 1.
Note(s): -S = negative and significant, +S = positive and significant, -NS = negative and not significant, +NS = positive and not significant. Source(s): Study's construction

5.5 Long-Run Parameter Estimates of Explanatory Variables on CO_2 Emissions of the System GMM Estimates.

Table 9 below reports the long-run parameter estimates of the significant short-run estimates of the system GMM results in column (5 – 7) of table 8 for the global economy, developed countries and emerging-developing countries. Hence, the long-run parameter estimates of mobile broadband subscriptions, fixed broadband subscriptions, GDP per capita, GDP per capital square, energy use and trade are in columns (2 – 4) of table 9 below.

Table 9. Long-run elasticity estimates of the significant variables

	Global economy	Developed countries	Emerging-developing countries
lnCO2			
lnGDPPC	2.201***		8.256***
	(0.683)		(2.306)
lnGDPPC^2	-0.105***		-0.490***
	(0.037)		(0.149)
MOBS			-0.004*
			(0.002)
FBS	-0.021***	-0.021*	
	(0.008)	(0.011)	
lnEU	0.819***	0.824***	0.820***
	(0.105)	(0.227)	(0.130)
TRADE	0.002*		
	(0.001)		

Notes: This is the report of the long-run estimates of significant variables of the study. lnCO_2 (CO_2 emissions) is dependent variable. Figures in parenthesis denote robust standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, indicate significance at 1%, 5%, and 10% levels, respectively.

Long-run effects for the k^{th} parameter was computed as:

$$\beta_k /[1 - \phi]$$

The above formula is the mathematical computation of how the long-run system GMM estimates of the k^{th} parameter was estimated.

From the results of the long-run estimates, mobile broadband has a negative long-run impact coefficient of -0.004 which is larger than its short-run coefficient of -0.002 in emerging-developing countries. This mean that a percentage change in mobile broadband subscriptions measure of broadband technology activity is associated with -0.00.4% reduction in CO_2 emissions in the long run, at 10% significant level. Implying that, mobile broadband component of broadband technology shows an inelastic relationship with CO_2 emissions.

Fixed broadband subscription has a long-run coefficients of -0.021 and -0.021 which are significant at 1% and 10% for the global economy and developed countries respectively. The long-run coefficient of fixed broadband (-0.021) is larger than the short-run coefficient (-0.006) for emerging developing countries. Hence, a percentage change in fixed broadband subscription is associated with -0.02% reduction in CO_2 emissions in the global economy and in developed countries at 1% and 10% respectively. This means that fixed broadband subscription and CO_2 emissions also have an inelastic relationship. Economic growth, energy consumption and trade also have significant long-run effects on CO_2 emissions. These long-run impacts in terms of economic growth occurs in emerging-developing countries and in the global economy only, whereas that of energy use occurs in the global economy and the two country groups. Trade has long-run impact on carbon emissions in the global economy only.

CHAPTER SIX

DESCRIPTIVE ANALYSIS AND DISCUSSION OF EMPIRICAL RESULTS: CLEAN TECHNOLOGY AND CARBON DIOXIDE EMISSIONS.

6.1 Introduction

Like chapter 5, this chapter also provides the descriptive analyses and discussions of the estimated results of the study on the role of clean technology on carbon emissions. It begins with presentation of preliminary descriptive analysis, followed by results of static panel model regressions, dynamic panel model estimations and long-run estimates of the dynamic short-run significant estimates.

6.2 Descriptive Statistics and Correlation Matrices for the Global Economy and the Two Country Groups.

Tables 10 below provides the descriptive statistics of the empirical statistical analysis of the impact of clean technology on CO_2 emissions for the global economy, developed countries and emerging-developing countries. It gives information in terms of the means, standard deviations, and the number of observations.

Table 10. Descriptive statistical analysis of data used.

	Global economy			Developed countries			Emerging-developing countries		
Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
lnCO2	0.633	1.534	2653	2.110	0.565	784	0.014	1.382	1869
lnGDPPC	8.698	1.462	3254	10.331	0.644	1118	7.844	0.956	2136
CFTECH	63.917	39.028	2829	100	0	855	48.289	37.077	1974
RECON	29.4659	29.241	2968	12.017	15.897	1050	39.018	30.447	1,918
RDEXP	0.964	0.977	1279	1.544	1.088	619	0.420	0.362	660
lnEU	7.261	1.127	1522	8.352	0.610	547	6.650	0.856	975
FDI	10.560	71.087	3064	23.520	124.477	979	4.474	6.311	2085
POPG	1.351	1.502	3447	0.967	1.825	1264	1.572	1.225	2183
FOREST	32.219	24.487	3379	29.432	22.415	1214	33.783	25.447	2165

Source: Author's computation using data from WDI.

From the summary statistics in table 10, the means of CO_2 emissions for the world environment, developed countries and emerging-developing countries are 0.633, 2.110, and 0.014, respectively. The corresponding standard deviations of CO_2 emissions for the world environment and the two country groups are 1.534, 0.565, and 1.382 respectively. For the research variable of interest (clean technology), the mean utilization of access to clean fuels and technologies for cooking, and renewable energy consumption, proxy measures of clean technology adoption are 63.917 and 29.466 for the global economy, 100 and 12.017 for developed countries, 48.289 and 39.018 for emerging-developing economies. Their corresponding standard deviations are 39.028 and 29.241; 0.000 and 15.897; 37.077 and 30.477 respectively. Inference from these statics imply that, emerging-developing countries on average have lower mean CO_2 emissions compared to developed countries, although deviation in emerging-developing countries is quite higher than developed countries. In terms of clean technology adoption, developed countries have higher mean adoption than emerging-developing countries. This shows that clean technology development and adoption is a priority and high in developed countries than in emerging-developing countries. Furthermore, results of the correlation matrices for the global economy, developed countries and emerging-developing countries did not show serious multicollinearity issue (see appendix A for the correlation matrix results).

Additionally, tables 11, 12 and 13 below present the panel data summary statistics of indicator measures of the research variables of the study for the global economy, developed and emerging-developing countries. They provide more statistical evidence on the within and between variations of the research variables of interest in terms of role of clean technology on carbon emissions.

Table 11. Overall, between and within variations of CO_2 emissions and clean technology (Access to clean fuels and technologies for cooking and renewable energy consumption) for the global economy.

Variable		Mean	Std. Dev.	Min	Max	Observations
lnCO2	Overall	0.63377	1.534292	-3.8293	3.86493	N = 2653
	Between		1.529828	-3.39621	3.56585	n = 190
	Within		0.190077	-0.45004	2.047477	T = 13.9632
lnGDPPC	Overall	8.698365	1.462788	5.60098	12.11016	N = 3254
	Between		1.484424	5.709105	12.02762	n = 210
	Within		0.132447	8.03067	9.24766	T-bar = 15.4952
GDPPCSQ	Overall	77.80065	25.59487	31.37097	146.6561	N = 3254
	Between		26.06963	32.5968	144.6637	n = 210
	Within		2.218828	63.32007	87.49237	T-bar = 15.4952
CFTECH	overall	63.91726	39.02821	0	100	N = 2829
	between		38.89517	0	100	n = 189
	within		3.913117	27.47059	95.7706	T = 14.9683
RECON	overall	29.46588	29.2408	0	97.4222	N = 2968
	between		29.0856	0	96.22302	n = 212
	within		3.571978	10.70935	52.37547	T = 14

Source: Author's computation using data from WDI.

Table 11 shows that for the CO_2 emissions, there are 2653 observations for 190 countries for the global economy. On average, a country's CO_2 emissions is observed 13.9632 times. The overall mean of CO_2 is 0.63377, and overall standard deviation is 1.534292. The between and within standard deviations of CO_2 emissions are 1.529828, and 0.190077 respectively. The within standard deviation of 0.190077 indicates that global CO_2 emissions is time-variant.

When it comes to clean technology adoption (proxied by access to clean fuels and technologies for cooking (CFTECH), and renewable energy consumption (RECON)), for access to clean fuels and technologies for cooking there are 2829 observations for 189 countries for the global economy. On average, a country's access to clean fuels and technologies for cooking is observed 14.9683 times. The overall mean and standard deviation are 63.91726 , and 39.02821 respectively. The between and within standard deviations are 38.89517 and 3.913117 respectively. For renewable energy consumption there are 2968 observations for 212 countries. On average, a country's renewable energy consumption is observed 14 times. The overall mean and standard deviation are 29.46588, and 29.2408 respectively. The between and within standard deviations are 29.0856 and 3.571978 respectively. The within standard deviations of access to clean fuels and technologies for cooking and renewable energy consumption, measures of clean technology adoption indicate that clean technology use is time-variant in global economy. Except for renewable energy use, the between variation are larger than the within variations.

Table 12. Overall, between and within variations of CO_2 emissions and clean technology (Access to clean fuels and technologies for cooking and renewable energy consumption) for developed countries.

Variable		Mean	Std. Dev.	Min	Max	Observations
lnCO2	overall	2.110214	0.565942	0.487743	3.86493	N = 784
	between		0.552853	0.690299	3.56585	n = 56
	within		0.140421	1.554223	3.175511	T = 14
lnGDPPC	overall	10.33132	0.644507	7.946198	12.11016	N = 1118
	between		0.654457	8.613892	12.02762	n = 74
	within		0.107467	9.663627	10.77187	T-bar = 15.1081
GDPPCSQ	overall	107.1512	13.32982	63.14205	146.6561	N = 1118
	between		13.62887	74.3598	144.6637	n = 74
	within		2.15068	92.67065	115.3917	T-bar = 15.1081
CFTECH	overall	100	0	100	100	N = 855
	between		0	100	100	n = 57
	within		0	100	100	T = 15
RECON	overall	12.0169	15.89684	0	78.2135	N = 1050
	between		15.76891	0	73.74246	n = 75
	within		2.670663	-1.1857	34.82747	T = 14

Source: Author's computation using data from WDI.

Table 12 shows that for the CO_2 emissions, there are 784 observations for 56 countries for the global economy. On average, a country's CO_2 emissions is observed 14 times. The overall mean of CO_2 is 2.110214, and overall standard deviation is 0.565942. The between and within standard deviations of CO_2 emission are 0.552853, and 0.140421 respectively. The within standard deviation of 0.140421 indicates that developed countries CO_2 emissions is time-variant.

When it comes to clean technology adoption (proxied by access to clean fuels and technologies for cooking (CFTECH) and renewable energy consumption (RECON)), for access to clean fuels and technologies for cooking there are 855 observations for 57 countries for developed countries. On average, a country's access to clean fuels and technologies for cooking is observed 15 times. The overall mean and standard deviation are 100 , and 0 respectively. The between and within standard deviations are 0 and 0 respectively and imply that access to clean fuels and technologies of each developed country is constant overtime. For renewable energy consumption there are 1050 observations for 75 countries. On average, a country's renewable energy consumption is observed 14 times. The overall mean and standard deviation are 12.0169, and 15.89684 respectively. The between and within standard deviations are 15.76891 and 2.670663 respectively. The within standard deviations of access to clean fuels and technologies for cooking and renewable energy consumption, measures of clean technology adoption indicate that clean technology use is time-variant in developed countries.

Table 13. Overall, between and within variations of CO_2 emissions and clean technology (Access to clean fuels and technologies for cooking and renewable energy consumption) for emerging-developing countries.

Variable		Mean	Std. Dev.	Min	Max	Observations
lnCO2	overall	0.014437	1.381708	-3.8293	2.711202	N = 1869
	between		1.373355	-3.39621	2.552308	n = 134
	within		0.207431	-1.06937	1.428145	T = 13.9478
lnGDPPC	overall	7.843662	0.956925	5.60098	9.70739	N = 2136
	between		0.951691	5.709105	9.475001	n = 136
	within		0.143826	7.192291	8.392957	T-bar = 15.7059
GDPPCSQ	overall	62.43831	14.76358	31.37097	94.23342	N = 2136
	between		14.66163	32.5968	89.7806	n = 136
	within		2.254173	51.30635	72.13003	T-bar = 15.7059

CFTECH	overall	48.28872	37.07694	0	100	N = 1974
	between		36.89976	0	100	n = 132
	within		4.684885	11.84205	80.14205	T = 14.9545
RECON	overall	39.01824	30.4467	0	97.4222	N = 1918
	between		30.28825	0.065629	96.22302	n = 137
	within		3.980528	20.26172	61.92783	T = 14

Source: Author's computation using data from WDI.

Table 13 shows that for the CO_2 emissions, there are 1869 observations for 134 countries for emerging-developing countries. On average, a country's CO_2 emissions is observed 13.9478 times. The overall mean of CO_2 is 0.014437, and overall standard deviation is 1.381708 . The between and within standard deviations of CO_2 emission are 1.373355, and 0.207431 respectively. The within standard deviation of 0.207431 indicates that emerging-developing countries CO_2 emissions is time-variant.

When it comes to clean technology adoption (proxied by access to clean fuels and technologies for cooking (CFTECH) and renewable energy consumption (RECON)), for access to clean fuels and technologies for cooking there are 1974 observations for 132 countries for emerging-developing countries. On average, a country's access to clean fuels and technologies for cooking is observed 14.9545 times. The overall mean and standard deviation are 48.28872, and 37.07694 respectively. The between and within standard deviations are 36.89976 and 4.684885 respectively. For renewable energy consumption there are 1918 observations for 137 countries. On average, a country's renewable energy consumption is observed 14 times. The overall mean and standard deviation are 39.01824, and 30.4467 respectively. The between and within standard deviations are 30.28825 and 3.980528 respectively. The within standard deviations of access to clean fuels and technologies for cooking and renewable energy consumption, measures of clean technology adoption indicate that clean technology use is time-variant in emerging-developing countries. Additionally, the between variations are larger than the within variations.

6.3 Preliminary Regression Results.

Static panel results

As was done in the previous chapter, pooled OLS (POLS), fixed effects (FE), and random effects (RE) estimation strategies were also carried out as a battery of preliminary investigation of the role of clean technology on CO_2 emissions. The static panel models (POLS, FE, RE) estimated gave different results on some of the explanatory variables of interest and the control variables. And since all the static model results could not be taken, but only those that appropriately fit or explain the data based on optimal tests of model selection should be selected; therefore, choosing between the FE and RE models, the Hausman test indicated that the FE model was appropriate for representing the data relative to the RE model. Besides, between the pooled OLS and the RE models, the Breusch and Pagan Lagrange Multiplier (ML) test also showed that the pooled OLS model was more appropriate and better in explaining the data than the RE model. Based on these test results, the study considered only the FE estimates as most appropriate. Table 14 below presents the estimated results of all the static panel regressions.

Table 14. Static panel regression results of CO_2 emissions and clean technology for the global economy, developed countries and emerging-developing countries.

	Pooled OLS			Fixed Effect		
	Global economy	Developed countries	Emerging-developing countries	Global economy	Developed countries	Emerging-developing countries
lnCO2						
lnGDPPC	1.729***	-1.070*	3.592***	0.613	0.829	1.263**
	(0.208)	(0.546)	(0.419)	(0.492)	(1.362)	(0.570)
GDPPCSQ	-0.086***	0.057**	-0.207***	-0.030	-0.034	-0.072**
	(0.011)	(0.026)	(0.026)	(0.026)	(0.068)	(0.034)
CFTECH	-0.004***	0.000	-0.004***	0.000	0.000	0.000
	(0.001)	(0.00)	(0.001)	(0.002)	(0.00)	(0.002)
RECON	-0.018***	-0.015***	-0.018***	-0.017***	-0.011***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.005)
RDEXP	0.020	-0.015	0.157***	0.020	0.038*	-0.032
	(0.014)	(0.013)	(0.033)	(0.025)	(0.018)	(0.057)
lnEU	0.741***	0.603***	0.771***	0.749***	0.645***	0.856***
	(0.022)	(0.030)	(0.038)	(0.094)	(0.126)	(0.093)
FDI	-0.000	0.000	0.004**	0.000	0.000	0.001
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.002)
POPG	-0.017**	0.044***	-0.005	0.014	0.006	0.020
	(0.008)	(0.012)	(0.016)	(0.010)	(0.009)	(0.014)
FOREST	-0.002***	0.002	-0.002**	0.003	-0.006	0.007
	(0.001)	(0.001)	(0.001)	(0.010)	(0.017)	(0.013)
R-Sq.	0.942	0.809	0.954			
F-statistic	1093.53***	349.54	981.44***	83.37***	93.52***	46.47***
Obs.	855	437	418	855	437	418
No. groups				112	47	65

Test	H_0 & H_1	Appropriate Model	Prob of chi2 & chi2bar	Decision
Breusch and Pagan	H_0	Pooled OLS	0.000	Reject H0
LM Test	H_1	Random Effects		
	H_0	Random Effects		
Hausman Test			0.000	Reject H0
	H_1	Fixed Effects		

Notes: This is the report of pooled OLS (POLS) and fixed effects (FE) estimates. $lnCO_2$ (CO_2 emissions) is dependent variable. Figures in parenthesis denote robust standard errors. ***p < 0.01, **p < 0.05, *p < 0.1, indicate significance at 1%, 5%, and 10% levels, respectively.

Table 14 continued

	Random Effects		
Variable	Global economy	Developed Countries	Emerging-developing countries
lnCO2			
lnGDPPC	1.033***	0.623	1.992***
	(0.374)	(1.076)	(0.505)
GDPPCSQ	-0.051***	-0.026	-0.113***
	(0.010)	(0.053)	(0.030)
CFTECH	-0.000	0.000	-0.000
	(0.002)	(0.000)	(0.002)
RECON	-0.018***	-0.010***	-0.016***
	(0.003)	(0.003)	(0.004)
RDEXP	0.022	0.032*	-0.039
	(0.022)	(0.017)	(0.059)
lnEU	0.749***	0.658***	0.858***
	(0.082)	(0.110)	(0.083)
FDI	0.000	0.000	0.001
	(0.000)	0.000	(0.002)
POPG	0.008	0.008	0.004
	(0.009)	(0.010)	(0.015)
FOREST	-0.000	0.000	-0.001
	(0.002)	(0.002)	(0.003)
Wald-test	1466.96***	841.34***	683.14***
Obs.	855	437	418
No. groups	112	47	65

Test	H0 & H1	Appropriate Model	Prob of chi2 & chibar2	Decision
Breusch and Pagan	H0	Pooled OLS	0.000	Reject Ho
LM Test	H1	Random Effects		
	H0	Random Effects		
Hausman Test			0.000	Reject Ho
	H1	Fixed Effects		

Notes: This is the report of pooled OLS (POLS) and fixed effects (FE) estimates. $lnCO_2$ (CO_2 emissions) is dependent variable. Figures in parenthesis denote robust standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, indicate significance at 1%, 5%, and 10% levels, respectively.

From table 14, the results of pooled OLS, fixed effects, and random effects are all reported, but the Hausman test and Breusch and Pagan LM test results favoured selection of the FE model. Hence, focusing on the estimated results of the FE model as most appropriate, the results are showing that, the parameter estimates of access to clean fuels and technologies for cooking are statistically insignificant and have positive relationship with CO_2 emissions for the global economy and the two country groups. Renewable energy consumption on the other hand, has a statistically very strong negative correlation with CO_2 emissions for all the country groups at 1% significant level. Economic growth is showing significant statistical relationship only in emerging-developing economies. For the control variables, energy consumption shows statistically significant positive relationship with CO_2 emissions for all the country groups. R&D expenditure shows significant effect in only developed countries, while foreign direct investment, population and forestation are not showing impacts.

Inferences from the descriptive results and these static regression results show somewhat evidence of some statistical relationship and effect between CO_2 emissions and clean technology use. This means that, further analysis and explanation are warranted, particularly since static panel data estimators do a poor job of accounting for endogenous effects possibility that could be associated with especially the use of unbalanced panel dataset with limited time span. Given this possible weakness likely to influence this regression results, the study, therefore, used a more appropriate dynamic alternative model (system GMM) of analysis and estimation in investigating the role of clean technology on CO_2 emission further which could cope with or eliminate endogenous problems or effects and weaknesses of static panel data models.

6.4 Dynamic Panel Estimation Results

The parameter estimates obtained using the FE often become biased in the presence of endogeneity and heteroscedasticity. Besides, Static panel models estimated on levels of variables can be expected to show serial correlation in the errors. These problems are likely present in the estimated results because for instance, access to clean fuels and technologies for cooking measure of clean technology was expected a priori to have negative effect on the environmental degradation, it is having a positive effect. Couples with this, the time series dimension of the study is very short (only 16 years), and the cross-sectional dimensions are very wide (190 countries for the global economy, 56 developed countries and 132 emerging-developing countries). To control for these issues, the dynamic econometric model system GMM is used as a more suitable alternative estimation technique, because system GMM estimators are more suitable for unbalanced panel data and better in producing consistent and efficient parameter estimates in the presence of omitted variables, large sample size, limited time periods, endogeneity issue, heteroskedasticity issue, serial autocorrelation, and individual specific distributed effects compared to static models. This makes estimated results of system GMM more preferable and credible. Table 15 provides the results estimated using system GMM.

Table 15. System GMM results of CO_2 and clean technology for the global economy, developed countries and emerging-developing countries.

	with full instruments			with collapsed instruments		
	Global economy	Developed countries	Emerging-developing countries	Global economy	Developed countries	Emerging-developing countries
lnCO2						
L1.lnCO2	0.847***	0.862***	0.710***	0.593***	0.470***	0.462***
	(0.033)	(0.061)	(0.062)	(0.116)	(0.148)	(0.139)
lnGDPPC	0.221	-0.559	0.962***	0.547**	2.389	3.045**
	(0.147)	(1.577)	(0.333)	(0.268)	(1.867)	(1.228)
GDPPCSQ	-0.012	0.025	-0.055***	-0.029**	-0.118	-0.183**
	(0.008)	(0.077)	(0.020)	(0.014)	(0.090)	(0.080)
CFTECH	-0.001	0.024	-0.002	-0.001	-0.138	-0.004
	(0.001)	(0.082)	(0.001)	(0.002)	(0.098)	(0.004)
RECON	-0.003***	-0.002*	-0.004***	-0.007***	-0.007**	-0.011***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
RDEXP	0.009	0.010	-0.028	-0.002	0.020	0.038
	(0.012)	(0.016)	(0.055)	(0.023)	(0.040)	(0.113)
lnEU	0.128***	0.121**	0.155***	0.346***	0.367***	0.496***
	(0.028)	(0.057)	(0.054)	(0.101)	(0.125)	(0.111)
FDI	0.000	0.000**	0.000	0.000	0.000	0.002
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.003)
POPG	0.001	0.005	0.004	-0.002	0.019	0.030
	(0.004)	(0.007)	(0.009)	(0.006)	(0.014)	(0.029)
FOREST	-0.000	-0.000	0.000	-0.000	-0.001	0.001
	(0.000)	(0.00)	(0.001)	(0.001)	(0.002)	(0.002)
Year dummies	YR	YR	YR	YR	YR	YR
F-test	1979.10***	21583.03***	1412.17***	613.71***	1363.48***	94.26***
AR (2)	0.090	0.144	0.411	0.147	0.190	0.626
Hansen test	1.000	1.000	0.998	0.126	0.219	0.126
No. of obs.	777	398	379	777	398	379
No. of groups	110	46	64	110	46	64
No. of instru.	266	153	101	69	39	30

Notes: This is the report of system GMM estimates. $\ln CO_2$ (CO_2 emissions) is dependent variable. Figures in parenthesis denote robust standard errors. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, indicate significance at 1%, 5%, and 10% levels, respectively. AR(2) and Hansen statistics p-values are reported

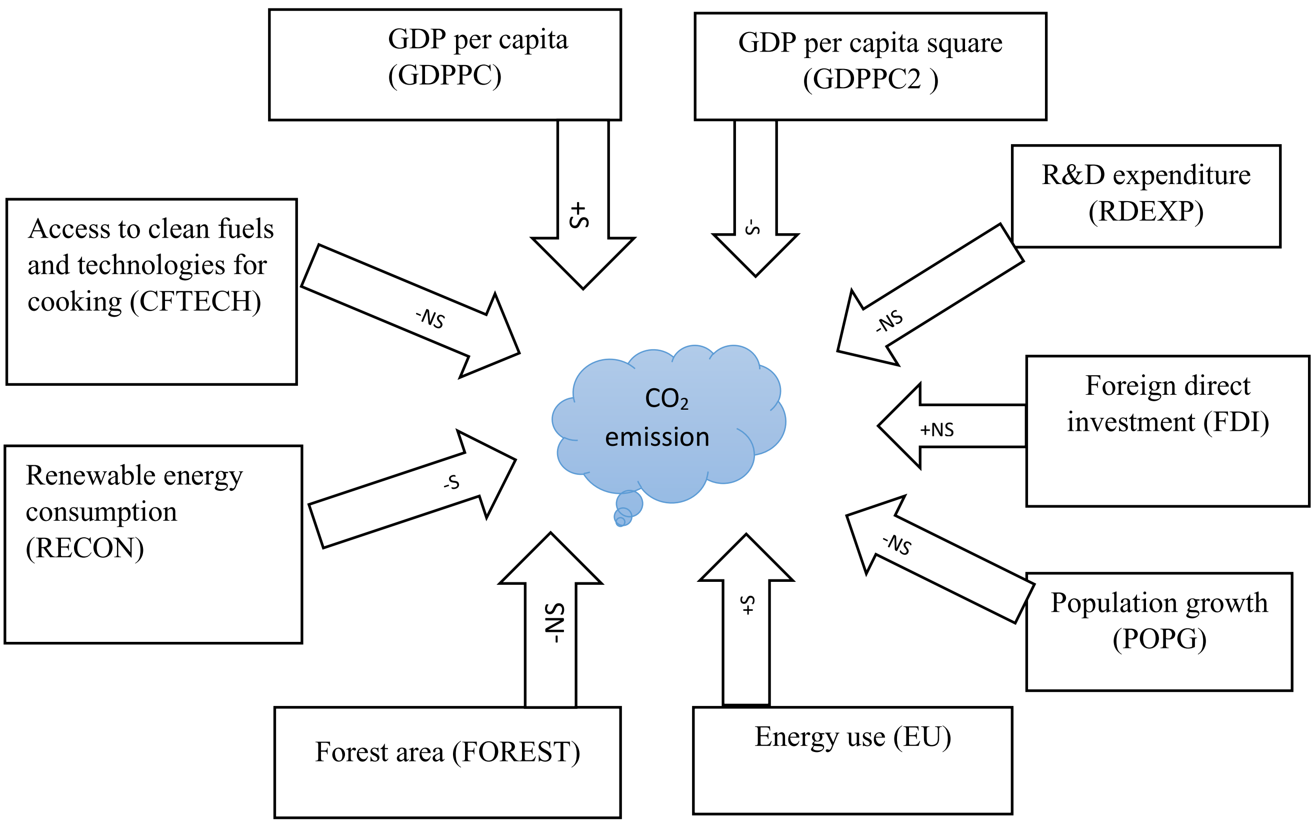
As was the case in the previous chapter, here to, the estimation was first carried out with full instruments for all the country groups in investigating the relationship between the use of clean technology, economic growth and CO_2 emissions, while controlling for R&D expenditures, forestation, energy use, FDI and population growth. However, from the results with full instruments in columns (2 – 4), it can be observed that, there is the issue of instrument proliferation confirmed by the p-values of the Hansen tests of 1.000, 1.000 and 0.998 for the global economy, developed countries and emerging-developing countries respectively. This was not a good development for the model because in the opinion of Roodman (2009), increasing instrumentation increases the estimates' bias which does not eliminate endogenous effects of the endogenous variables in analysing the nexus between CO_2 emissions and clean green technology. Thus, to control for this, re-estimation was done with collapsed instruments for all the country groups, with the results shown in the same table 15 in columns (5 -7) for the global environment, developed countries and emerging-developing countries respectively. The results with collapsed instruments for the world economy, developed countries and emerging-developing countries indicate that, the null hypothesis of the independent variables not significant in influencing the dependent variable (CO_2 emissions) against the alternative hypothesis of being significant is rejected at 1% level, reflected by the F-statistic p-values. Coupled with this, the second order serial correlations and the Hansen tests at 1% significant level for the global economy, and the two country groups is not significant. These tests of misspecification validate the appropriateness of the system GMM model specification and the consistency of the estimates, as well as the validity of the instruments used.

The results further show that the coefficient of access to clean fuels and technologies for cooking (proxy indicator of clean technology) has a negative impact on CO_2 emissions across all the country groups. In terms of impact, it insignificantly mitigates CO_2 emissions in all the country groups. This supports empirical arguments (Acharya & Marhold, 2019; Yasmin & Grundmann, 2019) that ICT application can stimulate transition from the use of unhealthy cooking fuels such as firewood and kerosene fuels for cooking to a cleaner source of energy such liquefied petroleum gas (LPG) and electricity which can help to avoid and mitigate pollution, particularly in developing economies.

The coefficient of renewable energy consumption of clean technology is also negative and statistically significant in mitigating CO_2 emissions across all the country groups. This implies that a percentage change in renewable energy consumption on average leads to -0.00.7%, -0.00.7% and -0.01.1% reduction in CO_2 emissions at 1% significant level in the global economy, developed countries and emerging-developing countries respectively. This results is in tandem with findings of existing studies on the impact of renewable energy consumption on carbon emissions (Anwar et al., 2021; Noorpoor & Kudahi, 2015; IEA, 2012). The results of these indicator measures of clean green technology adoption show that deepening clean technology use in economies of the world can contribute significantly to de-carbonization of the global environment and are in line with existing empirical studies (Carrion-Flores & Innes, 2010; Prakash et al., 2020; Noorpoor & Kudahi, 2015; IEA, 2012) supporting this argument but disagree with those (Weina et al., 2016; Alatas, 2021, Xu et al., 2021; Yuan et al., 2020) with other arguments about the role of clean technology activities on the environmental welfare. However, in terms of levels of development, the indicator measures of clean technology adoption did not show remarkable heterogenous outcomes in terms of their impact on CO_2 emissions in the two country groups.

The coefficients of economic growth (GDP per capita) and its square are positive and negative respectively for the global economy and the two country groups. In terms of impact, they are significant only in the global economy and in emerging developing countries. These results confirm the EKC hypothesis for emerging-developing countries and the global economy. However, the interpretation of these finding is similar to that of the previous chapter (page 72) regarding economic growth and CO_2 emissions, hence would not be repeated here. Additionally, the coefficients of the lag of CO_2 emissions for the global economy and the two country groups are statistically significant at 1% level which implies that carbon emissions history matters in the world economy, developed and emerging-developing countries. Besides, the coefficient of the lag of CO_2 further shows that the study's model is a dynamic model although it does not converge to its long run equilibrium. Among the control variables too, energy use has strong significant negative effect on environmental quality in the world economy, developed countries and emerging-developing countries, which supports empirical evidence (Wang et al., 2011; Paramati et al., 2016; Omri, 2013).

Pictogrammic Summary of Results of Clean Technology on Global CO_2 Emission.



Pictogramme 1

Note(s): -S = negative and significant, +S = positive and significant, -NS = negative and not significant, +NS = positive and not significant. Source(s): Study's construction

6.5 Long-Run Parameter Estimates of Explanatory Variables on CO_2 Emissions of the System GMM Estimates.

Table 16 below presents the long-run estimates of the significant short-run variables of the system GMM estimates in columns (5 – 7) of table 15 above. Hence, the long-run estimates of GDP per capita, GDP per capita square, renewable energy consumption and energy use of the system GMM estimates for the global economy the two country groups are in column (2 - 4) of table 16 below.

Table 16. Long-run elasticity estimates of the significant variables

	Global economy	Developed countries	Emerging-developing countries
lnCO2			
lnGDPPC	1.346**		5.661**
	(0.640)		(2.518)
$lnGDPPC^2$	-0.072**		-0.341**
	(0.341)		(0.163)
RECON	-0.017***	-0.013***	-0.021**
	(0.003)	(0.004)	(0.008)
lnEU	0.850***	0.693***	0.921***
	(0.086)	(0.110)	(0.120)

Notes: This is the report of the long-run estimates of significant variables of the study. $lnCO_2$ (CO_2 emissions) is dependent variable. Figures in parenthesis denote robust standard errors. ***p < 0.01, **p < 0.05, *p < 0.1, indicate significance at 1%, 5%, and 10% levels, respectively.

Long-run effects for the k^{th} parameter is computed as:

$$\beta_k \,/[1 - \Phi]$$

The above formula is the mathematical computation of how the long-run system GMM estimates of the k^{th} parameter was estimated.

Results of the long-run parameter estimates show that, renewable energy consumption has a negative long-run impact coefficients of -0.017, -0.013, and -0.021 for the global economy, developed countries and emerging-developing countries respectively. From these long-run coefficients of renewable energy consumption, that of the global economy is same as its short-run coefficient, whiles those of developed countries and emerging-developing countries are larger than their short-run estimated coefficients. This implies that a percentage change in renewable energy consumption measure of clean green technology activity is associated with -0.01.7%, -0.01.3% and -0.02.1% reductions in CO_2 emissions in the global environment, developed countries and emerging-developing countries respectively. Hence, renewable energy consumption shows an inelastic relationship with carbon dioxide emissions. Economic growth, and energy consumption also have significant long-run effects on carbon dioxide emissions. These long-run impacts in terms of economic growth occurs in emerging-developing countries and in the global economy, whereas that of energy use occurs in the global economy and the two country groups.

CHAPTER SEVEN

CONCLUSION, POLICY IMPLICATIONS AND RECOMMENDATIONS

7.1 Introduction

This chapter presents the conclusion and summary findings, policy implications, and recommendations of the research study. The chapter therefore comes in three main sections: section 7.2 containing the conclusion and main findings, section 7.3 touching on policy implications and 7.4 highlighting appropriate policy recommendations, including areas for further studies and some limitations of the study.

7.2 Conclusion and Summary Findings

Global warming and climate change are global challenges that need a holistic attention and measures to tackle. The potential of environmental technologies and in particular, the role of the information communication society and clean green technologies to influence sustainability of the environment in recent past decades has not only courted global attention but also generated a new line of research interests. This research study investigated the impacts of broadband technology and clean green technology adoption on the quality of the global environment from 2005-2020.

Scholarly works (Mathiesen et al., 2015; Laitner, 2015; Weina et al., 2016; Nikzad & Sedigh, 2017) have advanced arguments on the roles of general ICT and green technological innovations promoting energy efficiencies and mitigating carbon emissions. Several other studies (Walzberg et al., 2020; Braungardt et al., 2016; Zhou et al., 2018; Bernstein & Madlener, 2010) have also highlighted findings respecting the rebound effects associated with

ICT and green technological development and utilization which could have unfavourable effects on environmental welfare.

Besides, studies in empirical literature are not only biased towards cities, economic sectors, specific countries and economic blocs but also have their findings limited to only these settings rather than in a global context; with the exception of a few which also did not use broadband and clean green technology measures of this current study in a global context and simultaneously taking into account development levels of countries of the global economy. Given these gaps in literature coupled with the conflicting and inconclusive range of results in empirical literature, this research study set out to fill some of these limitations by investigating the relationship between broadband technology, clean technology and environmental sustainability in a global perspective using a common dynamic framework of investigation, and the following are the specific research questions posed and addressed in the study.

I. Can broadband technology significantly contribute to mitigation of CO_2 emissions in the global economy?
II. Can clean green technology adoption significantly contribute to mitigation of CO_2 emissions in the global economy?
III. Do development (income) levels of countries of the global economy affect the impacts of these technologies in mitigating CO_2 emissions?
IV. Consistent with the study period, can the EKC hypothesis be confirmed for the global economy, developed and emerging-developing countries in the diffusion of these technologies?

However, having employed a dynamic GMM estimator in addition to a battery of static models and other statistical techniques to analyse the impacts of broadband and clean green technologies quantitatively and empirically on carbon dioxide emissions in a global perspective, the following summary findings were discovered.

Findings of the research study showed that mobile and fixed broadband subscriptions, proxy measures of broadband technology activities both had negative impacts on global CO_2 emissions; and while the impact of mobile broadband measure of broadband technology did not significantly impact global CO_2 emissions, fixed broadband measure significantly impacted global CO_2 emissions. When it comes to the proxy measures of clean green technology adoption, both access to clean fuels and technologies for cooking, and renewable energy consumption also had mitigating impacts on global carbon emissions, but the mitigating impact of access to clean fuels and technologies for cooking was not statistically significant comparable to renewable energy consumption which was strongly significant in reducing global CO_2 emissions. Furthermore, the results constrained by the period of the study, nature of data and methodology used, confirmed the EKC hypothesis at the global level in the diffusion of these technologies.

Additionally, the comparative analysis of countries of the global economy classified into developed and emerging-developing countries to ascertain whether development levels could influence the impact of these technologies on CO_2 emissions showed that, the indicator measures of broadband technology showed heterogenous effects in terms of impact on carbon emissions between developed and emerging-developing countries while the indicator measures of clean green technology did not show remarkably heterogenous effects in terms of their impacts on emissions between the two country groups. Besides, while the EKC was confirmed for emerging-developing countries, it was not for developed countries in the diffusion of these technologies.

7.3 Policy Implications

While these findings, do not only contribute to advancing and filling gaps in extant literature on environmental technologies, general ICT and energy economics, they also serve as a source of useful information for policymakers in the global economy, developed and developing countries. Given the range of evolving technologies that could play crucial role toward carbon neutrality by the year 2050, investing in technologies that can be leveraged across households, firms, industries and countries of the world, and whose adoption can contribute to mitigation of carbon emissions in the shortest possible time is of significant importance. Broadband of ICT and clean green technologies are some of these technologies.

The ICT sector has many dimensions that can help influence environmental sustainability without limiting global economic growth. Networks, data centres and user devices are the three main part of the general ICT sector. These three components of the ICT sector have specific effects (negative and or positive) which could influence the overall impact of the sector on environmental quality. The footprint of the ICT sector comprises mobile and fixed networks, data centres, corporate networks, equipment and user devices (routers, smartphones, computers, iPad, IoT, cables, fibre optics, satellite, microwave, mobile wireless, among others); and because sectors are often interdependent, their carbon footprints could overlap. It is therefore important for countries to clearly understand the different carbon footprint and relative positive effects of these components on environmental quality. This is relevant because not only will inaccurate information and conclusion lead to increased ambiguity, uncertainty and confusion regarding the general impact of the ICT sector but could also lead to poor decisions or policy efforts from households, firms, industries, countries and policymakers in identifying the real carbon reduction opportunities inherent in the ICT industry. This informs the study's investigation of the net effect of broadband technology part of the ICT sector.

It is an established fact that, though broadband technology activity is not carbon free from total carbon footprint of the ICT sector often linked to operation, maintenance, manufacturing, disposal and related activity emissions due to electricity consumption according to the direct effects argument. However, its impact through the substitution and indirect effects perspective in depressing carbon emissions turns to be potentially much more promising than its carbon footprint (due to its enablement capacity and inherent energy efficiency) as discovered in this empirical study. The environmental implication of the research findings means that if broadband technology users and the general ICT sector rely heavily on green materials and energy or electricity consumption produced from clean, renewable sources, a significant chunk of the ICT sector and other anthropogenic footprints could be reduced which will subsequently facilitate the decarbonization efforts of the global environment.

Relatedly, the mitigating impact of the indicator measures of clean green technology on carbon emissions discovered in the study presupposes and consolidates the assertion that widespread development and diffusion of clean green technologies in general can potentially help to reduce over dependence on fossil sources to decarbonize the global economy and improve environmental quality. This evidence notwithstanding, when it comes to technical development capacity, developed countries have the technological edge and are in the process of these technologies' development and diffusion, but the same cannot be said holistically about developing countries. It is in the light of this, Aghion, Hemous and Veugelers (2009) argue that, though emerging-developing countries like China, India and Brazil are already part of the global technological innovation trajectory, most of the South, particularly the poor developing South are not yet, and can at best only imitate or adopt green technologies previously invented in the developed countries.

This mean that even though policy programmes targeted at developing and promoting technology transfers are advocated by global institutions, development and private partners, when it comes to the field of ICT and clean green technologies, the issue of capacity building of most developing economies, in terms of being capable to receive, manage, develop and improve clean technologies is still low and critical factor of consideration. In that, the technological gap between the developed North and the Developing South is still wide although over the last decades, reduction in this gap has been observed in emerging-developing economies (China, Brazil, India and South Africa) to complement the technological innovation and adoption efforts of developed economies in combating global climatic and environmental issues (Schembri & Petit, 2009).

7.4 Policy Recommendations

Study shows some inherent ambiguity when it comes to the relationship between innovation and technology, economic growth and sustainable development, in which sustainable development has been argued to depend on the application of clean technologies on a large scale by both OECD countries non-OECD countries (OECD, 2000). This means that sustainable development, irrespective of a country's level of development is conditional on technologies that are eco-friendly. On this premise and from policy point of view, this study recommends that broadband and clean green technologies be considered as important part of global short and long-term policy to support climate change adaptation and mitigation strategies. There should be collaboration between environmentalists, governments and the private sector to ensure widespread provision and improvement in universal broadband connectivity including its infrastructure in countries of the global economy. Policy measures and provisions including the use of subsidies and taxes to influence access to clean fuels and technologies and to discourage the use of non-renewables must become integral components of any national and international plans to combating increasing carbon emissions. Governments in countries of the global economy should come up with policy measures aimed at providing their private sectors which are critical players when it comes to these technologies development, application and diffusion with the right competitive environment.

At the country levels, both developed and developing countries should not only increase the use of these technologies but also make them cheaper and more accessible by encouraging investments in them and in other emerging green technologies such as CCS, electric automobiles, waste-sourced biofuels, geoengineering solutions and exponential technologies such as cloud computing, 5G, AI, IoT, and drones which depend on connectivity enabled by broadband, as growing evidence have shown the potentials of these emerging technologies in ensuring a sustainable and richer future. Acharya and Marhold (2019), and Yasmin and Grundmann (2019) argue that linking ICT applications and media communication can influence and facilitate the adoption of cleaner options (biogas, liquefied petroleum gas). However, because of capacity building constraints related to technical, institutional, human, financial and managerial capacities of technology-innovation and development in most developing countries; developed countries should continue to lead and direct change toward these technologies and subsequently facilitate their diffusion to developing countries as part of inclusive efforts in tackling global warming and climate change. Developing countries should also improve their capacities to adopt, develop and manage these technologies. Additionally, emerging-developing countries should come out with policies encouraging adoption of clean fuels and technologies to displace the use of conventional non-renewable energy and inefficient technologies to complement efforts of developed countries.

Limitations of the Study

Although the research study investigates the role of broadband and clean technology adoption on carbon emissions, it is not free from some possible limitations that sometimes affect research studies. First, the use of indicator or proxy measures of broadband technology, clean technology and environmental sustainability may not be comprehensive enough to fully reflect the activities of these variables of research interest. secondly, it must be mentioned that data unavailability was one of the challenges of the study as data on some of the sampled countries were missing. This affected the preferred time span, and the original sample size of the study. Admittedly, there are other indicators and composite measures of environmental pollution such as ecological footprint, sulphur dioxide, nitrous and methane, the study used CO_2 emissions to proxy environmental degradation. Future studies can consider some of these measures and other emerging environmental technologies such as CCS, geoengineering options, cloud computing, AI and IoT. Finally, the study was designed to focus on exploring the role of broadband and clean green technologies on carbon emissions from the perspective of the global economy, developed and emerging-developing countries only without regard to economic sectors, blocs and regions such as transport sector, OECD, EU, SSA, SEA.

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APPENDIX A

Table 3.1 Correlation between covariates

Global economy (Broadband technology and CO_2 emissions)											
Variable	lnCO2	lnGDPPC	GDPPCSQ	MOBS	FBS	lnEU	TRADE	FDI	POPG	FTS	EDUCS
lnCO2	1.000										
LnGDPPC	0.888	1.000									
GDPPCSQ	0.863	0.996	1.000								
MOBS	0.639	0.608	0.593	1.000							
FBS	0.589	0.781	0.797	0.522	1.000						
LnEU	0.892	0.851	0.846	0.626	0.639	1.000					
TRADE	0.336	0.356	0.359	0.324	0.281	0.278	1.000				
FDI	0.052	0.135	0.146	0.078	0.154	0.058	0.275	1.000			
POPG	-0.256	-0.270	-0.246	-0.205	-0.365	-0.032	-0.087	-0.007	1.000		
FTS	0.701	0.794	0.808	0.425	0.768	0.693	0.342	0.185	-0.368	1.000	
EDUCS	0.822	0.796	0.773	0.602	0.667	0.747	0.227	0.056	-0.468	0.646	1.000

Source: Author's computation using data from WDI.

Table 3.2 Correlation between covariates

Developed countries (Broadband technology and CO_2 emissions**)**											
Variable	lnCO2	lnGDPPC	GDPPCSQ	MOBS	FBS	lnEU	TRADE	FDI	POPG	FTS	EDUCS
lnCO2	1.000										
LnGDPPC	0.380	1.000									
GDPPCSQ	0.376	0.999	1.000								
MOBS	0.059	0.044	0.041	1.000							
FBS	-0.295	0.472	0.474	0.113	1.000						
LnEU	0.795	0.457	0.454	-0.032	-0.037	1.000					
TRADE	0.044	0.081	0.085	0.319	0.024	-0.027	1.000				
FDI	-0.078	0.160	0.165	0.038	0.121	-0.174	0.253	1.000			
POPG	0.531	0.201	0.198	0.096	-0.270	0.480	0.041	0.018	1.000		
FTS	-0.165	0.496	0.503	-0.185	0.438	-0.140	0.149	0.184	-0.161	1.000	
EDUCS	-0.018	0.223	0.212	-0.082	0.344	0.138	-0.144	-0.067	-0.074	-0.006	1.000

Source: Author's computation using data from WDI.

Table 3.3 Correlation between covariates

Emerging-developing countries (Broadband technology and CO_2 emissions)											
Variable	lnCO2	lnGDPPC	GDPPCSQ	MOBS	FBS	lnEU	TRADE	FDI	POPG	FTS	EDUCS
lnCO2	1.000										
LnGDPPC	0.879	1.000									
GDPPCSQ	0.868	0.998	1.000								
MOBS	0.553	0.554	0.554	1.000							
FBS	0.529	0.569	0.581	0.550	1.000						
LnEU	0.825	0.706	0.707	0.546	0.491	1.000					
TRADE	0.296	0.246	0.240	0.135	0.123	0.193	1.000				
FDI	0.037	0.023	0.026	0.029	0.012	0.080	0.336	1.000			
POPG	-0.498	-0.455	-0.445	-0.306	-0.502	-0.352	-0.175	0.006	1.000		
FTS	0.694	0.656	0.660	0.431	0.643	0.647	0.156	0.057	-0.650	1.000	
EDUCS	0.807	0.794	0.790	0.602	0.603	0.663	0.136	0.053	-0.664	0.689	1.000

Source: Author's computation using data from WDI.

Table 10.1 Correlation between covariates

Global economy (Clean technology and CO_2 emissions)									
Variable	lnCO2	lnGDPPC	GDPPCSQ	CFTECH	RECON	RDEXP	lnEU	FDI	POPG	FOREST
lnCO2	1.000									
LnGDPPC	0.888	1.000								
GDPPCSQ	0.863	0.996	1.000							
CFTECH	0.866	0.826	0.802	1.000						
RECON	-0.818	-0.676	-0.643	-0.754	1.000					
RDEXP	0.455	0.601	0.615	0.399	-0.141	1.000				
LnEU	0.892	0.851	0.846	0.774	-0.592	0.562	1.000			
FDI	0.052	0.135	0.146	0.076	-0.039	-0.043	0.058	1.000		
POPG	-0.256	-0.270	-0.246	-0.346	0.263	-0.182	-0.032	-0.007	1.000	
FOREST	0.005	0.021	0.006	-0.084	0.133	0.238	-0.077	0.037	-0.176	1.000

Source: Author's computation using data from WDI.

Table 10.2 Correlation between covariates

Developed countries (Clean technology and CO_2 emissions)										
Variable	lnCO2	lnGDPPC	GDPPCSQ	CFTECH	RECON	RDEXP	lnEU	FDI	POPG	FOREST
lnCO2	1.000									
LnGDPPC	0.380	1.000								
GDPPCSQ	0.376	0.999	1.000							
CFTECH	.	.	.	.						
RECON	-0.476	0.057	0.059	.	1.000					
RDEXP	0.074	0.358	0.346	.	0.184	1.000				
LnEU	0.795	0.457	0.454	.	-0.090	0.216	1.000			
FDI	-0.078	0.160	0.165	.	0.046	-0.155	-0.174	1.000		
POPG	0.531	0.201	0.198	.	-0.194	-0.096	0.480	0.018	1.000	
FOREST	-0.098	-0.122	-0.128	.	0.123	0.326	-0.105	0.062	-0.326	1.000

Source: Author's computation using data from WDI.

Table 10.3 Correlation between covariates

Emerging-developing countries (Clean technology and CO_2 emissions)										
Variable	lnCO2	lnGDPPC	GDPPCSQ	CFTECH	RECON	RDEXP	lnEU	FDI	POPG	FOREST
lnCO2	1.000									
LnGDPPC	0.879	1.000								
GDPPCSQ	0.868	0.998	1.000							
CFTECH	0.810	0.782	0.782	1.000						
RECON	-0.839	-0.729	-0.720	-0.745	1.000					
RDEXP	0.412	0.358	0.365	0.254	-0.279	1.000				
LnEU	0.825	0.706	0.707	0.694	-0.596	0.465	1.000			
FDI	0.037	0.023	0.026	0.001	-0.007	-0.086	0.080	1.000		
POPG	-0.498	-0.455	-0.445	-0.487	0.433	-0.274	-0.352	0.006	1.000	
FOREST	0.064	0.211	0.215	-0.063	0.114	0.118	-0.025	0.171	-0.114	1.000

APPENDIX B

Global economy

Afghanistan	Albania	Algeria	Andorra	Angola
Antigua and Barbuda	Argentina	Armenia	Australia	Austria
Azerbaijan	Bahamas, The	Bahrain	Bangladesh	Barbados
Belarus	Belgium	Belize	Benin	Bhutan
Bolivia	Bosnia and Herzegovina	Botswana	Brazil	Brunei Darussalam
Bulgaria	Burkina Faso	Burundi	Cabo Verde	Cambodia
Cameroon	Canada	Central African Republic	Chad	Chile
China	Colombia	Comoros	Congo, Dem. Rep.	Congo, Rep.
Costa Rica	Cote d'Ivoire	Croatia	Cuba	Cyprus
Czech Republic	Denmark	Djibouti	Dominica	Dominican Republic
Ecuador	Egypt, Arab Rep.	El Salvador	Equatorial Guinea	Eritrea
Estonia	Eswatini	Ethiopia	Fiji	Finland
France	Gabon	Gambia, The	Georgia	Germany
Ghana	Greece	Grenada	Guatemala	Guinea
Guinea-Bissau	Guyana	Haiti	Honduras	Hungary
Iceland	India	Indonesia	Iran, Islamic Rep.	Iraq
Ireland	Israel	Italy	Jamaica	Japan
Jordan	Kazakhstan	Kenya	Kiribati	Korea, Dem. People's Rep.
Korea, Rep.	Kuwait	Kyrgyz Republic	Lao PDR	Latvia
Lebanon	Lesotho	Liberia	Libya	Liechtenstein
Lithuania	Luxembourg	Madagascar	Malawi	Malaysia
Maldives	Mali	Malta	Marshall Islands	Mauritania
Mauritius	Mexico	Micronesia, Fed. Sts.	Moldova	Mongolia
Montenegro	Morocco	Mozambique	Myanmar	Namibia
Nauru	Nepal	Netherlands	New Zealand	Nicaragua
Niger	Nigeria	North Macedonia	Norway	Oman
Pakistan	Palau	Panama	Papua New Guinea	Paraguay
Peru	Philippines	Poland	Portugal	Qatar
Romania	Russian Federation	Rwanda	Samoa	Sao Tome and Principe
Saudi Arabia	Senegal	Serbia	Seychelles	Sierra Leone
Singapore	Slovak Republic	Slovenia	Solomon Islands	Somalia
South Africa	South Sudan	Spain	Sri Lanka	St. Kitts and Nevis
St. Lucia	Vincent and the Grenadi..	Sudan	Suriname	Sweden
Switzerland	Syrian Arab Republic	Tajikistan	Tanzania	Thailand
Timor-Leste	Togo	Tonga	Trinidad and Tobago	Tunisia
Turkey	Turkmenistan	Tuvalu	Uganda	Ukraine
United Arab Emirates	United Kingdom	United States	Uruguay	Uzbekistan
Vanuatu	Vietnam	Yemen, Rep.	Zambia	Zimbabwe

Developed countries

Andorra	Antigua and Barbuda	Australia	Austria	Bahamas, The
Bahrain	Barbados	Belgium	Brunei Darussalam	Canada
Chile	Croatia	Cyprus	Czech Republic	Denmark
Estonia	Finland	France	Germany	Greece
Hungary	Iceland	Ireland	Israel	Italy
Japan	Korea, Rep.	Kuwait	Latvia	Liechtenstein
Lithuania	Luxembourg	Malta	Nauru	Netherlands
New Zealand	Norway	Oman	Palau	Poland
Portugal	Qatar	Saudi Arabia	Seychelles	Singapore
Slovak Republic	Slovenia	Spain	St. Kitts and Nevis	Sweden
Switzerland	Trinidad and Tobago	United Arab Emirates	United Kingdom	United States
Uruguay				

Emerging-developing countries

Afghanistan	Albania	Algeria	Angola	Argentina
Armenia	Azerbaijan	Bangladesh	Belarus	Belize
Benin	Bhutan	Bolivia	Bosnia and Herzegovina	Botswana
Brazil	Bulgaria	Burkina Faso	Burundi	Cabo Verde
Cambodia	Cameroon	Central African Republic	Chad	China
Colombia	Comoros	Congo, Dem. Rep.	Congo, Rep.	Costa Rica
Cote d'Ivoire	Cuba	Djibouti	Dominica	Dominican Republic
Ecuador	Egypt, Arab Rep.	El Salvador	Equatorial Guinea	Eritrea
Eswatini	Ethiopia	Fiji	Gabon	Gambia, The
Georgia	Ghana	Grenada	Guatemala	Guinea
Guinea-Bissau	Guyana	Haiti	Honduras	India
Indonesia	Iran, Islamic Rep.	Iraq	Jamaica	Jordan
Kazakhstan	Kenya	Kiribati	Korea, Dem. People's Rep.	Kyrgyz Republic
Lao PDR	Lebanon	Lesotho	Liberia	Libya
Madagascar	Malawi	Malaysia	Maldives	Mali
Marshall Islands	Mauritania	Mauritius	Mexico	Micronesia, Fed. Sts.
Moldova	Mongolia	Montenegro	Morocco	Mozambique
Myanmar	Namibia	Nepal	Nicaragua	Niger
Nigeria	North Macedonia	Pakistan	Panama	Papua New Guinea
Paraguay	Peru	Philippines	Romania	Russian Federation
Rwanda	Samoa	Sao Tome and Principe	Senegal	Serbia
Sierra Leone	Solomon Islands	Somalia	South Africa	South Sudan
Sri Lanka	St. Lucia	Vincent and the Grenadi	Sudan	Suriname
Syrian Arab Republic	Tajikistan	Tanzania	Thailand	Timor-Leste
Togo	Tonga	Tunisia	Turkey	Turkmenistan
Tuvalu	Uganda	Ukraine	Uzbekistan	Vanuatu
Vietnam	Yemen, Rep.	Zambia	Zimbabwe	