The impact of technological progress on emissions levels: Evidence and lessons from different income-group countries

By

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DECLARATION

I, Chris Belmert Milindi 17269581, hereby declare that the thesis for the degree Doctor of Philosophy in Economics (Ph.D.) to be awarded is my own work and that it has not previously been submitted for assessment or completion of any postgraduate qualification to another University or for another qualification.

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LIST OF ABBREVIATIONS

BRICS	Brazil, Russia, India and China
BP	British Petroleum
EKC	Environmental Kuznets Curve
ECONS	Energy consumption
EDGARD	Emissions Database for Global Atmospheric Research
EPAT	Environmentally friendly patents
FDI	Foreign Direct Investments
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
GHG	Green House Gas
IEA	International Energy Agency
ICT	Information and Communication Technologies
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
NOREN	Non-Renewable Energy
OECD	Organization for Economic Co-operation and Development
PCA	Principal Component Analysis
R&D	Research and Development
REN	Renewable Energy
SDGs	Sustainable Development Goals
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology
TFP	Total Factor of Productivity
UNESCO	United Nations Educational and Cultural Organization
UNFCC	United Nations Framework Convention on Climate Change
WDI	World Development indicators
WIPO	World Intellectual Property Organization

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ABSTRACT

Global warming poses a serious threat to our ecosystem and our future. In this regard, reducing the use of fossil fuels by limiting energy consumption or improving energy efficiency is considered a critical path to combat climate change and environmental degradation. Among the main factors for reducing carbon emissions, technological progress's environmental impact has recently received considerable attention. Many scientists and political and economic leaders believe that technological progress will play a vital role in the low carbon path for both developed and developing economies. However, it would be interesting to determine whether technological progress has reduced carbon emissions over the past decades. Hence the purpose of this thesis. This thesis aimed to investigate the impact of technological progress on CO2 emissions. To do so, the specific research questions of the thesis were: What is the impact of aggregate technological progress on CO2 emissions? What is the effect of green technology on CO2 emissions? How are sectoral CO2 emissions (emissions from five energy sectors: Power, manufacture, transportation, petrol, and building sectors) affected by aggregate and green technological progress? In addition to these three specific questions, the thesis investigates how the relationship changes depending on countries' development stages. These three research questions were addressed through three chapters (chapters 3, 4, and 5) around which the thesis is structured.

This thesis was carried out on a panel of 60 countries divided into four income groups. Thus, we had 15 high-income countries, 15 upper-middle-income countries, 15 lower-middle-income countries, and 15 lower-income countries. The 15 countries chosen per income group are the largest CO2 emitters in their respective income groups. The study period ran from 1989 to 2018. The empirical analysis starts from chapter 3. In this chapter, various indicators of technological progress are used to evaluate their effect on CO2 emissions using the fixed effect and the Bruno LSDVC methodology. The full sample dataset analysis reveals mixed results. ICT expansion and science and technology publications reduce CO2 emissions. Patent applications and R&D expenditure did not significantly impact carbon emissions. TFP increases CO2 emissions in the full sample, suggesting that, in general, taking all its different aspects together, technological progress would increase carbon emissions. Subsample analysis revealed that ICT development decreases CO2 emissions in all income group countries. However, science and technology publication is negatively related to CO2 emissions only in high and upper-middle-income countries.

The fourth chapter examined the interaction between green technology and CO2 emissions using the same estimation methodology employed in chapter 3. The thesis investigated if countries could reduce CO2

emissions through renewable energy consumption and climate-related innovations. Results reveal that renewable energy consumption significantly reduces CO_2 emissions in the full sample and all subsamples. However, climate-related innovations represented by environmental-related patents significantly lower CO_2 emissions only in very high-income countries.

The fifth chapter investigated how aggregate and green technological progress affect CO_2 emissions in five important energy sectors. The thesis developed an aggregate technological index using various technological progress measurements. Then, the thesis evaluates the effects of the composite indicator created on carbon emissions from the power, manufacture, transport, petrol, and building sector, using the Generalized Method of Moments (GMM) and Feasible Generalized Least Square (FGLS) methodology. The full sample analysis results show that, on the one hand, the composite indicator increases carbon emissions in all sectors except the building sector. On the other hand, renewable energy significantly lowers emissions from all sectors, except the petrol sector. Results from subsamples indicate that, generally, the composite indicator of aggregate technology is positively associated with carbon emissions across sectors; however, it is negatively related to carbon emissions from the manufacturing and building sector in high-income countries. The thesis further demonstrated that technological progress induced by the private sector plays a significant role in reducing CO_2 emissions in these two sectors.

This thesis allowed us to draw important lessons and recommendations for policymakers and various stakeholders to understand better the relationship between different aspects of technological progress and CO_2 emissions and use technological progress as an essential tool to fight climate change.

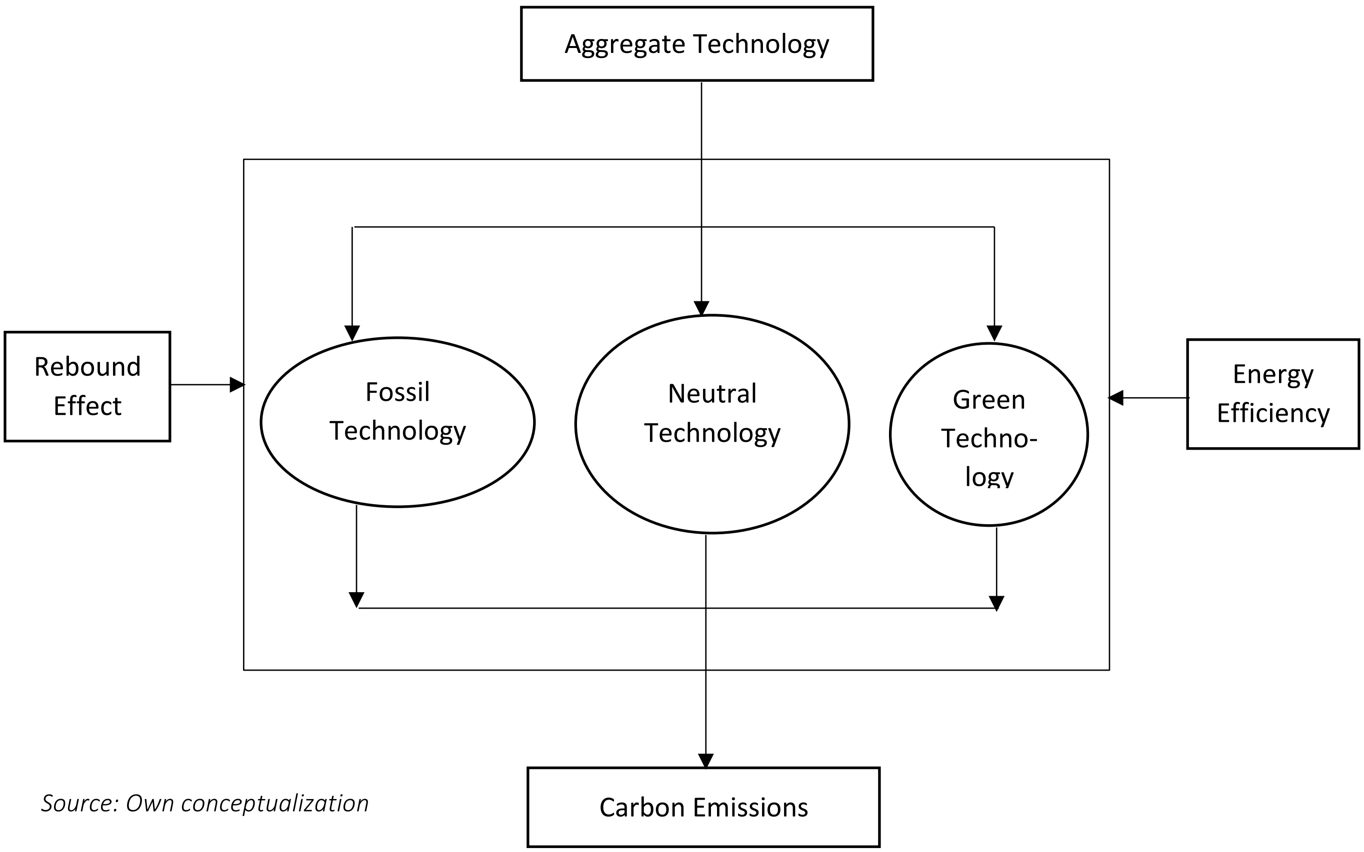
I. General introduction

Over the past two decades, global warming has become a major concern worldwide. Since the industrial revolution, the level of greenhouse gases (GHG) in the atmosphere has increased rapidly. The latest IPCC report, published in August 2021, outlines worrying prospects for the future, highlighting the alarming rise in temperatures despite government commitments. The temperature rise has already reached 1.1 degrees compared to the pre-industrial era, and it is expected to exceed 1.5 degrees by 2030 (IPCC, 2021). Numerous climate and energy policies have been proposed and implemented. Among them, the transition from fossil fuel energy (oil, coal, gas, etc.) to renewable energy (solar, hydro, wind, etc.) and the improvement in energy efficiency are considered the major solutions to global warming (Fare et al., 1994; Li and Lin, 2016). Due to its relatively high costs and technological barriers in many countries, renewable energy consumption and energy-efficient innovations are still limited despite having an upward trend. It is expected that the cost of green technologies development will decrease over time, and one of the major channels by which this can be achieved is through technological progress.

Technologies refer to the whole complex of scientific knowledge, industrial production and transformation technics, engineering practices, product characteristics, infrastructures, tools and machines, skills, and procedures used to resolve real-world problems (Mooney & Vaughn, 2011). The industrial revolution of the 19th century was a major turning point in the history of humanity. It triggered both technological and energy revolutions enabling continued economic growth in many countries. The Industrial Revolution was a transition process from a predominantly agricultural economy to one dominated by industry (Fisher, 1992). By the 19th century, the economy had become more industrialized with large-scale industries, more mechanized manufacturing industries, and a more organized work system. New industries were created, like the automobile industry at the end of the 19th century. The industrial revolution was characterized by several major changes, including, firstly, the massive use of iron and steel. Secondly, the invention of new machines, such as the spinning jenny and the power loom, made it possible to increase production with less human effort. Third, the large-scale use of new energy sources, including fuels and motive power, such as the steam engine, coal, electricity, and petrol. Fourth, there has also been a tremendous expansion in the communications and transportation sector, including the steamship, steam locomotive, automobile, aircraft, telegraph, and radio (Mooney & Vaughn, 2011). Undoubtedly, the industrial revolution was an amazing event that triggered a technological revolution and an economic transition on the planet; however, the industrial revolution would not have been possible without energy — a lot of energy mainly generated from coal, petrol, and gas. From 1800 to the present day, data show that the overall consumption of fossil fuels (petroleum, coal, and gas) has increased more than 1,300 times (Our World in Data, 2020). While fossil fuels have fueled the industrial revolution and the global economy since the 19th century, they are also the primary source of CO2 emissions emitted into the atmosphere. Therefore, the world must balance the role of energy in social and economic development with the need to decarbonize, reduce our reliance on fossil fuels, and transition towards lower-carbon energy sources (Hashmi & Alam, 2019). This can be achieved with substantial progress in technology.

The impact of aggregate technology on carbon emissions depends on the combination of several internal and complex factors, which can have both a positive and/or negative effect on the environment. Figure 1 proposes a broad conceptualization of the impact of aggregate technology on carbon emissions. The impact depends on the combination of three types of technology encompassed in aggregate technology. From an environmental point of view, aggregate technology can be divided into three components. The first component is constituted of fossil fuel technologies, which are technologies that only work with fossil fuels. Most means of transportation currently used to move populations and goods are included in this category—means of transportation such as combustion engine cars, airplanes, and boats. This category also contains technologies used to produce electricity in coal-fired, gas fire, and petrol power plants. Fossil fuel technologies are also innovations that are created and designed to accommodate or facilitate the utilization of fossil fuel energy. Green technologies constitute the second component of aggregate technology. Conversely to fossil fuel technologies, green technologies are technologies that reduce the harmful effects of human activity on the environment. They aim to optimize the exploitation of energies and find long-term solutions to prevent the degradation of ecosystems on which human life is dependent (Du, Li, and Yan, 2019). Green technology covers many areas, ranging from long-life bulbs to waste recycling, wastewater treatment, and renewable energy production. There are also promising new fields such as carbon capture storage technologies, green hydrogen, and electric vehicles. The third component of aggregate technology is referred in this thesis as "Neutral technologies". Neutral technologies are the largest component of aggregate technology. These technologies' internal working mechanisms do not need to be filled with oil, gas, or coal to function. Neutral technologies work with electrical energy produced from fossil fuels or renewable energies. When these technologies are powered by electricity from fossil sources, their utilization increases carbon emissions because of the strong positive correlation between fossil fuels and carbon emissions. Most households' appliances (TVs, washing machines, microwaves, dish-washer, air-con, etc.) and connected devices (mobile phones, laptops, tablets, etc.) can be categorized as "neutral technologies". So, neutral technology indirectly impacts carbon emissions through fossil fuel energy consumption.

Figure 1. conceptualizing the impact of technology on CO2 emissions



Source: Own conceptualization

The energy consumption of these three components is negatively affected by energy efficiency and positively affected by the rebound effect. Energy efficiency and the rebound effect play a significant role in influencing the way technology affects carbon emissions levels. Energy efficiency is a critical instrument for mitigating the effects of climate change (Gu et al., 2019). It designates all the practices and technological improvements that reduce energy consumption while maintaining optimal performance. This includes measures such as the insulation of buildings, changing incandescent light bulbs with LED light bulbs, changing old machinery, and energy-consuming equipment with new and more efficient machinery. For example, it is estimated that washing machines produced in 2020 consume three times less energy than those made in 1995 (Fakini et al., 2015). The importance of energy efficiency and energy savings is explained by the fact that energy consumption in the world is increasing disproportionately and that the use of conventional energy, the most widely used, contributes to the acceleration of climate change.

According to the IEA (2019), "energy efficiency improvements in 2019 avoided an increase of around 200 MtCO2 in global emissions, almost equivalent to the energy-related CO2 emissions of Spain. This was the second-largest source of avoided energy sector emissions, just behind renewable energies". The rebound effect increases GHG emissions. The rebound effect is when the additional energy saved due to improved energy efficiency (more efficient heating system, insulation, fuel-efficient vehicle, etc.) will be offset by increased energy demand (Gu & et al., 2019). For instance, the price reduction of energy-saving light bulbs and their widespread use in homes has sometimes led to less caution in energy use, compensating for or exceeding the energy savings made. Another example is when energy savings made by households following housing insulation work are reinvested in the purchase of a comfortable second vehicle, which consumes energy and pollutes.

The carbon footprint of the three components displayed in figure 1. determines the final impact of technology on the environment. This diagram does not present other important parameters essential in the nexus between technology and the environment; parameters such as environmental regulations, quality of institutions, or country-specific factor endowments. The complexity of the interactions between these different factors makes the effect of global technology on carbon emissions challenging to determine.

Unfortunately, despite its fundamental importance, technological progress is challenging to quantify. So why is it so challenging to measure technological progress? Some reasons are outlined here; firstly, there is not only one technological progress but several. This progress is inherent to each sector of the economy. Thus, some countries may be more technologically advanced in the IT sector, while others are more advanced in mining or oil extraction. Determining technological progress would require implementing standard sectoral basis measures to reveal which countries appear to be in the front of most sectors. Second, each type of technological change is different. They are different in terms of their nature and scope. The industrial revolution of the 19th century is different from the electro-mechanical revolution after world war two, which is different from the IT industrial revolution that we experience today. There are game-changing technological inventions that bring about a real revolution in the industry, leading to lower costs, economies of scale, or higher social connectivity. In contrast, other technologies make relatively modest contributions to industrial activities. This lack of predictability makes technological progress hard to identify and measure accurately over time. Third, while some innovations improve the quantity, others only affect quality. Economists have struggled to quantify quality because it often relies on each individual's subjective perception and preferences. The effect of technological change induced by a change in quality may sometimes be wrongly attributed to technological change that shows direct results in quantity. Fourthly, while the effects of some technological changes can be immediate and straightforward, some technological change takes time to produce results. We can think of electric vehicles and carbon capture technology in this regard. Even if they are considered game-changer technologies, particularly for climate change, they may take time to have market shares and be adopted by businesses and consumers.

Despite all these challenges, researchers have attempted to estimate and predict innovation trends through productivity, R&D spending, patent applications, renewable energy consumption, etc. The most common indicators used to quantify technological advancement will be necessary to measure and compare the technological evolution at countries and regional levels.

There is a vast body of literature estimating the impact of economic growth, population, energy consumption, and trade on carbon emissions (see Beckerman, 1992; Barbier, 1997; Dinda and Coondoo, 2006; Akinlo, 2008; Boutabba, 2014; Ertugrul et al., 2016; Antonakakis, Loanis, and Filis, 2017). However, relatively few studies have examined technology's effect on CO2 emissions. This thesis examines the role of technological progress in climate change. This thesis mainly explores the two direct links: aggregate technology – CO2 emissions and green technology – CO2 emissions. Particularly, the thesis accounts for the complex multidimensional nature of technology and evaluates how the CO2 emissions trend is responsive to various aggregate and green technology measures in a full sample of 60 countries and different income group countries.

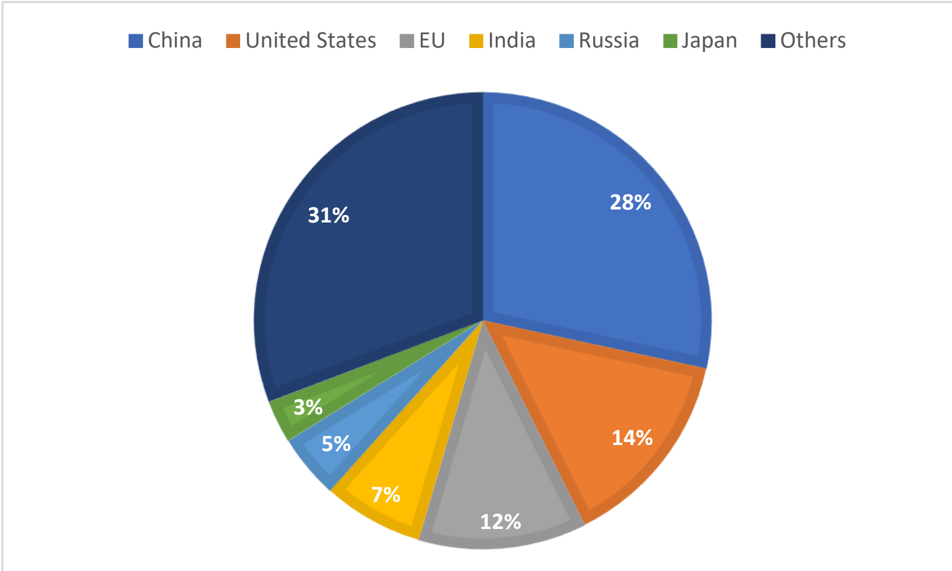
In analyzing the relationship between technology and carbon emissions, grouping countries according to their income level has several advantages that need to be emphasized. Firstly, intuitively, the environmental impact of technological progress also depends on the income level since developing game-changer innovations usually entail high costs. Technology acquisition is an expensive and time-consuming process. Developing autonomous capacities for technological innovation requires substantial investments in education, industrial facilities, and equipment (Du et al., 2018). Secondly, income level can also reflect the quality of institutions in a country. Generally, the more a country is economically advanced, the more it strengthens its institutions' quality. Therefore, ranking countries by income level would also be a way to capture the level of law enforcement in a country, environmental laws included (Hashmi and Alam, 2019). Many studies have confirmed the direct relationship between the strict application of environmental regulations and the level of carbon emissions. Ecological laws promote the development of eco-friendly technologies leading to lower emissions levels (Porter and Van der Linde, 1995). Thirdly, income level can also reflect, to some extent, the level of concern of a country about environmental problems. Low-income countries are, for example, less sensitive to environmental issues than high-income countries. Populations in these countries are more concerned about satisfying their basic needs (food, shelter, and clothing) that punctuate their daily lives. For individuals and nations, it is undoubtedly easier to sacrifice part of their consumption to protect the environment when incomes are high. Therefore, there will be a different approach to tackling environmental problems in these countries, affecting the relationship between technological progress and carbon emissions.

In conclusion, classifying countries into different income groups allow for capturing several aspects such as financial capacity, environmental regulations, and environmental awareness, which would enable a better analysis of the interaction between technology and carbon emissions in each group of countries. Because of the elements mentioned above, the impact of technological progress on carbon emissions may significantly vary across different income-group countries.

1.1. Background and motivation

The rapid deterioration of environmental ecosystems and the role played by technology in climate change motivates this research. The climate issue is gradually becoming a major concern for people around the world. In recent years, there has been a general awareness, not only among scientists but also among politicians and leaders. Indeed, the frequency of extreme weather events, storms, droughts, more frequent floods, or even the degradation of the ecosystem are all elements that cause concern. Figure 2 shows that, according to the IEA (2019), five countries and regions (China, United States, EU, Russia, and Japan) produce 62% of total carbon emissions. These countries are mostly categorized as developed economies (except China and Russia, which are still classified as emerging economies) and account for 35% of the world population. A question then arises from this fact: what would happen to our climate when the remaining 65% of the world population reaches the same income level as these developed and emerging economies? The most probable answer to this question is an unavoidable degradation of the environment and climate, which would lead to unknown consequences for humanity.

Figure 2. Share of global CO2 emissions per country and region in 2019

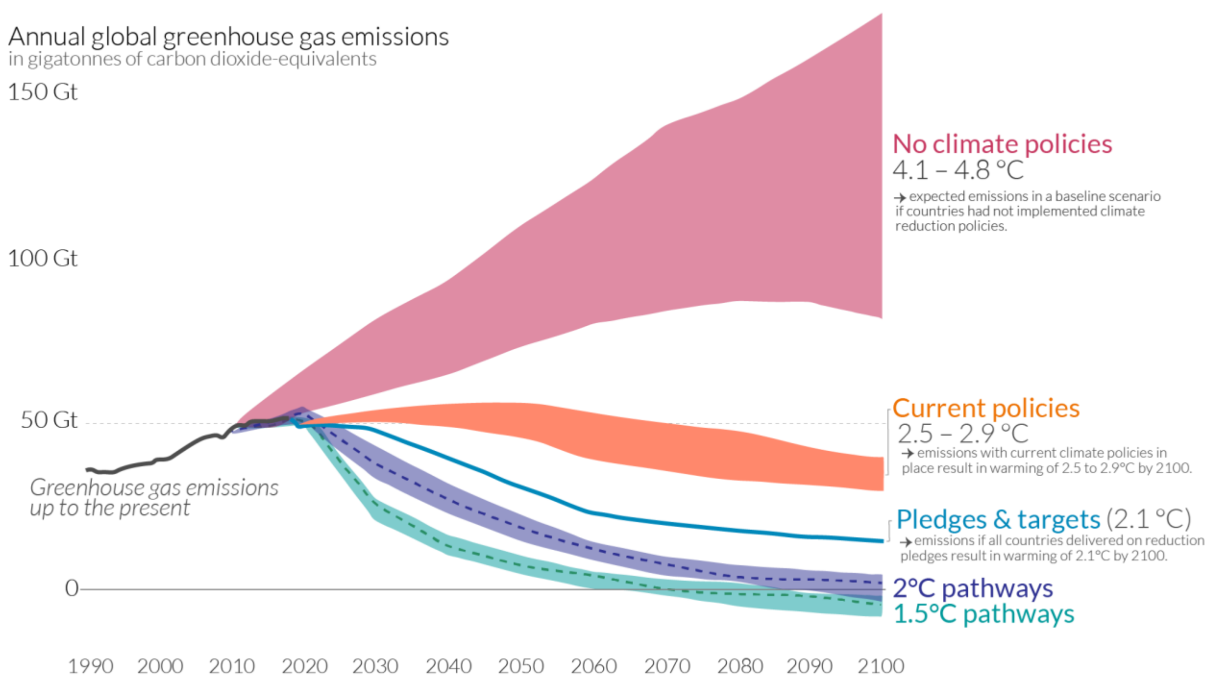


Source: IEA (2018)

When a country experiences continuous economic growth, one of the policy maker's major priorities would be to secure additional energy supply to meet the growing energy demand. They will import more energy or invest in large-scale oil power plants, gas, coal, or renewable energy to supply energy to industries, households, and businesses. In lower-income countries, in particular, access to energy helps fight poverty. In Africa, access to electricity remains an immense challenge. For example, only 45% of the sub-Saharan African population has regular access to electricity (IEA, 2019). Inclusive economic growth is the only effective way to reduce poverty and promote shared prosperity. However, most economic activities are not possible without an adequate and reliable energy supply at a competitive price. A constant economic growth also means greater financial capacity for companies, allowing them to increase their energy sources to produce goods and services. Companies will increase their demand for fossil fuels (oil, coal, gas) and extend their fuel storage capacities to face market supply uncertainty. This scenario is even more amplified in developing countries, including those in Africa, since these countries are exporters of raw materials for the most part. Therefore, they constantly need more energy to expand mining value chain activities and supply the increasing world demand for raw materials. Constant economic growth is also related to higher purchasing power for households, which can buy more goods and services. Higher purchasing power may lead to the acquisition of more energy-intensive appliances and the installation of the lighting, heating, and cooling systems in residences, causing energy consumption to increase.

Therefore, it is expected that an increase in income is inevitably accompanied by an increase in energy demand, which damages the environment when the energy generation sources are fossil fuels. It is critical to find sustainable ways to develop economies without further worsening the current environmental situation. Many measures have been proposed and implemented to mitigate climate change—solutions such as adopting and expanding renewable energy, promoting energy efficiency, and implementing sustainable transportation. Also, promoting sustainable infrastructure, forest management, responsible consumption, and waste recycling (e.g., Herring and Roy, 2007; Boden, Marland and Andres, 2017; Higon and al., 2017; Gu et al., 2019). Despite several ambitious climate policy implementations, the IPCC (2018) climate report does not predict any scenario in which we can keep global warming to 1.5°C under current conditions. Figure 3 shows that the current climate policies will reduce the effects of climate change, but this will not be enough to keep the temperature change below 2 degrees Celsius. Current forecasts predict temperature levels between 2.7 and 3.1 degrees Celsius by 2100. Despite these concerning previsions, many scientists, political and economic leaders believe that technological progress will play a vital role in the low carbon path for both developed and developing economies. However, it would be interesting to determine whether technological progress has reduced carbon emissions over the past decades. Hence the purpose of this thesis.

Figure 3. Global GHG emissions and warming scenarios



Source: Our world in data (2020)

1.2. Problem statement

The main purpose of this thesis was to achieve a comprehensive analysis of the relationship between technological progress and climate change in a full sample of 60 countries that represent 92 per cent of total CO2 emissions and 88 per cent of Global GDP in 2015. In addition, this thesis establishes comparisons on how this relationship changes across country income groups. This thesis uses carbon dioxide emission (CO2), the most prevalent greenhouse gas, as a proxy for climate change. The thesis first started by analyzing how Aggregate technological progress represented by a number of proxies affect CO2 emissions. Secondly, the thesis examined the relationship between green technology and CO2 emissions. Thirdly, the thesis investigated how aggregate and green technology affect sectoral CO2 emissions from five important energy sectors.

More specifically, this thesis offers three points of contribution. Firstly, the thesis compares the relationship between technological progress and carbon emissions in four income group countries: high-income, upper-middle, lower-middle, and lower-income countries. Most economic studies that make comparative analyzes are based on two groups of countries: developed countries and developing countries. Given the higher disparity of GDP per capita across countries, we believe that this categorization is too broad and not very distinctive. Grouping low- and middle-income countries as "developing countries" puts countries such as Madagascar (GDP per capita of $472 in 2010) in the same group as Brazil (GDP per capita of $11,290) (World Bank, 2019). That is an almost 24-fold difference within the same group. Due to large income differences, it can be expected that the relationship between technological change and carbon emissions may significantly vary across the four income groups.

Secondly, measuring technological progress is challenging as its realization and representation vary. Unlike many studies in the literature that use one proxy of aggregate technological progress – in the third chapter – this thesis employs various technological progress indicators and assesses their effect on carbon emissions individually. This thesis accounts for the multidimensional nature of technological progress and argues that each indicator captures some aspect of technological progress, and the impact of each aspect on carbon emissions can differ significantly. By doing so, this thesis will be able to provide specific policy recommendations to promote particular aspects of technology to reduce CO2 emissions.

Thirdly – in the fourth chapter – the thesis investigates the relationship between green technology and CO2 emissions. Green technology is divided into two components: renewable energy and environmentally-friendly innovation. The fourth chapter also examines the "reverse causality" of CO2 emissions to technological progress. This is how CO2 emissions influence the development of green technology and carbon-intensive technology.

Fourthly – in the fifth chapter – the thesis analyses how carbon emissions from the power, manufacture, transport, petrol, and building sectors are affected by aggregate and green technology. A growing number of existing studies in the broader literature have examined the relationship between technology and CO2 emissions. These studies have generally neglected differences in carbon emissions per economic sector. This thesis argues that because each sector's contribution to total carbon emissions varies, the environmental impact of technological advancement may also differ across sectors. The fifth chap contributes to the literature by constructing a productivity index and assessing its impact on sectoral carbon emissions in the five energy sectors. This allowed us to identify which sector aggregate technology and green technology significantly affect CO2 emissions and the reasons that can explain such impact.

Fifthly, this thesis also contributes to identifying how important drivers of CO2 emissions employed in empirical analysis throughout this thesis - such as GDP per capita, energy consumption, population density, oil price, urbanization, financial development, export, and trade openness - can positively or negatively impact CO2 emissions, depending on one group of countries to another.

Research question and objectives

Following the purpose statement, this thesis seeks to answer the following research questions:

- What is the impact of Aggregate technological progress on CO2 emissions? Does this impact differ across income group countries?

(The above research question has been answered through a published paper titled: "Impact of technological progress on carbon emissions in different country income groups,"[1] referred to as Paper 1)

There is no common agreement in the literature on the influence of technology on GHG emissions. This thesis takes a different approach by using several technological progress indicators and assessing their effect on carbon emissions. The thesis starts by examining the nexus between technology and carbon emissions in a full sample of 60 countries, and then it evaluates how this relationship changes in different income groups. The strength and weaknesses of each indicator of technological progress are

[1] Milindi, C. B., & Inglesi-Lotz, R. (2022). Impact of technological progress on carbon emissions in different country income groups. *Energy & Environment*. https://doi.org/10.1177/0958305X221087507

thoroughly discussed in the dissertation. This thesis also sheds some light on the rebound effect and determines whether the rebound effect of energy consumption is higher or smaller than energy savings caused by technological progress.

- ❖ What is the impact of green technologies, demonstrated via two different proxies (environmental-related patents and renewable energy consumption) on carbon emissions? Does this impact differ across income group countries?

(The above research question has been answered through a published paper titled: "The role of green technology on carbon emissions: does it differ across countries' income levels?"[2] referred to as Paper 2)

Although it is theoretically predicted that the higher the number of climate-related technologies and eco-innovations, the better for combating climate change, there is limited empirical evidence to support this (Barbieri et al., 2016; Su and Moniba, 2017). This thesis evaluates how the carbon emissions trend is affected by two indicators of green technology development: renewable energy and eco-friendly innovations. These two indicators are considered "two sides of the same coin." This thesis argues that for an optimal impact on carbon emissions, energy decarbonization induced by renewable energy should be coupled with massive eco-friendly innovations such as electric cars, energy efficiency, circular economy, etc. The thesis first examines the green technology and carbon emissions nexus in the full sample and then evaluates how the relationship changes in each income group. Particularly, the thesis determines which income group country successfully achieved carbon emissions reduction through renewable energy development and eco-friendly innovations. The reverse causality — carbon emission to technology — is also examined. The thesis determined how CO2 emissions influence the development of green technology and carbon-intensive technology. Notably, the thesis examined countries' reactions in terms of technology used when carbon emissions and GDP increase.

- ❖ What is the impact of aggregate and green technology on sectoral CO2 emissions? Emissions from five energy sectors: Power, manufacture, transportation, petrol, and building sectors

In chapter five, using various technological development measurements, the thesis develops an aggregate technological index and examines its effect on five energy sectors' carbon emissions (power, manufacture, transport, petrol, and building sector). Doing so, allowed us to determine in which sector the aggregate technological index is positively or negatively associated with CO2 emissions and the reasons that can

[2] Chris Belmert Milindi & Roula Inglesi-Lotz (2022) The role of green technology on carbon emissions: does it differ across countries' income levels? Applied Economics, DOI: 10.1080/00036846.2021.1998331

explain such association. It will also help policy-makers identify the sector where more efforts must be made in terms of technological advancement to curb the CO2 emissions curve.

1.3. Objectives of the research

To answer the research questions mentioned above, the following broad objectives were set:

- First research question

i. To determine the effect of various measurements of technological progress (which also represent different aspects of technology) on carbon emissions in a full sample and different country income groups.

- Second research question

ii. To evaluate the impact of green technology, represented by renewable energy and eco-friendly innovations, on carbon emissions in a full sample and across country income groups.

iii. To analyse the influence of the carbon emissions trend on renewable energy and climate-related technology in different country income groups.

- Third research question

iv. To create an index of aggregate technology and evaluate its impact on sectoral carbon emissions (emissions from the power, manufacture, transport, petrol, and building sector).

v. To determine which sectoral CO2 emissions are positively or negatively associated with the aggregate technological index.

1.4. Contribution of this thesis

This thesis considers the complex multidimensional nature of technology to assess how various aspects of technological progress influence carbon emissions on national and sectoral levels in different income group countries. Many empirical studies have explored the linkage between technological change and pollutant emissions, particularly carbon and methane. Even if several studies have investigated this relationship, they focus on specific country groups, such as the OECD, the G7, G20, or the BRICS. In contrast to previous studies, this thesis attempts an aggregate and disaggregate approach of technological progress to analyze how the relationship between technological progress and CO2 emissions would depend on countries' development stages. We believe that the relationship between technological progress and carbon emissions may differ across different country income groups. This is due to the differences in terms of financial capacity (Grossman and Krueger, 1995; Dinda and Coondoo, 2006), the level of CO2 emissions specific to each group of countries (Hashmi and Alam, 2019), and the presence of stable political institutions and environmental regulations that are stronger and more enforced in some groups of countries than in others (Cheng et al., 2019). Analyzing how differently technology interacts with climate change in lower, lower-middle, upper-middle, and high-income countries will provide an insightful and interesting contribution to the literature.

The research will:

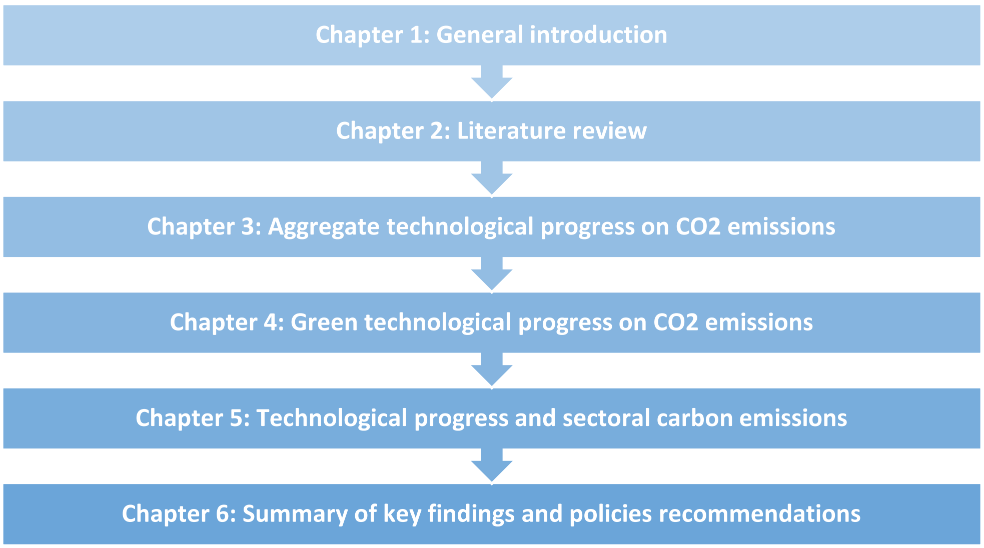
- Contribute to the growing body of literature by providing better insight regarding the multidimensional role of technological progress in climate change
- Investigate how different aspects of aggregate technological progress affect CO2 emissions levels in groups of countries at different development stages.
- Analyze the role of green technology in climate change and identify which group of countries experienced carbon mitigation due to both renewable energy production and climate-related technology development.
- Examine the effect of aggregate and green technology on sectoral carbon emissions of five important energy sectors, and identify which sectors are positively or negatively affected by the aggregate technological index trend.

1.5. Organization of this thesis

The thesis is structured in six chapters, as illustrated in Figure 4. Chapter 1 introduces the thesis topic by providing the background and the motivation for this thesis. Chap 1 also provides the research purpose and objectives and highlights the contribution of this thesis. Chapter 2 reviews the most recent literature on the topic. This chapter is divided into four sections. The first section reviews studies that have examined the relationship between technology and GHG emissions – including research that evaluated the role of environmental regulations and government intervention in climate change. The second section reviews studies that have analyzed green technology's effect on CO2 emissions – including empirical studies on the reverse causality: CO2 emissions to green technology. The third section summarizes papers that have examined the influence of technology on sectoral carbon emissions. The fourth section reviews studies that identified the major drivers of global CO2 emissions.

Chapter 3 empirically analyzes aggregate technology's effect on CO2 emissions, and chapter 4 uses the same sample employed in chap 3 to investigate the interactions between green technologies and CO2 emissions. Chap 5 creates an aggregate technology index and empirically evaluates its impact on CO2 emissions from the power, manufacture, transport, petrol, and building sectors. Lastly, chapter 6 summarizes research findings and provides recommendations.

Figure 4. Organization of the thesis



II. Literature review

2.1. Aggregate technology and GHG emissions

Over time, a growing literature has developed on the role played by technological progress in the environment, particularly in climate change. Existing studies can be divided into three categories. The first strand of the literature comprises research that has used R&D expenditure as a proxy for technological progress.

Bosetti et al. (2008, 2009, and 2011) are among this stream of research. The authors have published several papers which analyze the relationship between technology, international knowledge spillover, and carbon emission, using aggregate R&D as a proxy for technology (Bosetti et al., 2008, 2009, 2011; Bosetti and Tavoni, 2015). Generally, the authors have found that fostering R&D expenditure and de-carbonization of energy is essential to reducing carbon emissions. The authors showed that massive investment in R&D would bring energy efficiency and allow the development of renewable energy sources such as solar, wind, and geothermal. Fernandez, Lopez, and Blanco (2018) employed Ordinary Least Square (OLS) technics to analyze technological innovation's impact on GHG emissions in the United States, European Union, and China from 1990 to 2013. The findings support the hypothesis that government spending on R&D translates to a reduction of GHG emissions. Unlike Fernandez and Lopez's findings, Garron and Grilli (2010) found that government R&D expenditure fails to significantly impact CO2 emission reduction in 13 developed countries over the 1980-2004 period. The authors argue that for R&D spending to mitigate CO2 emission, it should be coupled with intensive energy efficiency policy implementations. Li and Wang (2017) identified a dual effect of technological progress on CO2 emissions. On the one hand, technology reduces aggregate CO2 emissions by reducing energy intensity. On the other hand, technology increases CO2 emissions through increased economic growth. The authors showed that technology reduces aggregate CO2 emissions in a panel of 95 countries from 1996 to 2007. Churchill et al. (2019) employed panel data technics to examine the effect of R&D expenditures on carbon emissions in the G7 countries. The study is particular because it is the first research that analyses this relationship over 145 years, from 1870 to 2014. Results revealed that the relationship between R&D and CO2 emissions varies over time. R&D's estimated time-varying coefficient was negative for three-quarters of the period studied but was positive for 35 years (1955–1990) during the second half of the twentieth century.

The second strand of the literature has used ICTs as a proxy for technological progress to estimate their impact on GHG emissions (see Moyer and Hugues, 2012; Higon, Gholami and Shirazi, 2017, Asongu, Le Roux and Biekpe, 2017; Zhou et al., 2019). These studies identify two opposite effects of ICTs on carbon emissions. On the one hand, ICTs can increase CO2 emission by increasing manufacturing production, energy consumption, production of devices and machinery, and recycling electronic waste. On the other hand, ICTs can lower CO2 emissions on a global scale through energy savings, smart cities, efficient production processes, ecological transportation systems, and electrical grids. These studies have generally found that the net effect of ICT on CO2 emissions is negative.

The third strand of the literature has employed patents as a proxy for technological progress. The paper by Cheng et al. (2019) falls into that category. The researchers investigated the impact of the various variable on CO2 emissions: renewable energy, foreign direct investment, GDP per capita, environmental patent, and exports. The analysis is performed for the BRICS countries, and the period runs from 2000 to 2013. The authors emphasized two strategies at the centre of the BRICS's action against global warming: (1) the development of renewable energy sources and (2) the development of energy efficiency technology. The results indicated that environmental patents, exports, and GDP per capita increase carbon emissions while renewable energy and foreign direct investment decrease them. The authors explained the positive impact of patents on carbon emission by the lack of environmental regulation allowing the diffusion of sophisticated technology in the BRICS countries. Other papers have found similar results for different countries or regions (Su and Moaniba, 2017; Du, Li, and Yan, 2019; Hashmi and Alam, 2019).

The discussion on the relationship between TFP and environmental degradation is very limited in the literature. Dogan, Tzeremes, and Altinoz (2020) investigated the non-linear relationship between TFP and carbon emissions in 17 African countries. They found that TFP increases carbon emissions in most countries in the sample. Amri, Ben Zaied, and Ben Lahouel (2019) analyzed the same relationship in Tunisia using the ARDL technic. Results showed that the level of TFP in Tunisia does not translate into environmental improvement.

Many studies have emphasized the critical role of governments in fostering the adoption of new technologies for carbon emissions reduction. There is a consensus in the literature that technological progress needs to be coupled with strict environmental regulation, such as carbon tax, to have a significant impact on carbon emissions (Moyer and Hugues, 2012; Hashmi and Alam, 2019; Churchill et al., 2019; Cheng et al., 2019). Mees, Uittenbroek, Hegger, and Driessen (2019) have proposed a “ladder of government participation” to explore the role of local governments in citizens’ initiatives for climate adaptation in the Netherlands. They have found government support for citizens' climate change initiatives allows raising communities' awareness on climate change challenges. Cheng et al. (2021) have investigated the potential role of fiscal expenditure on carbon emissions differences in different provinces of China. The authors argued that modifying the structure and scale of budgetary spending would directly impact GDP as well as energy consumption and CO2 emissions. Results revealed that fiscal decentralization is a significant driver of provincial CO2 emissions in China. Reducing CO2 emissions can hardly be achieved with an inefficient distribution of expenditure authority between the provincial and central governments. Besides, some scholars investigated how environmental regulation can promote green technology adoption and reduce green gas emissions. Xie, Zhou, and Hui (2022) demonstrated that china's carbon emissions trading market system had improved the power generation technology structure. Marques, Fuinhas, and Tomas (2019) have shown that economic growth increases energy efficiency technology in the European Union. The authors have pointed out the critical role of policymakers in incentivizing green investment and controlling energy pricing.

As mentioned in the introduction, the third chapter of this thesis proposes to estimate the impact of various indicators of technological progress on carbon emissions in a full sample of 60 countries and subsamples of different income categories. Technology is a broad concept, and a single indicator can hardly represent it. Therefore, instead of using one indicator of technology as the majority of papers cited in the literature above, chapter three used six indicators of technological progress. This third chapter also follows Gu et al.'s (2019) paper and analyses the rebound effect by assessing the joint impact of technological progress and energy consumption on CO2 emissions.

2.2. Green technology and GHG emissions

A growing number of studies in the broader literature have examined the relationship between green technology and CO2 emissions. These studies can be divided into two categories. The first category analyses the impact of eco-innovation, represented by green patents, on CO2 emissions, while the second investigates the effect of renewable energy consumption on CO2 emissions.

2.2.1. Green patents and CO2 emissions

The paper by Zhang et al. (2017) falls in the first category. The authors use panel data technics (SGMM) to analyze the impact of environmental innovations on reducing carbon emissions in 30 provinces in China.

They describe environmental innovations as measures taken by relevant entities (private households, unions, firms) that apply new technology, introduce new efficiency processes of energy, and new ideas to contribute to a sustainable and proper environment. These environmental measures comprise innovation performance (economic development level and energy performance), innovation resource (R&D investment), knowledge innovation (number of patents produced, expansion of ICT), and innovation environment (pollution and environment regulation). They showed that most environmental innovations help in reducing carbon emissions. In particular, R&D expenditure, patent, and energy efficiency. They also found that initial measures taken by china for green gas emission reduction are effective. Unlike other research, this study used comprehensive standards of environmental innovation. Du, Li, and Yan (2019) investigated the impact of green technology innovation on GHG emissions in 71 countries from 1996 to 2012. The researchers use environmental-related patents as a proxy for green technology. They also look at how technology innovation and income affect carbon emissions. The authors pose two questions. First, can green technology innovations effectively reduce CO2 emissions? Second, are there some regime transitions for the effect of green technology innovations on CO2 emissions under different income levels? Findings revealed the existence of a per capita income threshold which is around 35000$. Green technology does not appear to reduce green gas emissions in countries where income is below that threshold. But it significantly mitigates GHG emissions in countries above that income threshold. Hashmi and Alam (2019) estimate the effect of innovation and environmental regulations on carbon emission in OECD countries from 1999 to 2014. The authors highlighted that adopting eco-friendly technology and deploying stringent environmental regulations are key factors in fighting against global warming. Environmental tax revenue is used as a proxy for environmental regulations. The authors employ panel fixed and random effect, GMM methodology to estimate the results. The findings showed that a 1 per cent increase in technology innovation patent lowers carbon emissions by 0.017 per cent. When environmental tax revenue per capita increases by 1 per cent, carbon emissions decrease by 0.03 per cent in OECD countries. The particularity of this study is that it separates two concepts: aggregate technology and green technology, and compares their different effects on carbon emissions. Tobelmann and Wendler (2019) employed the GMM methodology to assess the impact of green technology innovations on carbon emissions in 27 European Union countries from 1992 to 2014. Environmental-related patents are used to represent green technology innovations. The results showed that green technology has contributed to reducing carbon emissions. However, its effect is insufficient to offset the positive impact of economic growth on carbon emissions. The authors also found that the impact of innovative activities on carbon emissions varies across countries depending on their level of development.

While many papers in the literature have focused on how innovation impacts GHG emissions, Su and Moaniba (2017) proposed examining the reverse effect, which is how innovations respond to climate change. The authors examine how climate change affects technological innovation in a panel of 70 countries, using environmental patents as a proxy for technological innovation. To explore how the trend in the development of environmentally friendly technology has shifted in response to the number of carbon emissions, the authors used various econometrics techniques such as the generalized method of moment, fixed-effect logistic regression, and random effect. The empirical findings suggested that green gas emissions influence the development of eco-friendly innovations. Furthermore, countries with very high carbon emissions tend to respond more to developing environmentally friendly technology. Hakimi and Inglezi-Lotz (2019) have also examined the reverse causality of CO2 emissions to the green innovation process in 60 countries split into 36 developed and 24 developing economies between 2008 and 2014. The paper employed environmentally-related patents as an indicator of the green innovation process. Findings indicated that, in developed economies, the innovation process responds positively to total CO2 emissions and CO2 emissions from natural gas. Climate change in developing economies has no significant impact on the green innovation process. Paramati, Mo, and Huang (2020) examined the effect of financial development, foreign direct investment, green technology, trade openness, and per capita income on green gas emissions in 25 OECD countries from 1991 to 2016. The paper includes financial development in the model and assesses its impact on carbon emissions. The authors argue that financial development facilitates the obtention of capital to invest in green technology projects. The results from Group mean estimators revealed that green technology, trade openness, and FDI reduces green gas emissions while per capita income and financial development increase emissions.

2.2.2. Renewable energy and CO2 emissions

The second stream of the literature has explored the impact of renewable energy on carbon emissions. Nguyen and Kakinaka (2019) found clear evidence that, in the long run, the relationship between carbon emissions and renewable energy consumption is related to the development stage. The authors have examined the above relationship in 107 countries from 1990 to 2013. After applying fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) estimators, the results suggested that renewable energy consumption is positively related to carbon emissions and negatively related to output in high-income countries. In lower-income countries, renewable energy consumption is negatively associated with carbon emissions and positively associated with output. This study uses a large dataset, which contains countries at different levels of development.

Chen and Lei (2018) used a panel quantile regression methodology to revisit the environment–energy–growth nexus on a panel of 30 countries from 1980 to 2014. The results showed that renewable energy consumption has a limited impact on carbon emissions in high-emissions countries due to smaller proportions of renewable energy use. Jin and Kim (2018) investigated the determinants of carbon emissions on a panel of 30 countries between 1990 and 2014. Nuclear energy and renewable energy consumption are adopted as determinants, and real GDP and real oil price are included as additional independent variables. After employing panel cointegration technics and Granger causality tests, the results revealed that renewable energy consumption reduces carbon emissions, whereas nuclear energy increases carbon emissions. The authors explain the positive impact of nuclear energy consumption by its radioactive waste and harmful environmental effects. Khan and al. (2020) investigated the role of renewable energy consumption, eco-innovation, and industrial value-added in determining consumption-based carbon emissions in the G7 countries from 1990 to 2017. Results showed that consumption-based carbon emissions are positively stimulated by income and imports in the long run. But eco-friendly innovations, exports, and renewable energy consumption negatively affect consumption-based carbon emissions.

Alessandro and Colantonio (2020) noted that despite increasing renewable energy consumption worldwide, carbon emissions-related energy is also growing globally. Thus, the authors proposed investigating the determinants of renewable energy consumption that can bring countries that do not have energy independence to invest in fossil fuel instead of renewable energy. The study investigates renewable energy drivers, focusing on the socio-technical aspect rather than the economic aspect. These aspects are lobbying, policy stringency, education, and public awareness. The study is performed on a panel of 12 European Union net energy importing countries. The results indicated that policy stringency and lobbying help adopt renewable energy sources, thus reducing carbon emissions. However, public awareness is not enough to facilitate the transition to renewable energy. Wang et al. (2020) used the Common Correlated effect Mean Group (CCEMG) and the Augmented Mean Group (AMG) to investigate the impact of human capital, financial development, renewable energy, and GDP on carbon emissions in a panel of 11 countries, from 1990 to 2017. The findings suggested that GDP and financial development positively relate to carbon emissions. In contrast, renewable energy consumption and technological innovations are negatively associated with carbon emissions. The authors recommend developing and expanding renewable energy to fight carbon emissions.

Hussain et al. (2020) have investigated the role of environmental-related technology in abating consumption-based carbon emissions in a panel of 7 emerging countries (China, Brazil, Russia, India, Turkey, Mexico, and Indonesia) from 1990 to 2016. Results showed that environmental-related technology must include renewable energy to mitigate carbon emissions. The authors also found that imports and GDP growth deteriorate the environment. Mongo, Belaid, and Ramdani (2021) have employed an autoregressive distributed lag model (ARDL) to analyze the effect of environmental innovations, renewable energy consumption, trade openness, and GDP per capita on CO2 emissions for 15 countries in Europe from 1991 to 2014. Findings indicated that environmental technologies lower carbon emissions in the long term; however, they increase carbon emissions in the short term. The authors explain this opposite effect by the existence of the rebound effect in the European energy sector. Razzaq et al. (2021) have examined the asymmetric inter-linkages between green technology innovation and carbon emissions in the BRICS countries from 1990 to 2017. The authors have employed a quantile to quantile framework to estimate the results, arguing that the nexus between green technology and carbon emissions is non-linear due to technological advancement, structural changes, and social and economic reforms in the BRICS countries. Results indicated that green innovations reduce carbon emissions only at higher emissions quantile in BRICS countries. However, green innovation is positively related to carbon emissions at the lower quantile. Results also suggested that higher carbon emissions create pressure on the government, increasing its investment in green technologies and reducing carbon emissions. Lyguan et al. (2021), have found similar results for highly decentralized economies.

Chapter four follows the paper by Du, Li, and Yan (2019) and Nguyen and Kakinaka (2019). However, in addition to examining the impact of green technology on CO2 emissions in countries at different development stages, this chapter contributes to the climate change debate by analysing the technological innovations response of each country's income group to climate change. Specifically, we analyze countries' reactions regarding the type of technology used when carbon emissions and GDP increase. This kind of relationship has not yet been extensively examined in the literature, such as those identified above.

2.3. Aggregate, green technology, and sectoral CO2 emissions

Although many studies have been devoted to analyzing the relationship between technology and carbon emissions, rather less attention has been paid to examining the impact of technology on sectoral carbon emissions. This literature review summarises some recent studies investigating the nexus between technology and sectoral carbon emissions.

Erdogan et al. (2020) investigated the impact of the innovation process on sectoral CO2 emissions for 14 countries in the G20. The period of the study runs from 1991 to 2017. Patents application is employed as a proxy for the innovation process. Results showed that innovations do not significantly impact carbon emissions from the energy and the transport sector in the long term. However, innovation decreases carbon emissions from the industrial sector but increases carbon emissions in the construction sector. This paper is one of the scarce studies that have analyzed the effect of innovation (represented by patent applications) on carbon emissions in the different energy sectors (power sector, manufacturing sector, transport sector, and agriculture sector). Lee and Min (2015) analyze the impact of green R&D on carbon emission and financial performance in Japan's firms. The researchers argued that existing studies have not clearly distinguished between R&D and green R&D and their influence on carbon emission and a firm's financial performance. They define green R&D as activities that promote operational efficiencies and eco-innovation in the production process. The results indicated that investment in green R&D negatively affects carbon emission and positively affects the firm's financial performance. Given that the construction industry is developing and expanding in developing countries, Erdogan (2021) proposed to analyze the effect of technological innovation on carbon emissions caused by the building sector in the BRICS countries for the period between 1992 and 2018. After applying the Dynamic common correlated effects methodology, the findings indicated that technology innovation lowers carbon emissions from the building sector. Yang et al. (2021) have examined the impact of three technological progress channels (technology spillover from foreign direct investment, research and development expenditure, and interprovincial technology spillover) on carbon emissions from six energy sectors in China from 2000 to 2017. The authors argue that the relationship between technological progress on carbon emissions also depends on sectoral and regional heterogeneity. Therefore, they proposed a geographically and temporally weighted (GWR) model to estimate the results. After estimation, results revealed that R&D spending slows down carbon emissions caused by the industrial, agriculture, and wholesale sectors. However, R&D expenditure increases CO2 emissions from the transportation, residential, and construction sectors. Li, Qiu, and Wu (2021) have observed regional differences in green gas emissions in China's building sector. Therefore, they proposed investigating the drivers of carbon emissions in china's building sector at the provincial level. Results indicated that energy intensity, income, and energy mix explain regional differences in carbon emissions per capita in the building sector. Economic growth helps in reducing regional disparities for residential buildings, but it does not significantly decrease regional disparities in public buildings. The authors conclude that energy intensity is the principal driver of emissions inequality in the building sector in China. Apergis and Payne (2017) extend the literature on the convergence of green gas emissions by investigating the presence of the convergence club of carbon emissions per capita, by sources of fossil fuel, and by sector of emissions, in 50 U.S. states for the period 1980 to 2013. After applying the Phillips and Sul club convergence approach, results revealed the presence of multiple convergence clubs in five sectors (electric power, commercial, transport, residential, and industrial). Carbon emissions convergence clubs have also been found for coal and natural gas. Sedat Alatas (2021) analyses green technology's impact on carbon emissions from the transport sector in 15 European countries. The period of the study ran from 1977 to 2015. The authors consider that the increasing trend observed recently in the E.U. transport sector CO2 emissions needs to be addressed by effective policies and strategies. The authors use the Common Correlated Effect Mean Group and the Augmented Mean Group to estimate the results empirically. Findings suggested that environmentally friendly technologies do have a significant impact on transport CO2 emissions. He, Fu, and Liao (2021) establish a multi-objective optimization model to investigate the optimum energy efficiency improvement induced by R&D investment necessary to reduce carbon dioxide emissions in China's industrial sector. Results suggested that under the optimized scenario, R&D intensity investment should grow annually by 11.14 per cent and physical capital investment by 10.61 per cent. If these two conditions are fulfilled, energy intensity would be reduced by 78 per cent in 2030 compared to its level in 2005, resulting in lower energy consumption and carbon emissions. Robaina and Neves (2021) identify the main factors that explain variations in carbon emissions intensity in the E.U. transport sector from 2008 to 2018. The Complete Decomposition method has been used in this study to identify six different factors. Results identify two main drivers of carbon emissions intensity in Europe: change in total energy consumption (negative sign) and change in capital per inhabitant (positive sign). The authors argue that a negative change in total energy consumption indicates that less and less energy is consumed in the transport sector due to more efficient motor vehicles. A positive change in per capita per inhabitant means that increasing carbon emissions in the E.U. is mainly driven by higher capital (mainly vehicles) per inhabitant. The authors proposed strengthening environmental regulations in place in the transport industries and promoting the development of electric vehicles. Isik, Ari, and Sarica (2021) use the Logarithmic Mean Divisia Index to identify principal drivers of carbon emissions from the Turkish power sector. Findings indicated that energy efficiency has a negative but limited impact on power sector carbon emissions. However, changes in fossil fuel share have a bigger and more significant impact over time.

2.4. Carbon emissions and key economic drivers

This subsection presents a brief literature review of other key drivers of carbon emissions. Economic growth, energy consumption, population, urbanization, financial development, and trade are often regarded as critical drivers of carbon emissions in the literature.

2.4.1. Economic growth and CO2 emissions

The relationship between economic growth and carbon emissions has been extensively discussed in the literature. There is a consensus that economic growth has been related to environmental deterioration for decades (Hertin and Berkout, 2005; Bousquet and Favard, 2005; Sorrell, Dimitropoulos, and Sommerville, 2009). Greater economic growth leads to greater energy consumption to meet the growing energy demand of companies, industries, and households. Unfortunately, the energy developed and used globally is extracted mainly from fossil fuels. It is thus expected that economic growth will lead to higher CO2 emissions. However, as postulated by the Environmental Kuznets Curve (EKC) theory, Many studies showed that economic growth is harmful to the environment in the early stages of development. But after reaching a certain level of wealth, economic growth would be accompanied by improved environmental quality (Borghesi, 1999). The enrichment of populations will be accompanied by the demand for a healthier environment, which would lead to higher standards and improved environmental quality in many areas (Shahbaz & Sinha, 2018). The EKC hypothesis has not yet reached a consensus in the literature. Some studies, such as the one by Apergis and Ozturk (2015), have validated the EKC for 14 Asian countries. Jardon, Kuik, and Tol (2017) have found similar results for 20 Latin America and Caribbean countries, and Kais and Hammami (2016) found support for the existence of an inverted U shape relationship between GHG emissions and economic growth for 58 countries from various regions between 1990 and 2012. In contrast, some other studies, such as the one by Holtz-Eakin and Selden (1995), Yang et al. (2015), and Narayan et al. (2016), did not find evidence of the EKC in their empirical results.

2.4.2. Energy consumption

Energy consumption is another well-known driver of carbon emission, and empirical studies have generally reported a positive and unidirectional association between energy consumption and carbon emissions. (Dimitropoulos and Sommerville, 2009; Hall, 2011; Jin et al., 2017; Cheng et al., 2019). Payne (2009) employed a VECM causality test and found a unidirectional relationship between energy consumption to carbon emissions in a panel of six central American countries. Pao and Tsai (2011) reported a unidirectional causal relationship between energy consumption and carbon emissions in the BRICS countries. Likewise, Omri (2013) reported the same results for 14 MENA countries. Alom (2014) used a panel cointegration causality test to analyze the relationship between economic growth, energy consumption, and carbon emissions in Five Asian countries from 1972 to 2010. Results revealed that, in the short term, there exists a causal relationship between energy consumption, economic growth, and carbon emissions. However, no causal relationship exists between energy consumption and carbon emissions in the long run. Gu et al. (2019) found that energy consumption positively affects carbon emissions in a panel of 30 provinces in China between 1980 and 2010. Acheampong (2018) analyzed the nexus between energy consumption, economic growth, and carbon emissions in a panel of 116 countries. Results indicated mixed evidence; the relationship varies from region to region.

Generally, the impact of energy consumption on carbon emissions depends on the type of energy used. If energy consumption comes from fossil fuels, which is usually the case, carbon emissions will increase (Dimitropoulos and Sommerville, 2009). However, if the energy produced comes from renewable energy, the negative impacts of energy consumption on the environment are extremely limited (IEA, 2018).

2.4.3. Population and CO2 emissions

Population growth is considered one of the main drivers of carbon emissions (Shi, A. 2003; Fan, Ying, et al., 2006; Liddle, Brant, and Sidney Lung, 2010). More people means more demand for oil, gas, coal, and other fuels mined or drilled from below the earth's surface, leading to higher GHG emissions. According to the Maddison Project Database (2018), the world population has increased from 1.6 billion to 6 billion in the twentieth century (Maddison Project Database, version 2018). During the same period, CO2 emissions grew 12-fold (IEA, 2018). With a population expected to exceed 9 billion in the next 50 years, environmentalists are increasingly concerned about the earth's ability to cope with the increasing destruction of the ecosystem caused by human activities.

2.4.4. Urbanization and CO2 emissions

The relationship between urbanization and CO2 emissions has been the subject of many studies over the past decades. However, there is no clear consensus in the literature about the impact of urbanization on carbon emissions. The literature can be divided into three groups. The first strand advocate that higher urbanization leads to environmental degradation (Liddle, 2014; Wu et al., 2016; Khoshnevis and Dariani, 2019). According to these studies, higher urbanization increases the demand for basic infrastructure, leading to deforestation and environmental degradation. Also, it increases demand for transportation, thus implying higher fuel consumption and air pollution. Urbanization also threatens the natural ecosystem when there is no well-functioning waste management and recycling system. The second strand of the literature advocates a negative relationship between urbanization and carbon emissions (Pachauri and Jiang, 2008; Barla, Moreno, and Lee-Gosselin, 2011). Urbanization can benefit the environment because it leads to optimal use of energy resources. The diversity and expansion of urban public transport allow transporting large numbers of people, thus reducing the number of vehicles on the roads and traffic congestion. The last strand of the literature postulates an inverted U shape effect of urbanization on carbon emissions (Ehrhardt-Martinez, Crenshaw, and Jenkins, 2002; Zhang, Xu et al., 2016; Yu and Chen, 2017). These studies consider the existence of the Kuznets curve in the urbanization-carbon emissions nexus. That is; initially, urbanization deteriorates the environment. But after reaching a certain threshold, the environment starts improving.

2.4.5. Financial development and CO2 emissions

Financial deepening is an essential driver of economic growth and environmental quality (Majeed, Tariq, Tauqir, & Aisha, 2020). The literature suggests both positive and negative effects of financial development on carbon emissions. On the one hand, financial development can increase carbon emissions by providing credit facilities to fossil energy extraction and development projects or financing activities that heavily rely on traditional energy to function, thus creating environmental pollution (Zhang, 2010). On the other hand, financial development can help reduce carbon emissions by promoting investments in green technology, climate mitigation, and adaptation technologies that are essential in the fight against climate change (Saidi & Mbarek, 2017). The financial sector can play a key role in directing financial flows toward the transition to a more sustainable economy. However, many studies have shown that the financial sector is more attracted to financing polluting activities that seem more profitable than eco-friendly activities (Zhang, 2010; Cetin and Ecevit, 2017; Paramati, Mo, Huang, 2020). And this is facilitated by the weakness of environmental regulations in several countries, especially developing countries (Jiang & Ma, 2019).

2.4.6. Terms of trade and CO2 emissions

The globalization that shapes the world today is essentially based on flows, which reflect the explosion of world trade. Facilitated by multiple factors, this boom certainly concerns commodities and increased flows of information or capital (Shahbaz et al., 2017). Several factors, such as the establishment of free trade zones, maritime and land transport development, and multinational companies scattered around the world, explain the explosion of global trade. According to the IEA (2018), pollution from international trade constitutes a substantial share of world CO2 emissions. Recently, a significant amount of research has been conducted to determine the relationship between carbon emissions and trade (Antweiler, Copeland and

Taylor, 2001; Sebri and Ben-Salha, 2014; Shahbaz et al., 2017). Results revealed mixed outcomes, and a specific consensus has not yet been found. Studies that have found a positive relationship assume that trade promotes economic growth, which negatively affects the environment by increasing carbon emissions into the atmosphere (Coll and Elliot, 2003; Managi et al., 2008). Studies that have found a negative relationship argue that trade liberalization is often associated with the efficient use of resources; also, the relationship mainly depends on whether the merchandise exported by a country is environmentally friendly or not (Ertugrul et al., 2016). As an illustration, it can be expected that countries that export oil and coal will experience higher carbon emissions since these merchandises are carbon-intensive. In contrast, countries that export cleaner energy or more eco-friendly products will experience fewer carbon emissions problems.

2.5. Conclusion

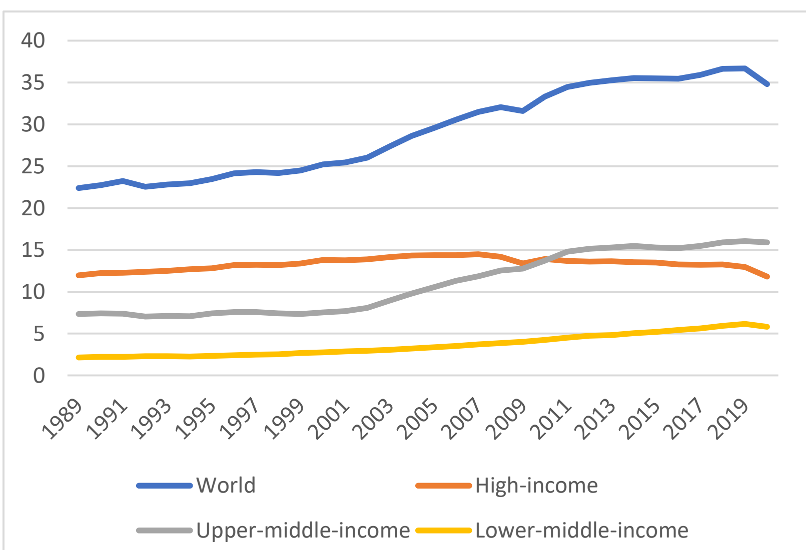
After thoroughly evaluating the literature on aggregate technology and carbon emissions - green technology and carbon emissions - aggregate and green technology and sectoral carbon emissions; certain gaps in the literature were identified. Firstly, most studies focus their analysis on only two groups of countries: developed and developing countries. However, given the significant differences in the level of per capita income among countries and the fact that the level of income plays an essential role in the relationship between technology and the environment, it is necessary to examine this relationship on different income levels. Therefore, this thesis proposes to analyze the responsiveness of carbon emissions to technological progress in four subsamples: high-income, upper-middle-income, lower-middle-income, and lower-income countries. Second, most research in the literature has assessed the relationship between aggregate technology and carbon emissions using a single technology indicator. Technological progress is a multifaceted and complex concept. Using only one indicator of technological advancement may reveal only one aspect of technology's effects on CO2 emissions. Several technological progress indicators are used in this dissertation. The thesis assesses the impact of each indicator on carbon emission levels. Third, while many studies have examined the effects of green technology on carbon emissions, few have looked at the inverse relationship: how rising carbon emissions affect the development of green and carbon-intensive technologies. In addition to examining how green technology affects CO2 emissions, this dissertation investigates reverse causality in various country income groups. Notably, the thesis examined countries' reactions regarding the technology used when carbon emissions and GDP increase. Fourth, few empirical studies have investigated the relationship between technology and sectoral CO2 emissions. This thesis differs from previous studies by constructing a technological progress index and evaluating its impact on sectoral carbon emissions in five major sectors: power, manufacturing, transportation, petroleum, and the building sector. In 2014, these five energy sectors accounted for 75% of total green gas emissions (IPCC, 2014). This enabled us to determine which sectors' aggregate and green technology significantly impact CO_2 emissions and the reasons for such an impact. It will also assist policymakers by determining which sectors require more efforts in terms of technological advancement to reduce the CO_2 emissions curve.

III. Impact of aggregate technological progress on CO2 emissions

3.1. Introduction

Global warming has been one of the most critical environmental issues of our time. According to the IPCC (2000), burning coal, gas, and oil to feed human activity is the leading cause of global warming. Figure 5. shows the world carbon emission trend from 1989 to 2019. The Global Carbon Project (2021) reported that 36.7 billion tons of CO2 were emitted into the atmosphere in 2019, an increase of 62% compared to 1990, the reference year of the Kyoto Protocol. In 2019, 16.05 billion tonnes (43 per cent) were emitted by upper-middle-income countries, 12.97 billion (35 per cent) by high-income countries, and 6.15 billion (16 per cent) by lower-middle-income countries. To combat climate change, scientists recommend the adoption and expansion of renewable energy, the promotion of energy efficiency, the implementation of sustainable transportation, sustainable infrastructure, and forest management, and the promotion of responsible consumption and waste recycling (e.g., Herring and Roy, 2007; Boden, Marland and Andres, 2017; Higon and al., 2017; Gu et al., 2019). For these solutions to be applied optimally, it is fundamental to promote technological progress at the service of sustainable development. Many scientists and policymakers believe that if technology initially favoured GHG emissions through the industrial revolution, it is also part of the solutions that could save our planet from the harm that has been done.

Figure 5. World CO2 emissions (billions of tons)



Source: Global Carbon Project (2021)

Technological progress has recently been at the centre of the fourth industrial revolution, transforming our lives as ever before. Although this revolution operates differently, depending on whether you are in a rich or developing country, it does affect the entire planet and the environment. Technology plays a significant positive role in developing a country (Solow, 1957; Romer, 1986, 1987, 1990). It promotes economic growth by improving productivity and infrastructure and increasing the quality of goods and services produced. However, the impact of technological progress on the environment and the climate is still unclear (Asongu, Le Roux, and Biekpe, 2017; Cheng et al., 2019; Churchil et al., 2019).

The relationship between technological change and carbon dioxide emissions is complex. Numerous studies revealed that technological progress has a dual effect on global CO2 emissions. On the one hand, technology reduces overall CO2 emissions by reducing energy intensity, adjusting the energy structure, and fostering green technology diffusion in industries and countries (Bosetti et al., 2009; Moyer and Hugues, 2012; Higon, Gholami, and Shirazi, 2017). On the other hand, technology increases CO2 emissions by increasing energy consumption and economic growth` (Grossman and Krueger, 1995; Bongo, 2005; Hu, Li, and Wang, 2006; Bosetti et al., 2008; Zhang and Cheng, 2009; Garrone and Grilli, 2010; Ghosh, 2010; Gu et al., 2019). An obvious fact is that CO2 emissions have increased dramatically since the industrial revolution (Boden, Andres, & Marland, 2015), following the similar evolution of technological progress. Any immense advancement in technology not only brings about an improvement in the environment and energy supply but also tremendously stimulates economic development and energy consumption on a large scale (Hertin and Berkout, 2005; Herring and Roy, 2007; Sorrell and Dimitropoulos, 2008; Sorrell, Dimitropoulos and Sommerville, 2009; Jin et al., 2017; Cheng et al., 2019).

Measuring technological progress quantitatively is challenging as its representation and realization vary. How technology interacts with the environment, in general, has been the subject of several studies (Jin L. , Duan, Shi, & Ju, 2017; Gu, Zhao, Yan, Wang, & Li, 2019; Chen, Gao, Ma, & Song, 2019; Chen, Gao, Mangla, Song, & Wen, 2020; Khan, Raza, Khan, & Ali, 2020). But, to our knowledge, there has not yet been an analysis of how technology influences CO2 emissions by assessing various “proxies” of technology[3] since each proxy may yield different results. Moreover, technology's positive and negative impact on CO2 emissions has not been comprehensively investigated on different “income level” scales. Given that the response to the environmental challenges mostly depends on each country's financial capacity, it is

[3] Technological progress has been proxied by the Solow residual (or Total Factor Productivity TFP) (Chen et al.,2019; Chen et al., 2020), or specific energy innovation measures such as energy patents (Gu et al., 2019) and energy intensity technology adoption (Khan et al. 2020) or investment in the development of technology in R&D expenditures (Jin et al., 2017).

necessary to look at this relationship in countries at all levels of development. The recent literature has focused primarily on single-country analysis to examine the impact of technological progress on emissions, while some other studies have also proceeded with sectoral or regional (provincial) disaggregated research (for example, Khan et al. (2020) conducted a sectoral study for Pakistan, and Chen et al. (2020) conducted a regional analysis on 30 provinces in China).

Therefore, this chapter's purpose is to contribute to the overall discussion on the nexus between technology and the environment by addressing the following research questions:

1) What is the impact of technological progress on CO2 emissions when using various technology measurements? Notably: R&D expenditure, patents, information and communication technology (ICT), science and technology publications, and Total factor of productivity (TFP).
2) Does this impact depend on the level of economic development?

This chapter uses two methodologies to answer these questions: The fixed effect with Driscoll and Kraay standard errors (1998) and Bruno's (2005) biased-corrected LSDV methodology. In this chapter, the analysis was carried out on a panel of 60 countries divided into four income groups. Thus, we had 15 high-income countries, 15 upper-middle-income countries, 15 lower-middle-income countries, and 15 lower-income countries. The study period runs from 1989 to 2018. A comparison of how technology interacts with climate change in low-income, lower-middle, upper-middle, and high-income countries was conducted.

Measuring the responsiveness of GHG emissions to technological progress is essential for economic and environmental policies for several reasons. First, if the net effect of technological change on carbon emissions is negative, it would imply that technology has contributed to carbon reduction within our study period. Secondly, since technology is complex to quantify, using different technological progress indicators would reveal which indicator works better for carbon reduction. For instance, one may find that, on the one hand, public R&D expenditure positively affects carbon emissions because they are mainly directed to carbon-intensive projects. On the other hand, the proliferation of mobile phones (ICT) in countries may reduce the transportation of people from point A to point B[4], thus reducing carbon emissions. In this scenario, the Government may consider redirecting public R&D expenditure toward environmentally friendly projects and fostering the proliferation of mobile phones to combat climate change. Thirdly, the fact that the research was conducted in different income group countries is also important. Because some

[4] People can communicate easily via telephone and do not necessarily have to move to see each other. They can use different meeting platforms like WhatsApp, Skype or Zoom. This can reduce the movement of the population, and hence, decrease CO2 emission.

dimensions of technological advancement may work better in reducing carbon emissions in some groups of countries than in others, in this regard, high-income countries were particularly monitored since they are more advanced in R&D spending, patent applications, and TFP.

This chapter contributes to the literature by studying the impact of technological progress on CO2 emissions while using various technology measurements. Additionally, this chapter attempts to evaluate the effect of technological progress on CO2 emissions in different country income groups. More specifically, this chapter offers three points of contribution after considering the gaps in the field. Firstly, the research appreciates the complexity of technological progress and the multi-faceted impact it may have on emissions. So this research uses a battery of technological progress indicators such as the number of patents, R&D spending, TFP, and others, while other studies in the literature chose only one.

As an illustration, Gu et al. (2019) used patent application as a technological advancement indicator to investigate the impact of technology on CO2 emissions in China. Garrone and Grilli (2010) employed R&D expenditure as a technology-push instrument to analyze its causality link with carbon emissions in a sample of 13 OECD countries. Higon, Gholami, and Shirazi (2017) utilized ICTs variables as indicators of technology development and examined the same relationship in 142 economies. While a growing number of studies examine the relationship between technological progress and climate change, the previous literature does not provide comparable empirical evidence on how various technology measurements may affect carbon emissions differently. Therefore, this chapter uses six indicators of technological progress and assesses their impact on emissions levels. It is argued that since each indicator capture a particular aspect of technology, their respective effects on CO2 emissions may differ. By doing so, the study will be able to provide specific policy recommendations to promote particular aspects of technology to reduce CO2 emissions. The strengths and weaknesses of each technology proxy are also thoroughly discussed in this chapter – such a detailed comparison will also contribute to future studies' choice of technological progress indicators.

Secondly, this chapter considered the rebound effect, which has been left out in many studies (e.g., Li and Wang, 2017; Higon et al., 2017, Jin et al., 2017; Gu et al., 2019). They have treated technological progress and energy consumption as general independent variables in CO2 model estimation, thus neglecting the interaction effect between technological progress and energy consumption on CO2 emissions. This chapter takes into account the rebound effect by interacting technological progress with energy consumption and assessing their joint impact on carbon emissions.

Thirdly, this chapter uses a panel of 60 countries divided into four income groups: high-income, upper-middle-income, lower-middle-income, and lower-income countries. Doing so constitutes another novelty of this chapter and the thesis in general, because most studies examining technology's impact on emissions have a single-country focus. This chapter thus aims to explore the potential differences in the nexus depending on the countries' development and economic level.

The remainder of this chapter is structured as follows: Section II presents the theoretical model. The methodology and the data set are discussed in sections III. Section IV addressed the strength and weaknesses of each technological progress indicator. In section V, the econometric results are presented and analyzed. Section VI concludes.

3.2. Theoretical Framework

The theoretical framework of this chapter is based on the STIRPAT model proposed by Dietz and Rosa (1997). This model draws its origin from the IPAT model developed by Ehrlich & Holdren (1971). The IPAT model suggests that "environmental impact (I) depend on three factors: population (P), affluence, and technology (T)." The following identity represents the IPAT model:

$$\mathrm{I} = \mathrm{P} \times \mathrm{A} \times \mathrm{T} \tag{1a}$$

The IPAT model cannot be used for hypothesis testing since it represents an accounting identity (Majeed, Tariq, Tauqir, & Aisha, 2020). Therefore, Dietz and Rosa (1997) proposed an augmented version of the IPAT model called the "Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT). The STIRPAT model allows calculating elasticities of different factors while calculating the error term (Dietz and Rosa, 1997). The model is written as follows:

$$\mathrm{I} = \beta_{\mathrm{i}} \mathrm{P}_{\mathrm{it}}^{\theta} \mathrm{A}_{\mathrm{it}}^{\alpha} \mathrm{T}_{\mathrm{it}}^{\gamma} \mu_{\mathrm{it}} \tag{1b}$$

After log linearizing, the STIRPAT equation (1b) takes the following form:

$$\ln \mathrm{I}_{\mathrm{it}} = \beta_{\mathrm{i}} + \theta \ln \mathrm{P}_{\mathrm{it}} + \alpha \ln \mathrm{A}_{\mathrm{it}} + \gamma \ln \mathrm{T}_{\mathrm{it}} + \mathrm{u}_{\mathrm{i}} + \mathrm{v}_{\mathrm{it}} \tag{1c}$$

In equation (1c), the subscripts i and t refer to countries and time. u_i is the unobservable country-specific characteristics and $v_{i,t}$ is the i.i.d (independent and identically distributed) disturbance terms. I represents carbon emissions. P denotes population, expressed in this chapter by population density $(\mathrm{POP}_{\mathrm{it}})$. A denotes affluence, represented by GDP per capita $(\mathrm{GDP}_{\mathrm{it}})$ and energy consumption $(\mathrm{ECONS}_{\mathrm{it}})$, and T

stands for technology represented by aggregate technological indicators $(\mathrm{TECH_{it}})$. As suggested by previous literature (Boutabba, 2014; Ohlan, 2015; Ertugrul et al., 2016; Shahbaz et al., 2017; Murat, Ecevit, and Yucel, 2018), equation (1c) is augmented by adding another important factor that can explain variations in carbon emissions: exports $(\mathrm{EXP_{it}})$.

Therefore, the final version of our theoretical model can be written as:

$$\mathrm{lnI_{it}} = \beta_i + \theta \mathrm{lnPOP_{it}} + \alpha \mathrm{lnGDP_{it}} + \vartheta \mathrm{lnECONS_{it}} + \gamma \mathrm{lnTECH_{it}} + \omega \mathrm{EXP_{it}} + u_i + v_{it} \tag{1d}$$

3.3. Methodology and Data

This section describes the methodology and the data used in this chapter. As mentioned in the introduction, this chapter uses proxies to represent the level of technological progress reached in a given country. The data section discusses the strengths and weaknesses of each proxy employed.

3.3.1. Empirical model

This chapter establishes three panels model to investigate how technological progress affects carbon emissions. The first empirical specification is a static panel model.

$$\ln CE_{it} = \beta_0 + \beta_1 lnTECH_{it} + \beta_2 lnECONS_{it} + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} + Y_i + u_{i,t} \tag{2}$$

Where the subscripts i and t refer to countries and time. Y_i is the unobservable country-specific characteristics and $u_{i,t}$ is the i.i.d. disturbance terms. CE_{it} refers to carbon emissions in metric tons per capita. $TECH_{it}$ is our variable of interest, it represents technological progress which is replaced by six different proxies of technology. More specifically, model (2) is divided into six different sub-models, and each sub-model has its proxy of technological progress:

$$\ln CE_{it} = \beta_0 + \beta_1 lnMob\_cel_{it} + \beta_2 lnECONS_{it} + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} + \rho_i + u_{i,t} \tag{2a}$$

$$\ln CE_{it} = \beta_0 + \beta_1 lnInternet_{it} + \beta_2 lnECONS_{it} + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} + \theta_i + u_{i,t} \tag{2b}$$

$$\ln CE_{it} = \beta_0 + \beta_1 lnPatent_{it} + \beta_2 lnECONS_{it} + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} + \vartheta_i + u_{i,t} \tag{2c}$$

$$\ln CE_{it} = \beta_0 + \beta_1 lnR\&D_{it} + \beta_2 lnECONS_{it} + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} + \varphi_i + u_{i,t} \tag{2d}$$

$$\ln CE_{it} = \beta_0 + \beta_1 lnTFP_{it} + \beta_2 lnECONS_{it} + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} + \omega_i + u_{i,t} \tag{2e}$$

$$\ln CE_{it} = \beta_0 + \beta_1 lnScien\_tech_{it} + \beta_2 lnECONS_{it} + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} + Y_i + u_{i,t} \tag{2f}$$

In this set of equation Mob_cel_{it} represents mobile cellular subscriptions per 100 people, $Internet_{it}$ stands for the percentage of the population using the internet, $Patent_{it}$ represents the number of patents application, $R\&D_{it}$ refers to public expenditure in research and development, TFP_{it} represent the total factor of productivity, and $Scien\_tech_{it}$ stand for the number of science and technology publications.

Many studies have shown that most environmental indicators, CO2 emissions included, have a certain time lag effect and that environmental impacts present some dynamic sustainability. (Kais and Sami, 2016; Zhang et al., 2017). Based on these issues, our second empirical specification is a dynamic panel model with a first-order lag term for carbon emissions. This study has adopted a one lag model specification to preserve the maximum possible freedom available for the estimates.

$$\ln CE_{it} = \beta_0 + \rho \ln CE_{it-1} + \beta_1 lnTECH_{it} + \beta_2 lnECONS_{it} + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} + Y_i + u_{i,t} \quad (3)$$

Similar to model (2), $TECH_{it}$ is successively replaced by six different proxies of technological progress. Therefore, there will be six different sub-models[5].

Finally, this chapter considers the rebound effect, which has been left out in many previous studies (e.g., Li and Wang, 2017; Higon et al., 2017). The rebound effect is when the additional energy saved due to improved energy efficiency (more efficient heating system, insulation, fuel-efficient vehicle, etc.) will be offset by increased energy demand (Gu et al., 2019). For instance, if households heat more, live in larger dwellings, and have to travel long distances to get to work, in the end, energy consumption will keep increasing. Technological progress implies the production of energy-saving technology, which leads to lower carbon emissions, but the energy consumption is stimulated to a certain extent at the same time, which is consistent with the rebound effect (Gu et al., 2019). This shows that the impact of technology on carbon emission emissions is difficult to predict when considering human behaviour to new technology. This chapter accounts for the rebound effect by interacting technological progress with energy consumption and assessing their common impact on carbon emissions. Therefore, our third empirical specification is a static panel model that includes an interaction term:

$$\ln CE_{it} = \beta_0 + \beta_1 lnTECH_{it} + \beta_2 lnECONS_{it} + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} + \boldsymbol{\beta_7 lnTECH_{it}} * \boldsymbol{lnECONS_{it}} + Y_i + u_{i,t} \quad (4)$$

[5] We will have six different sub models with different proxies: 2(a) - Mobile phone, 2(b) - internet, 2(c) - patents, 2(d) – R&D expenditure, 2(e) - TFP and 2(f) – science and technology publications.

Here $TECH_{it}$ is also replaced by six different proxies of technological progress[6]. β_7 is the coefficient on the interaction term. It determines the impact of technological progress on CO2 emissions through energy consumption. The interaction term only indicates whether the rebound effect of energy consumption is higher or smaller than energy savings caused by technological progress. A positive coefficient on the interaction terms suggests that as technology increases (and therefore energy efficiency), it also increases the positive impact of energy consumption on carbon emissions. Thus, energy savings brought by technological progress is offset by higher energy consumption. A negative coefficient on the interaction term means that as technology increases, it reduces the positive impact of energy consumption on carbon emissions. This indicates that energy savings caused by technological progress offset the rebound effect.

3.3.2. Econometric methodology

This chapter employs the fixed-effect method with Driscoll and Kraay's standards errors to estimate the results of empirical models (2) and (4). Countries are different from each other, and each country's carbon emissions are not affected by the same factors in the same way. By incorporating country-specific effects in the models, all the effects that may influence each country's carbon emissions (beyond those variables already included in the model) will be incorporated. Another reason for using a fixed effect is to correct potential endogeneity problems since the within estimator wipes out the individual effects through demeaning, thus making the OLS coefficients unbiased and consistent (Baltagi, 2008). Potential limitations of the fixed effect method include the presence of serial correlation, heteroskedasticity, and cross-sectional dependence in the model. In this case, estimated coefficients are still consistent, but they will no longer be efficient. The standard errors of the estimates will be biased. This chapter uses Driscoll and Kraay's standard errors to solve this problem. Besides being heteroscedasticity consistent, these standard error estimates are robust to general forms of cross-sectional and temporal dependence (Hoechle, 2007).

The fixed-effects panel model has the following general specification (Baltagi, 2008):

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \tag{4}$$

The one-way error component model allows cross-section heterogeneity in the error term:

$$u_{it} = u_i + v_{it} \tag{5}$$

[6] Panel model (4) will also be divided into six different sub models with different proxies: 4(a) - Mobile phone * energy consumption (EC), 4(b) – internet * EC, 4(c) – patents * EC, 4(d) – R&D expenditure * EC, 4(e) – TFP * EC and 4(f) – science and technology publications * EC.

The error becomes the sum of an (unobservable) individual-specific effect (time-invariant) and a "well behaved" (remainder) disturbance. The individual-specific effect can be estimated with a fixed or random-effect methodology. The fixed effect "WITHIN" estimation demeans the data and "wipes out the individual effects" to estimate only β, and then calculates the individual effects. In order to "wipe out" these individual effects, a Q matrix is introduced, where Q is defined such that:

$$Qy = QX\beta + Qv \quad (6)$$

Where, $Q = I_{NT} - P$ and $P = Z_u(Z_u'Z_u)^{-1}Z_u'$ and $Z_u = I_N \times i_T$

I_{NT} is an identity matrix of N×T, and i_T is a vector of ones (T×1)

Thus, pre-multiplying the original regression with the Q matrix allows to obtain the deviations from the means (the average over time) WITHIN each cross-section, and the "WITHIN" model becomes a simple (OLS) regression:

$$(y_{it} - \bar{y}) = \beta(X_{it} - \bar{X}) + (v_{it} - \bar{v}) \quad (7)$$

Following the consolidated literature on dynamic panel data models (Kiviet, 1995, 1999; Blundell and Bond, 1998; Bun and Kiviet; 2003, Bruno, 2005), this chapter used the Bruno's (2005) biased-corrected LSDV methodology to estimate model specification (3). When a lagged dependent variable is included among the regressors, the Nickell (1981) biased will arise as a possible violation of the classical assumptions. There will be an endogeneity problem since CE_{it-1} is correlated with the unobserved heterogeneity Y_i. The LSDVC method corrects the alleged endogeneity bias of the lagged dependent variable without using any instrumental variable (Piva and Viveralli, 2007; Justesen, 2008; Abrate et al., 2009; Garrone and Grilli, 2010). In our case, the LSDVC estimator is initialized by a consistent dynamic panel estimator (Arellano and Bond) and then rely on a recursive correction of the bias of the fixed effects estimator.

The LSDVC is preferred to alternative Nickell biased correction methodology, such as the GMM method, for two reasons. First, Judson and Owen (1999), by performing a Monte Carlo experiment, show that for a large period (T ≥ 30) with moderately large entities (N), the LSDVC methods may outperform the GMM method in terms of efficiency, bias, and Root Mean Square Error (RMSE). Moreover, GMM that uses a full set of moments available can be severely biased, especially when instruments are weak and the number of moment conditions is relatively large to the number of entities (N) (Alvarez and Arellano, 2003). Secondly, the Bruno LSDVC estimator is suitable for unbalanced panels, which is the case for some subsample data used in this study.

In conclusion, since the two methods (fixed effect and Bruno LSDVC methodology) have some differences in terms of assumptions, any eventual similarities of the estimates obtained with them would prove the robustness of the findings. The diagnostic test performed in the results section will give us a preference of which method between the two will be more considered in the result discussion.

3.3.3. Estimation procedure

The following steps are taken to check the full sample dataset and estimate the results:

Step 1. A series of diagnostic tests are conducted to identify a suitable method for correctly estimating the results. We check for heteroscedasticity, serial correlation, cross-sectional dependence; panel effect; and time fixed effect in the dataset. Cross-sectional dependence in the dataset is verified with the Pesaran cross-sectional dependence (CD) test (2004). Breusch-Pagan's (1980) LM-test and Wald tests are used to check the presence of panel and time-fixed effects in the model specifications. A modified Wald test for GroupWise heteroscedasticity is performed to check for heteroscedasticity. Serial correlation in the dataset is verified using the Wooldridge test (2002) for autocorrelation in panel data.

Step 2. The Im, Pesaran, and Shin (2003) (IPS) test is performed to investigate the univariate characteristic of each variable.

Step 3. Cointegration among variables is verified using the Kao (1999), Pedroni (2004), and Westerlund (2005) cointegration test.

Step 4. A fixed-effect method is used to estimate the panel model (2) and (4). Bruno's (2005) biased-corrected LSDV methodology is employed to estimate panel model (3).

3.3.4. Data

This chapter uses a balanced panel dataset of 60 countries, split into 15 high-income, 15 upper-middle-income, 15 lower-middle-income, and 15 lower-income economies (see table 1). The dataset provides a period of 30 years, from 1989 to 2018. The World Bank classifies countries according to their income level into four income groups (high income, upper-middle-income, lower-middle-income, and low-income countries). Following this classification, we have selected 15 countries in each income group. The 15 countries chosen per income group are the largest CO_2 emitters in their respective income groups. To clarify further, the sample was selected based on three criteria. The first criterion is the average level of GDP per capita throughout the study period. When considering the average GDP per capita, each country selected in the sample has always belonged to a specific income group throughout the study period (1989

– 2018)[7]. The second criterion is the national level of carbon emissions. We have selected the countries that emitted the most CO2 in each income group from 2000 to 2018. The third criterion is data availability, particularly on technological proxies. Combining these three criteria led to the selection of 15 countries per income group[8]. This selection method allows us to examine how the CO2 emissions in the top 15 emitting countries of each income bracket respond to technological progress. In 2015, the 60 countries selected in this chapter represented 94 per cent of global GDP and 91 per cent of global CO2 emissions (World Bank, 2019). Table 1 presents the list of countries selected in this chapter.

The variables used in this chapter were collected from different sources. Table 2 shows the descriptions and sources of the data collected. Descriptive statistics for the full sample are reported in table 3. Subsamples of descriptive statistics are presented in the Appendix. Data on CO2 emissions (metric tons per capita), energy consumption (tons of oil per capita), GDP per capita (in constant 2010 US$), trade (exports in constant 2010 US$), science and technology publications, and population density were drawn from the World Bank's Development Indicators (WDI, 2019). This chapter uses two ICT variables: mobile cellular subscriptions per 100 people and individuals using the internet (percentage of the population). The ICT variables were also drawn from the WDI. Data on Research and development expenditure (as a percentage of GDP) was collected from the United Nations Educational and Cultural Organization (UNESCO) and the OECD database. Data on patents was collected from the World Intellectual Property Organization (WIPO).

Table 4 reports the pairwise correlation matrix among variables. The correlation matrix helps in revealing potential multicollinearity problems among variables. It also helps in the choice of relevant variables affecting carbon emissions. It is important to emphasize that the correlation matrix shows the correlation among variables but cannot be considered a causal relationship (Baltagi, 2008).

Table 1. Sampled countries (1989-2018).

High-income	Upper-middle income	Lower-middle income	Lower income
60 countries			
Germany	China	Angola	Benin
France	Argentina	Bangladesh	Ethiopia
United Kingdom	Brazil	Cote d'Ivoire	Mozambique
United States	Mexico	Egypt	Nepal
Italy	Iran	Indonesia	Tajikistan
Canada	Russia	India	Yemen
Spain	Turkey	Kenya	Tanzania

[7] However, there is an exception for China, Bangladesh, Pakistan, and Kenya. These countries are at the limit of entering their respective income group.

[8] Initially, we have selected 25 countries per income groups (100 countries in total). However, due to data unavailability, notably data on technological proxies, several countries were excluded from the sample.

Japan	South Africa	Morocco	Burkina Faso
Saudi Arabia	Thailand	Nigeria	Rwanda
South Korea	Algeria	Pakistan	Congo Rep.
Australia	Colombia	Philippines	Guinea
Belgium	Jordan	Tunisia	The Gambia
Netherland	Kazakhstan	Uzbekistan	Madagascar
Poland	Malaysia	Venezuela	Mali
Chile	Romania	Vietnam	Uganda

Table 2. Data sources and descriptions

Panel 1A: Variable Description		
Variables	Description	Sources
$\ln CE_{it}$	Carbon dioxide emissions in metric tons per capita. CO2 emissions include the combustion of fossil fuels for electricity generation and heat production (in industries, households, etc.), transportation, and industrial processes, including cement manufacture.	WDI (World Bank, 2019)
$\ln GDP_{it}$	Per capita real gross domestic product in 2010 constant US$ term.	WDI (World Bank, 2019)
$\ln ECONS_{it}$	Energy use in tons of oil equivalent per capita. It refers to the use of primary energy before transformation to other end-use fuels such as liquefied petroleum gas, kerosene, diesel, gasoline, etc.	WDI (World Bank, 2019)
$\ln Mob\_cel_{it}$ $\ln Internet_{it}$	Two ICT variables are used in this chapter: mobile cellular subscriptions per 100 people and individuals using the internet (percentage of the population)	WDI (World Bank, 2019)
$\ln Patent_{it}$	Patent applications by residents and nonresidents in each country.	WIPO (World Intellectual Property, 2020)
$\ln R\&D_{it}$	Public expenditure in Research and development as a percentage of GDP.	United Nations Educational, Science and Cultural Organization (UNESCO, 2019), Organization for Economic Co-operation and Development (OECD, 2019)
$\ln TFP_{it}$	Total factor of productivity index	Penn World Table data[9]
$\ln Scien\_tech_{it}$	These are scientific articles. They include research published in the following field: energy, physics, chemistry, biology, mathematics, earth and space sciences, biomedical research, engineering, and technology.	WDI (World Bank, 2019)
$\ln EXP_{it}$	Exports in 2010 constant US$ term	WDI (World Bank, 2019)
$\ln POP_{it}$	Population density per square kilometers	WDI (World Bank, 2019)

[9] Dataset of various economic indicators developed by The Groningen Growth and Development Centre (GGDC). The GGDC provides comparative trends in the world economy in the form of datasets, which can be used to analyze productivity, structural change, and economic growth across countries.

Table 3. Descriptive statistic: full sample

variables	Observations	Mean	Stand dev	Min	Max
CO2 emissions	1753	4.333644	4.751069	.0335559	20.17875
GDP per capita	1798	10849.17	15133.8	164.3366	56842.3
Energy cons	1517	1.917049	1.911527	0.1188983	8.455547
Population	1729	124.0924	167.6538	2.18872	1239.579
Exports	1683	28.79679	18.17593	5	108
Mobile cell	1664	48.30433	49.57067	0	191.0315
Internet	1592	21.97556	27.69128	0	96.02286
patents	1767	14259.04	53650.86	1	606956
R&D	1471	1.034388	.9593146	.0000862	5.108209
TFP	1559	.6288156	.2452978	.1254694	1.22886
Science and Technology Pub.	1140	26540.41	65870.67	3.14	528263.3

Table 4. Correlation matrix

Panel 1B: Correlation matrix										
	CO2	GDP	Energy cons	R&D	Mobile cell	Patent	Sc. Tech Pub	TFP	Population	Exports
CO2	1									
GDP	0.83*	1								
Energy con	0.84*	0.58*	1							
R&D	0.63*	0.62*	0.59*	1						
Mobile cell	0.31	0.41*	0.36*	0.23*	1					
Patent	0.64*	0.60*	0.63*	0.59*	0.31*	1				
Sc. tech Pub.	0.60*	0.62*	0.64*	0.68*	0.44*	0.55*	1			
TFP	0.50*	0.58*	0.50*	0.52*	0.20*	0.37*	0.60*	1		
Population	0.27*	-0.17	-0.28	0.08*	0.05*	0.02	0.14*	0.08*	1	
Exports	0.69*	0.67*	0.63*	0.58*	0.47*	0.62*	0.61*	0.41*	0.03	1

3.3.5. Technology indicators discussion

The strengths and weaknesses of each proxy of technological progress used in this chapter are discussed in this subsection.

a) Public R&D expenditure

R&D expenditure is of fundamental importance in creating new technology, knowledge, and products. It is a common remedy for knowledge spillovers and market failure, which does not foster innovation in the production sector (Churchill et al., 2019). R&D may be regarded as an essential technology push measure (Garrone & Grilli, 2010). However, Garron and Grill (2010) note that considering R&D spending as a climate technology policy toward low carbon energy is sometimes controversial. In reality, R&D spending cannot be viewed as a climate technology policy unless there is initially a market for low-carbon and energy-efficient products. Otherwise, R&D expenditure will only benefit the most common products on the market, often carbon-intensive products. Moreover, when funds are spent to finance an R&D project, it does not necessarily mean that the project will lead to technological advancement in the short term; it may be an attempt that will bear fruit only in the long term. Particular R&D projects may fail to give results due to possible corruption and embezzlement of public funds, which undermine many countries, especially lower-income countries. From an environmental angle, it is important to understand that aggregate R&D can be divided into green and non-green R&D expenditure. It follows from this fact that the final impact of R&D expenditure on carbon emission is uncertain as the two components clash together (Sagar and Holdren, 2002; Sagar and Zwaan, 2006). Despite all its limits, R&D spending remains a good indicator of technological progress in a country.

b) Patents

Modern intellectual property laws (patents, trademarks, copyrights, etc.) appeared during the industrial revolution era since there was a need to protect the inventions that were created and could then be reproduced in large numbers mechanically (Sherman & Bently, 1999). A patent is an exclusive right that authorities grant to its owner to protect his invention and allow him to use and exploit it while preventing others from using it without permission (WIPO, 2020). Patents are good indicators of technical progress because they are often the result of intense research leading to the manufacture of products or the creation of techniques that bring added value to industries and positively impact economic growth. Patents indicate the existence of output or "finished product," unlike R&D expenditure which are the inputs that can lead to the creation of new products. Patents stimulate technical progress and indicate the technological progress level reached by a nation. However, using patents as a proxy for technology has potential limitations, which are important to note. Firstly, the number of patents granted in a country does not necessarily reflect the inventions' quality. The utility or the quality of patents in terms of "technological contribution" is not the same. Some patents bring a real revolution to the industry, while others have a minor impact instead (Cremers et al., 1999; Scherer and Harhoff, 2000; Hall, Jaffe, and Trajtenberg, 2005). Secondly, patents can reflect technological development but cannot represent the situation of technological adoption (Du et al., 2019). A patent can be created, but it does not necessarily mean that the industry or the society will automatically adopt it.

c) Science and technology publications

Another potential indicator of technological progress in a country is the number of peer-reviewed science and technology publications. Scientific journals aim to provide information about new research to increase the stock of knowledge and facilitate knowledge transmission. Research results provided must be strong, relevant, reliable, and capable of being replicated in a given context (Monteiro, Devan, Soans, & Jeppu, 2012). The scientific knowledge acquired is further transformed into a tangible product or procedure that participates in technological progress. Science and technology publications are also linked with the improvement in human capital. A country with a high level of tertiary education is likely to produce more science and technology publications than other countries with lower educational attainment. From our point of view, science and technology publications have two major limitations in representing technological progress. Firstly, not all published articles are intended to produce a tangible product or procedure. Some articles may be published only to criticize or review other studies that have come up with contestable findings. Articles can be published to contribute to the scientific debate between specialists. Secondly, the quality and relevance of articles sometimes significantly differ. As explained above, most scientific journals ensure that articles published have a certain standard quality, but different scientific journals do not have the same ranking. Some are more prestigious and reliable than others. However, despite these limitations, the number of science and technology publications remains a good indicator of the level of debate, knowledge, and technical progress reached by a country.

d) Information and communication technologies (ICT)

ICT includes all tools, services, and techniques used to create, record, process, and transmit information. Therefore, it is mainly about computers, the internet, radio and television, and telecommunications. There is a common consensus in the literature that the ICT sector contributes to technological progress, productivity, and economic growth (see Wang, 1999; Bongo, 2005; Ahmed and Ridzuan, 2013, Sassi and

Goaied, 2013; Niebel, 2018). However, using the number of mobile phone users as an indicator of technological progress should be done with caution. Having a high number of mobile phone users does not necessarily mean that the country is technologically advanced[10]. Some countries with a high number of mobile phone users are not mobile phone producers. This is the case in many developing countries. These countries adopt this technology but are not producers of this technology. In those countries where mobile phones are not produced, the number of mobile phones or internet users can be seen as an input that boosts technological progress. For example, for students and researchers, a smartphone allows them to acquire new knowledge and information and download valuable applications and procedures that will increase their knowledge.

e) The total factor productivity (TFP)

TFP is the part of economic growth unexplained by capital or labor accumulation (Haider, Kunst, & Wirl, 2020). TFP is also called the Solow residual (Solow, 1957). In 1956, Solow attempted to explain the factor that allows the economy to grow in the long run. He developed a growth model that shows an increase in production with constant capital and labour. The model developed by Solow was able to tell whether output growth is attributed to a rise in the two factors of production or more efficient use of these two factors. Solow found that the capital increase in the United States between 1910 and 1950 could explain only twelve per cent of labour productivity (Solow, 1956). In other words, the increase in productivity was due to a more knowledgeable workforce due to technological progress (Solow, 1956). The drawback of TFP as a measure of technological progress comes from its estimation (Hall B. H., 2011): Quantifying TFP requires measures of real output, real labour, and real capital stock (as well as possible other inputs, such as energy and materials). Hall (2011) notes that researchers, agencies, or organizations use many approaches to measure the inputs and outputs. Unfortunately, TFP measurement can be significantly impacted by the choices made in these approaches. The difficulty lies in evaluating real inputs and outputs while holding constant the unit of measures over time. Unlike other recorded proxies, such as R&D expenditure and the number of patents, TFP needs reliable data on a given economy's labor and capital stock to be calculated. Moreover, TFP measures need to be used carefully, with a good understanding of the approach used to deflation and quality adjustment (Hall B. H., 2011). The TFP measure used in this

[10] As an illustration, according to the World Bank database, Gambia which is among lower-income countries has more mobile cellular subscriptions (139 mobile phones per hundred people) than France which is part of high-income group (108 mobile phones per 100 people).

chapter comes from Penn World Table. To calculate TFP, they use a procedure where the nominal value of capital is adjusted for inflation, and the quality of labour is also adjusted to allow comparisons.

3.4. Diagnostic test results

3.4.1. Basic test results

Before estimating our models, this chapter starts by conducting basic diagnostic tests for the presence of heteroscedasticity, serial correlation, panel fixed effects, time fixed effect, and cross-sectional dependence for all six sub-models in panel model (1). Table 5 shows that we fail to reject the null hypothesis of no cross-sectional dependence, no serial correlation, and no heteroscedasticity in all six sub-models. The diagnostic test also confirms the presence of a panel effect in the data. The time-fixed effect is only present in one sub-model. The empirical results might be biased and inconsistent if these diagnostic issues are not addressed. Thus, this chapter considers these issues in the result estimation.

Table 5. Serial correlation, heteroscedasticity, cross-sectional dependence, time fixed effect, and panel effect.

	Model (2a)	Model (2b)	Model (2c)	Model (2d)	Model (2e)	Model (2f)
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Serial correlation	38.928 0.000***	37.689 0.000***	45.313 0.000***	30.120 0.000***	32.275 0.000***	32.504 0.000***
Heteroscedasticity	33726 0.000***	35457.92 0.000***	50829.81 0.000***	25997.66 0.000***	33066.23 0.000***	39646.84 0.000***
Pesaran CD	15.174 0.000***	20.912 0.000***	26.409 0.000***	21.337 0.000***	20.152 0.000***	20.450 0.000***
Time fixed effect	0.882 0.637	1.697* 0.096	0.822 0.721	1.218 0.208	0.690 0.796	0.700 0.867
Panel effect	538.24 0.000***	518.16 0.000***	495.54 0.000***	464.47 0.000***	477.84 0.000***	447.20 0.000***

Notes: *(**) [***] indicate rejection of the null hypothesis at a 10(5)[1] % level

3.4.2. Panel unit root test and cointegration results

Before estimating our regressions, it is important to define which variables in the data are stationary and which are non-stationary. This chapter uses the IPS unit root test to inspect the univariate characteristic of each variable. The IPS has been chosen since it assumed the individual unit root process, thus better suited for detecting cross-section heterogeneity in the dataset (Baltagi, 2008). The Akaike information criterion is used to determine the optimal number of lags within a maximum value of 2. The cross-sectional means are subtracted by demeaning the series to assist with cross-sectional correlation and cross-sectional dependence. We fail to reject the null hypothesis of a unit root for most variables and conclude that most series are not stationary. Consequently, cointegration tests are necessary to avoid spurious relationships when estimating regressions with non-stationary variables.

Table 6. IPS unit root tests.

Variables	IPS	
	Specification without trend	Specification trend
$\ln CE_{it}$	3.7398 (0.999)	3.3439 (0.999)
$\ln GDP_{it}$	2.1258 (0.983)	1.7564 (0.874)
$\ln ECONS_{it}$	6.2513 (1.000)	7.9012 (1.000)
$\ln R\&D_{it}$	0.3586 (0.640)	3.4411 (0.999)
$\ln Patent_{it}$	-1.5039 (0.066) *	-1.6513 (0.049) *
$\ln Mob\_cel_{it}$	-2.4299 (0.007) ***	-2.9685 (0.001) ***
$\ln Internet_{it}$	-3.9694 (0.000) ***	-11.759 (0.000) ***
$\ln Scien\_tech_{it}$	5.6321 (1.000)	1.6940 (0.954)
$\ln TFP_{it}$	-2.0377 (0.020) **	-1.1386 (0.127)
$\ln POP_{it}$	9.3182 (1.000)	4.3708 (1.000)
$\ln EXP_{it}$	0.8517 (0.802)	2.4186 (0.992)

Notes: P-values are in parenthesis. *(**) [***] indicate rejection of the null hypothesis of a unit root at a 10(5)[1] % level.

Westerlund (2005), Pedroni (1999, 2004), and Kao (1999) tests are performed to check for cointegration. When there is cointegration in the models tested, it means that the results of the regressions are not spurious, and there is a long-run relationship amongst variables. Cointegration results are presented in Table 7. Except for the Augmented Dickey-Fuller statistic in panel models (2b), (2c), (2d), and (2f), all other statistics are statistically significant, at least at a 10% level. Therefore, it is concluded that cointegration exists in all six-panel sub-models.

Table 7. Test for cointegration for sub-models 2(a)-2(f)

	Model 2(a)	Model 2(b)	Model 2(c)	Model 2(d)	Model 2(e)	Model 2(f)
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Kao test						
Modified Dickey-Fuller t	-4.5932***	-5.5177***	-2.7559***	-3.1239***	1.3568*	-3.1634***
Dickey-Fuller t	-2.4074***	-4.4601***	-1.5457*	-2.5187***	2.3198**	-2.1672**
Augmented Dickey-Fuller t	-2.8838***	-1.2235	0.0121	0.7206	3.0841***	-0.0776
Unadjusted modified Dickey-Fuller t	-4.8990***	-5.6122***	-4.6171***	-5.4236***	-0.3210	-5.3256***
Unadjusted Dickey-Fuller t	-2.5512***	-4.4999***	-2.5344***	-3.6819***	0.9489	-3.2439***
Westerlund test for cointegration						
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Variance ratio	-3.3849***	-2.9680***	-3.1875***	-4.8331***	-2.7905***	-3.7546***
Pedroni test for cointegration						
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
Modified Phillips-Perron	1.6462*	2.4351***	1.904**	-0.3152*	7.2719***	1.5503*
Phillips-Perron t	-7.0753***	-12.90***	-8.472***	-11.607***	-10.077***	-11.493***
Augmented Dickey-Fuller t	-5.3472***	-9.3053***	-8.687***	-10.445***	-9.7140***	-9.3530***

*(**) [***] indicate rejection of the null hypothesis of no cointegration at a 10(5) [1] % level.

3.5. Empirical results and discussions

The remainder of section 3.5. discusses the empirical analysis results. This chapter applies two methods for estimating the regression results: the fixed-effect method with Driscoll and Kraay standard errors and the Bruno LSDVC corrector for robustness check. Our preferred model will be the fixed effect with Driscoll and Kraay standard errors because these standard errors are unbiased and robust in the presence of serial correlation, cross-sectional dependence, and heteroscedasticity in the dataset (Hoechle, 2007).

The section is divided into four subsections. The first subsection examines the relationship between technology advancement and carbon emissions in the full sample[11]. The study assesses carbon emissions' responsiveness to six technological progress proxies (ICT, R&D expenditure, patents, TFP, and science and

[11] For all 60 countries in the dataset

technology publications). The same relationship is analyzed in the second subsection with the Bruno LSDVC corrector. In the third subsection, chapter 3 considers the rebound effect and tests how the joint effect of technology and energy consumption influence carbon emissions using the fixed effect with Driscoll and Kraay standard errors. Finally, in the fourth subsection, we examine the influence of technology on C02 emissions at different income group levels[12].

3.5.1. Full sample analysis

Tables A to F in the appendix[13] present detailed results from the full sample analysis. Table 8 below presents a summary of these results. Table 8 shows the responsiveness of carbon emissions when each technology variable is included with all other explanatory variables at once[14]. It can be observed from table 8 that a rise in ICTs variables causes a decline in CO2 emissions. When all other independent variables remain constant, a 1 per cent increase in mobile cellular subscriptions and internet use lower carbon emissions by 0.016 and 0.018 per cent, respectively. Mobile cellular subscriptions and internet use are significant at 5 and 10 per cent levels, respectively. Regarding the impact of patents and R&D expenditure on carbon emissions, when only GDP and energy consumption are included as explanatory variables, patents and R&D expenditure increase carbon emissions. 1 per cent rise of patents and R&D expenditure, increase carbon emissions by 0.032 and 0.033 per cent, respectively[15]. Patents and R&D expenditure have opposite signs after including additional explanatory variables, and they are both statistically insignificant at conventional levels of significance (see table 8). When all explanatory variables are included in the model, the sign of TFP is positive and statistically significant at 5 per cent level of significance, while the sign of science and technology publications is negative and statistically significant at 5 per cent level of significance. A 1 per cent rise in TFP increases carbon emissions by 0.1449 per cent, while a 1 per cent increase in science and technology publications reduces carbon emissions by 0.0374 per cent.

Regarding other core drivers of carbon emissions, the results show that GDP per capita, energy consumption, and population density have a positive and statistically significant impact on carbon emission in all six sub-models. This result follows the vast majority of literature that has found a positive relationship between these variables and carbon emissions (Selden and Song, 1994; Akinlo, 2008; Bosetti et al., 2009;

[12] We divide the full sample into 4 groups according to their income level: 15 high income, 15 upper-middle income, 15 lower-middle income and 15 lower-income countries.
[13] These tables contain a series of regression for each sub model [Model 2(a) to model 2(f)] where each explanatory variable is included once at a time. We could not include these tables in this section because of space limitation.
[14] Table 5 just contains all six "regressions 5" of panel sub model A to F, which are presented in the appendix.
[15] Please refer to table C and D in the appendix.

Hashmi and Alam, 2019; Gu et al., 2019). Export is associated with an increase in carbon emissions only in two sub-models.

Table 8. Full sample fixed effect results with all explanatory variables included (Panel model 2)

Dependent variable: CO2 emissions						
	model (2a)	model (2b)	model (2c)	model (2d)	model (2e)	model (2f)
$\ln Mob\_cel_{it}$	-.01686*** (-8.44)					
$\ln Internet_{it}$		-.01896*** (-5.80)				
$\ln Patent_{it}$			.009291 (0.78)			
$\ln R\&D_{it}$				-.021502 (0.86)		
$\ln TFP_{it}$					.14493** (2.60)	
$\ln Scien\_tech_{it}$						-.03740** (-2.61)
$\ln GDP_{it}$	.154921** (2.34)	.16373*** (2.85)	.19216*** (17.66)	.15954** (2.56)	.118187* (1.70)	.07730* (1.68)
$\ln ECONS_{it}$	.933625*** (22.67)	.91670*** (27.46)	.86201*** (17.66)	.93984*** (20.37)	.90441*** (25.28)	1.0339*** (30.37)
$\ln POP_{it}$	.471601*** (10.46)	.63268*** (10.14)	.30051*** (4.85)	.43019*** (6.48)	.41710*** (10.72)	.42035*** (6.48)
$\ln EXP_{it}$	.037715 (1.42)	.02572* (0.81)	-.003307 (-0.11)	-.02504 (0.64)	-.01068 (-0.35)	.08263** (3.58)
Constant	-11.688*** (-78.85)	-10.464*** (-18.97)	-8.2919*** (-25.34)	-12.969*** (-60.57)	-7.7284*** (-19.73)	-10.861*** (-19.78)
F-test	1600.09 (0.000)	1868.35 (0.000)	1507.26 (0.000)	425.25 (0.000)	1571.14 (0.000)	220.06 (0.000)
Observations	1800	1800	1800	1800	1800	1800
Groups	60	60	60	60	60	60

Note: Driscoll and Kraay's standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

The full sample results confirm the complex relationship between technological progress and carbon emissions stated in the literature. The results show that technological progress indicators do not necessarily have the same impact on carbon emissions. Findings reveal that ICT can be considered a good instrument for carbon reduction. The net effect of ICT (internet and mobile phone subscriptions) on CO2 emission is negative and statistically significant. ICT includes many benefits that can explain its negative impact on carbon emissions. According to a 2015 report by the Global e-Sustainability Initiative (GeSI, 2015), mobile communications technology and the internet are making a considerable contribution to action on climate change. Analyzes revealed that mobile phones and other telecommunications devices save more than 180 million tons of CO_2 emissions per year in the US and Europe (GeSI, 2015). Mobile phones create energy savings in many different ways across several key categories. As an illustration, communication has overcome the distances and physical barriers that separate people who no longer need to travel to meet. Many public and private services have become available online and accessible through mobile phones. Online banking reduces the number of people going down to the local bank branch. The transition to cloud computing is one of the main trends in modernization. Another example is energy reductions in buildings, resulting from technologies that improve energy efficiencies, such as building management systems and smart meters.

The number of science and technology publications is also an indicator that scientific debate and research can progressively foster a green economic transformation across countries. Since global warming is increasingly becoming a subject of great concern, the scientific debate is gradually more directed toward ensuring economic growth without damaging the environment. Scientific discussions also help raise the awareness of governments, businesses, and the general public.

R&D expenditure and patents do not have a clear impact on carbon emissions. A possible explanation is the dual effect of these two technology measures on carbon emissions. R&D expenditure and patents may increase or decrease carbon emissions, depending on whether they are environmentally friendly or not. The two effects tend to cancel each other out, resulting in an insignificant impact on CO_2 emissions. As mentioned in the data section, R&D expenditure and patents data used in this chapter are in aggregate. This means they are not necessarily green R&D or patents. Another explanation is that R&D expenditure and patents did not increase enough to impact carbon emissions during our study period. Thus, there is a possible inverted U-shape relationship between carbon emissions and technological progress. When R&D expenditure and patents are at a low level, they increase carbon emissions, while when they exceed a certain turning point[16], R&D expenditure and patents progressively reduce carbon emissions. If this is the case, it suggests that R&D spending and patents have not yet reached the turning point where CO_2 emissions are declining. Further research will therefore be necessary to verify these hypotheses.

[16] In this case, a quadratic term should be added in the model to verify nonlinearities and confirm or infirm the inverted U-shape.

3.5.2. Bruno LSDVC estimation

The Bruno LSDVC is used as a robustness check for the fixed effect methodology results. Results are presented in table 9. The sign of the lagged dependent variable is positive as expected, indicating persistence in the carbon emissions process. ICT variables in the models are still negative and statistically significant at 1 per cent level of significance. Similar to the fixed effect results, science and technology publications have a negative sign while TFP has a positive sign. They are both statistically significant at 5 per cent level of significance. The dynamic term coefficient is positive and statistically significant in all sub-models. R&D expenditure is the only variable that changes when using the LSDVC methodology. While R&D expenditure has a negative sign in both methods, it turns out to be statistically significant only in the LSDVC results.

Table 9. Bruno LSDVC results estimation (Panel model 3)

Dependent variable: CO2 emissions						
	model (3a)	model (3b)	model (3c)	model (3d)	model (3e)	model (3f)
$\ln CE_{it-1}$	.772628*** (253.56)	.75296*** (96.58)	.781399*** (48.42)	.79162*** (195.84)	.74646*** (32.85)	.747742*** (26.15)
$\ln Mob\_cel_{it}$	-.00194*** (-29.49)					
$\ln Internet_{it}$		-.0053*** (-4.86)				
$\ln Patent_{it}$			.0019081 (0.24)			
$\ln R\&D_{it}$				-.031062* (-1.70)		
$\ln Scien\_tech_{it}$					-.020659** (-2.00)	
$\ln TFP_{it}$						.042138** (2.11)
$\ln GDP_{it}$	.018423** (2.42)	.046714 (0.77)	.054716** (2.29)	.046240 (1.16)	-.026234 (-0.42)	.031559*** (6.91)
$\ln ECONS_{it}$	.21007*** (9.69)	.214531*** (4.07)	.144765*** (4.12)	.237714*** (17.06)	.337586*** (5.25)	.194748*** (40.35)
$\ln POP_{it}$	.066015** (1.96)	.164314*** (11.02)	.079287 (1.51)	.121199*** (1.40)	.152597*** (5.48)	.11602*** (6.73)
$\ln EXP_{it}$	.019070** (2.38)	.014434 (1.50)	.010548* (1.64)	.007011 (0.66)	.031492 (1.17)	.0057858 (0.60)
Groups	60	60	60	60	60	60

Notes: Standard errors in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

As we mentioned earlier, our preferred results are those estimated with Driscoll and Kraay standard errors since they are robust to many types of bias, including cross-sectional dependence, heteroscedasticity, and serial correlation.

3.5.3. The rebound effect

Panel model three introduces an interaction term to account for the rebound effect. The coefficient on the interaction term indicates how technological progress affects carbon emissions through energy consumption (Gu et al., 2019). A negative coefficient would suggest that technological progress through channels such as energy savings and renewable energy development attenuates the positive impact of energy consumption on carbon emissions. A positive coefficient would suggest that additional energy savings induced by technological progress are offset by higher energy consumption caused by the rebound effect, thus increasing carbon emissions[17].

Table 10. Rebound effect estimation results (Panel model 4)

Dependent variable: CO2 emissions						
	model (4a)	model (4b)	model (4c)	model (4d)	model (4e)	model (4f)
$\ln Cons\_Mob\_cel_{it}$	-.0169*** (-7.42)					
$\ln Cons\_Internet_{it}$		-.0149*** (-4.66)				
$\ln Cons\_Patent_{it}$			-.0719*** (-10.04)			
$\ln Cons\_R\&D_{it}$				-.0880*** (-11.64)		
$\ln Cons\_Scien\_tech_{it}$					-.0818*** (-10.33)	
$\ln Cons\_TFP_{it}$						-.2429*** (4.71)
$\ln Tech_{it}$	-.0102*** (7.36)	-.0879*** (4.40)	.04936*** (1.95)	.5901 (0.85)	-.05520*** (-8.97)	1.766*** (16.27)
$\ln GDP_{it}$	.2495*** (3.53)	.2443*** (3.63)	.3196*** (6.01)	.3024*** (5.44)	.2351*** (5.31)	.1331** (2.26)
$\ln ECONS_{it}$	.9112*** (28.44)	.8954*** (25.38)	1.409*** (18.25)	1.833*** (16.45)	1.657*** (19.78)	.8145*** (16.27)
$\ln POP_{it}$	.2761*** (5.56)	.4054*** (7.31)	.2149*** (3.49)	.1971*** (3.42)	.1586** (2.51)	.4135*** (10.11)
$\ln EXP_{it}$	.0226 (0.95)	.0197* (1.91)	-.0396 (-1.31)	-.0379 (-1.36)	.0199 (0.82)	-.0327 (-1.05)

[17] It is important to note that the assumption made about the interaction between technology and energy consumption and its impact on carbon emissions is more general and theoretical. The purpose of model 4 is not to calculate the rebound effect but to give an indication on its magnitude, and on whether it offset the energy savings induced by technological progress.

Constant	-9.509*** (-22.92)	-9.872*** (-20.36)	-11.65*** (-21.05)	-20.95*** (-16.60)	-13.87*** (-22.52)	-6.930*** (-13.05)
F-test	944.06 (0.000)	1528.60 (0.000)	1590.02 (0.000)	1065.08 (0.000)	527.13 (0.000)	1476.45 (0.000)
Observations	1800	1800	1800	1800	1800	1800
Groups	60	60	60	60	60	60

Note: Driscoll and Kraay's standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

The results indicate that carbon emissions decrease despite the rebound effect for all joint interactions between energy consumption and technological progress proxies. This is an indication that there is an inverted U shape relationship between energy consumption and carbon emissions across technological progress. It suggests that as technology increases, the impact of energy consumption on carbon emission turns from positive to negative[18]. It is important to note that this mechanism is not only due to energy efficiency gains induced by technological progress but also to the rise of green technologies such as renewable energies, which fundamentally change energy consumption structure. In conclusion, this chapter's results indicate a positive relationship between energy consumption and carbon emissions. That is, in general, energy consumption increases carbon emissions. However, model 3 reveals that technological progress can play a role as a regulatory mechanism in that process by mitigating the positive effect of energy consumption through energy efficiency and energy mix structure changes.

3.5.4. Subsample analysis

Table 11 presents the results of the impact of technology advancement on carbon emissions across different income levels, using a Fixed Effect methodology with Driscoll and Kraay standard errors. The full sample is divided into four subsamples: High-income countries (subgroup 1), Upper-middle income countries (subgroup 2), Lower-middle income countries (subgroup 3), and lower-income countries (subgroup 4). In general, the signs of ICT proxies are negative and significant across all income levels. In high income and upper-middle-income countries, 1% increase in mobile cellular subscriptions decreases carbon emissions by 0.011% and 0.010%, respectively; and a 1% increase in internet use decreases CO_2 emissions by 0.007% and 0.006%, respectively. The results are similar in lower-middle-income and lower-income countries. 1% increase in mobile cellular subscriptions decreases CO_2 emissions by 0.013% in lower-middle-income countries and 0.05% in lower-income countries. Carbon emissions decline by 0.036%

[18] This is the case for at least two important indicators of technological progress: Patent application and TFP.

and 0.033% when internet connection increases by 1% in lower-middle-income and lower-income, respectively. Globally, ICT appears to be a good tool to reduce CO2 emissions.

The coefficient on patent is positive and statistically significant in 3 out of 4 income-group countries. 1% increase in patent application increases carbon emissions by 0.032% in high-income countries, 0.047% in lower-middle-income countries, and 0.06% in lower-income countries. R&D expenditure causes CO2 emissions to rise only in lower-middle-income countries by 0.055%. Science and technology publications are negatively associated with carbon emissions only in high-income and upper-middle-income countries. This can be explained by the number of science and technology publications produced in high-income economies compared to lower-income economies. According to the WDI database (2019), on average, during our study period, high-income countries have published about 70 000 articles each year, while low-income countries have only published approximately 165 science and technology publications. TFP increases carbon emissions in Upper-middle income and Lower-middle income countries.

Energy consumption is positive and statistically significant in all regressions. This is consistent with the literature since we expect a positive relationship between energy consumption and carbon emissions (Dinda and Coondoo, 2006; Akinlo, 2008). In most regressions, GDP per capita is statistically significant and positively related to carbon emissions. In half of the regressions, population density appears to be positive and statistically significant. Population growth has always been considered one of the major factors of global warming (Seldan and Song, 1994; Borghesi, 1999). High population density means more demand for fossil fuels to provide more energy and fuel to an increasingly mechanized life.

Another interesting result is about exports. In most regressions, exports are negatively related to carbon emissions in high-income countries while positively related to carbon emissions in lower-income countries. An explanation might be that, despite being the biggest consumers of fossil fuel energy, high-income countries also export more green-friendly products than other countries. Another reason is that they easily exchange and implement green technologies since they are part of organizations where the free trade regime is fully and effectively implemented. Also, developed countries have gradually put in place and imposed stricter and more environmentally friendly regulations. Therefore, countries that export their products to developed countries ensure that their goods comply with environmental regulations in place.

Table 11. Subsample regressions results

Dependent variable: CO2 emissions								
	Technology – Mobile				*Technology – Internet*			
	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4
$\ln TECH_{it}$	-.01144*** (-3.87)	-.01074*** (-4.90)	-.01309** (-2.06)	-.05697*** (-5.12)	-.00748*** (-3.35)	-.00622* (-1.88)	-.00368* (-1.92)	-.03378** (-2.67)
$\ln GDP_{it}$	.15863** (2.13)	.05808* (1.93)	.04536 (0.37)	1.0664*** (8.31)	.15497** (2.16)	.024814 (0.51)	.10644 (0.85)	.78996*** (6.18)
$\ln ECONS_{it}$	.98442*** (24.52)	1.0167*** (27.76)	1.0747*** (20.25)	1.4445*** (6.35)	1.0037*** (23.98)	1.0320*** (23.07)	1.0700*** (23.28)	1.1955*** (5.27)
$\ln POP_{it}$	.0938974 (0.73)	.0276064 (1.05)	.32013** (2.17)	.56710* (1.83)	.048451 (0.41)	-.00014 (-0.05)	.17147 (1.15)	.55098** (2.11)
$\ln EXP_{it}$	-.09221*** (-3.71)	.02159 (1.45)	.12829** (2.62)	.07072 (1.24)	-.09389*** (-3.54)	.00382 (0.28)	.05449 (1.49)	.05399 (0.73)
Constant	-5.5115*** (-11.17)	-7.1692*** (-18.05)	-11.689*** (-10.13)	-20.845*** (-14.06)	-5.4119*** (-12.40)	-6.4642*** (-22.73)	-9.6474*** (-15.03)	-17.265*** (-8.97)
F-test	466.80 (0.000)	1782.00 (0.000)	139.62 (0.000)	139.62 (0.000)	1011.85 (0.000)	2052.96 (0.000)	892.18 (0.000)	32.71 (0.000)
Observations	450	450	450	450	450	450	450	450
Groups	15	15	15	15	15	15	15	15
	Technology – Patent				*Technology – R&D*			
	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4
$\ln TECH_{it}$	.03200* (1.91)	-.00183 (-0.24)	.04766** (2.07)	.06031** (2.09)	.0176199 (0.37)	.00259 (0.09)	.05523* (1.77)	.00990 (0.27)
$\ln GDP_{it}$	.19035** (2.59)	.01961 (1.30)	-.02650 (-0.24)	.79436*** (6.50)	.148569* (1.87)	.08021*** (3.03)	.12814 (0.92)	.78957*** (6.37)
$\ln ECONS_{it}$	.95866*** (22.47)	1.0561*** (28.82)	.95445*** (11.46)	1.0624*** (3.92)	.97276*** (27.86)	.97069*** (27.17)	1.0206*** (17.07)	1.6470*** (8.33)
$\ln POP_{it}$	-.00118 (-0.05)	-.05520 (-1.53)	.12896** (1.99)	.17980 (0.88)	-.007788 (-0.07)	-.03803 (-0.84)	-.14929 (-0.93)	-.26542* (-1.92)
$\ln EXP_{it}$	-.14761*** (-7.25)	-.01930** (-2.17)	.12222*** (3.21)	-.04810 (-0.62)	-.13368*** (-7.61)	-.04402** (-2.67)	.05821 (1.50)	.08102 (0.99)
Constant	-4.0776*** (-13.85)	-5.7985*** (-17.98)	-9.686*** (-36.03)	-13.024*** (-6.24)	-4.2226*** (-12.70)	-5.2001*** (-19.92)	-9.1747*** (-31.63)	-17.585*** (-9.04)

F-test	321 (0.000)	779.98 (0.000)	2186.24 (0.000)	32.71 (0.000)	409 (0.000)	1176.74 (0.000)	4383.35 (0.000)	47.03 (0.000)
Observations	450	450	450	450	450	450	450	450
Groups	15	15	15	15	15	15	15	15

	Technology – Articles				*Technology – TFP*			
	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4
$\ln TECH_{it}$	-.19050*** (-5.01)	-.01291* (-1.90)	.01789 (0.60)	.14772 (1.22)	.06825 (1.31)	.04891** (-2.69)	.22824*** (4.22)	.02029 (0.18)
$\ln GDP_{it}$	.43937*** (4.01)	.16310*** (5.74)	-.06271 (-0.79)	.59554*** (4.15)	.13375* (1.79)	.02723 (1.23)	.20652* (-2.10)	.74166*** (6.98)
$\ln ECONS_{it}$	1.0057*** (17.01)	.93735*** (30.22)	1.0620*** (14.36)	1.7362*** (7.68)	.96974*** (22.57)	1.0521*** (28.43)	1.1403*** (23.07)	1.8970*** (7.73)
$\ln POP_{it}$	.42653* (2.05)	.05574* (1.72)	.04524 (0.26)	-.75502** (-2.68)	.085676 (0.79)	.06385* (1.74)	.22742** (2.20)	.96544*** (5.60)
$\ln EXP_{it}$	-.06086** (-2.46)	-.08416*** (-7.25)	.10041*** (3.17)	.19568*** (3.12)	-.12700*** (-6.31)	-.01920* (-1.74)	.12104*** (3.49)	.23041*** (3.05)
Constant	-8.9548*** (-9.89)	-4.8398*** (-17.46)	-8.9752*** (-13.59)	-17.917*** (-10.33)	-4.1999*** (-12.18)	-5.8452*** (-18.34)	-9.5029*** (-28.35)	-16.212*** (-8.11)
F-test	1045 (0.000)	3136.36 (0.000)	2622.34 (0.000)	130.62 (0.000)	274.72 (0.000)	1220.88 (0.000)	492.04 (0.000)	90.73 (0.000)
Observations	450	450	450	450	450	450	450	450
Groups	15	15	15	15	15	15	15	15

Notes: Driscoll and Kraay robust standard errors in parentheses. * (**) [***] indicate the level of significance at 10 (5) and (1)

In all four groups of countries, mobile cellular subscriptions and internet connections reduce carbon emissions. This result aligns with previous studies (see Asongu, Roux, and Biekpe, 2017; Anon Higon et al., 2017; Moyer and Hugues, 2012). ICT lowers carbon emissions via three mains[19] channels: increasing energy efficiency, decreasing the cost of renewable energy adoption, and *reducing* travel-related GHG emissions (Anon Higon et al., 2017; Moyer and Hugues, 2012). This negative impact seems to outweigh ICT's positive impact on carbon emissions as a result of also contributing to the increase in GDP. Even though the magnitude of mobile cellular subscriptions and internet connection coefficients in the estimation results are not very high, they remain negative and statistically significant in all income groups. Thus, investment in the ICT sector can be recommended as a good policy to combat climate change. Science and technology publications are associated with decreased carbon emissions in high-income and upper-middle-income countries. However, it fails to impact carbon emissions in lower-middle and low-income countries significantly. This is not surprising given the considerable scientific publications gap between high-income and low-income countries.

In high-income countries, patent applications are positively and significantly related to carbon emissions. This indicates that most of the patents granted within our study period in these countries were not necessarily environmentally friendly. The industry sector (iron and steel production, chemical production, machinery production, etc.) accounted for 37 per cent of global energy used in 2018 (IEA, 2020). Most of the energy-intensive industries are located in high-income countries. These industries are continuously innovating and expanding, thus increasing their energy demand. According to IEA (2020), industrial energy consumption increased by 0.9 per cent annually between 2010 and 2018. It seems like patents granted in these countries, specifically in energy-intensive industries with the most significant share in energy used, are not environmentally friendly enough. Therefore, it will be necessary to encourage green patent applications and intensify policies that encourage firms and industries to produce less damaging products to the environment. R&D expenditure and TFP do not have a clear impact on carbon emissions in high-income countries. The coefficients of R&D expenditure and TFP are positive but not statistically significant at the conventional significance level.

Regarding upper-middle-income countries, the results are not very clear. This chapter could not find a significant impact of R&D expenditure and patents on carbon emissions. Their coefficients in the regression results were, at first, positive and statistically significant when they were the only explanatory variables

[19] Many other channels exist. Higon et al. (2017) note that ICT can also foster the development of smarter cities, electrical grids, transportation system and industrial processes.

used in their respective regressions. However, their coefficients became statistically insignificant as additional explanatory variables were added to the regressions. An explanation might be that upper-middle countries are reaching a point where the gains from energy savings due to technological improvement equal the increase of energy consumption due to technological improvement, resulting in an insignificant impact on carbon emissions. Another explanation is the lack of stringent environmental regulations that can convince industries to adopt green-friendly products. Green patents and green R&D expenditure can very well be present in the market. But if there are no solid regulations to “force” industries to adopt and use them, they may not have the expected negative effect on carbon emissions.

In lower-income countries, patent applications and R&D expenditure enhance carbon emissions. This suggests that public spending on R&D is still more directed toward carbon-intensive projects in these countries since they have been experiencing constant economic growth over the past decades (WDI, 2019). Also, patents granted in these countries reflect inventions that might benefit households, companies, or industries but damage the environment. Another explanation is the limited funds allocated to R&D expenditure in annual state budgets. Also, these countries do not often have the means, skills, and high-tech infrastructures necessary to develop inventions that lead to the creation of patents. Similar to the results found by Li and Wang (2017), lower-income countries pay little attention to developing low-carbon production technologies. This is not very surprising as these countries seek to expand their economic growth to join other groups of high-level income countries. Therefore, they invest significantly in energy-intensive projects that do not often consider environmental sustainability.

3.6. Conclusion

The relationship between technological change and carbon emissions is complex. Numerous studies show that technological progress has a dual effect on global CO2 emissions. On the one hand, technology reduces overall CO2 emissions by reducing energy intensity, adjusting the energy structure, and fostering the diffusion of green technology in industries and countries. On the other hand, technology increases CO2 emissions by increasing energy consumption and economic growth. The purpose of this chapter was to re-examine the above relationship in a group of 60 countries divided into four categories based on their per capita income level for the period 1989-2018.

Chapter three aimed to answer two questions. The first question was to determine the impact of technological progress on CO2 emissions when using various technology measurements. Notably:

Information and telecommunication technology (mobile cellular subscription and percentage of internet users); the number of patents applications; public R&D expenditure; total factor of productivity (TFP); and the number of science and technology publications.

The chapter used a full sample of 60 countries to answer this question. After applying the fixed-effect method with Driscoll and Kraay standard errors and complementing the latter with the Bruno (2005) LSDVC methodology as a robustness check, the following mixed results have been found: ICT variables appear to be good instruments for carbon reduction. The net effect of ICT variables on CO2 emissions is negative and statistically significant. However, R&D expenditure and patents do not have a clear impact on carbon emissions. Their coefficients are positive but not statistically significant. TFP increases carbon emissions, while science and technology publications are negatively related to carbon emissions. Results also reported that key determinants of carbon emissions such as GDP per capita, energy consumption, population density, and exports are positively related to carbon emissions. This chapter also considered the rebound effect by interacting technological progress with energy consumption and assessing their common impact on carbon emissions. Results revealed that carbon emissions decrease despite the rebound effect for all joint interactions. There is an inverted U shape relationship between energy consumption and carbon emissions across technological progress. It suggests that as technology increases, the impact of energy consumption on carbon emission turns from positive to negative because of the energy efficiency induced by technology and the increasing share of green technology in the energy mix.

The second question was to determine whether the impact of our measurement of technological progress depends on a country's economic development level. Following the World Bank classification of income, the full sample is divided into four sub-samples according to their income level. Thus, we had 15 high-income countries, 15 upper-middle-income countries, 15 lower-middle-income countries, and 15 lower-income countries. After running several regressions with the fixed effect methodology with Driscoll and Kraay standard errors for the four subsamples, the results revealed that ICT development is associated with a decline in CO2 emissions in all four groups of countries. The coefficient on patents is statistically significant and positively affects carbon emissions in 3 out of 4 groups of countries (high-income, lower-middle-income, and lower-income countries). R&D expenditure causes CO2 emissions to rise only in lower-middle-income countries but fails to impact carbon emissions in high-income countries. Science and technology publications are negatively associated with carbon emissions only in high-income and upper-middle-income countries.

The policy implications drawn from chapter three are as follows: (1) Governments and industries should continue to support the development and adoption of ICT, as it can be used as an important instrument to tackle climate change. (2) Countries should agree on a comprehensive policy that supports and promotes green patent applications and encourages companies to develop products and services with the lowest environmental impact. (3) Public R&D spending should be more directed towards projects and initiatives that create eco-friendly goods and technologies. (4) It is essential to promote the publication of scientific and technical articles as they also participate in the debate on green and sustainable development strategies. Scientific articles allow discussion on ideas that promote energy efficiency, revealing channels or technological processes that reduce energy consumption. (5) These policy recommendations might not be successful without strict environmental laws and a commitment from the government to gradually cut back on traditional energy use and increase its share of renewable energy.

Appendix

Table AA1 Descriptive statistic: Sub-sample

	Observations	Mean value	Standard deviation	Minimum value	Maximum value
			CO2 emissions		
High-income	450	10.08686	4.192539	2.321076	20.17875
Upper-middle income	427	5.231199	3.316332	1.308847	17.42437
Lower-middle income	450	1.602891	1.642865	.133613	7.701744
Lower-income	426	.2412384	.2613759	.0335559	1.697945
			GDP capita		
High-income	449	33700.83	13617.77	5510.662	56842.3
Upper-middle income	449	6682.485	2793.98	712.1154	15068.98
Lower-middle income	450	2469.366	2871.945	398.8521	14920.45
Lower-income	450	585.5048	236.4174	164.3366	1334.785
			Energy consumption		
High-income	404	4.351784	1.75897	1.00411	8.455547
Upper-middle income	391	1.856053	1.11506	0.61606	5.928661
Lower-middle income	386	0.711106	0.55271	0.11889	2.545027
Lower-income	336	0.445947	0.118864	0.211177	0.100453
			Population		
High-income	439	179.0955	165.0725	2.18872	529.6521
Upper-middle income	450	54.81616	41.2086	5.503698	148.3488
Lower-middle income	450	190.0089	249.634	9.188078	1239.579
Lower-income	390	66.05524	54.03424	6.799691	225.3065
			Exports		
High-income	433	.3257275	.1817291	.07	.88
Upper-middle income	448	.3341493	.1994115	0	.9818581
Lower-middle income	408	28.68873	18.60527	3	128
Lower-income	394	.195079	.106577	.02	.5949994

R&D expenditure					
High-income	423	1.997422	.9313076	.477058	5.108209
Upper-middle income	369	1.095182	.8507465	.0008862	4.872204
Lower-middle income	334	.561821	.3235109	.0328966	1.258751
Lower-income	345	.2460996	.0928364	.01465	.72657
Patents					
High-income	450	42260.74	98495.01	70	606956
Upper-middle income	450	11071.12	21211.33	72	148187
Lower-middle income	432	2742.065	7236.495	10	50055
Lower-income	435	26.85517	24.2772	1	193
Mobile cell					
High-income	449	65.90508	51.41677	0.9	191.0315
Upper-middle income	435	54.49689	54.49927	.0002027	180.4934
Lower-middle income	414	39.7524	44.62241	.0002315	164.4406
Lower-income	366	29.02564	35.82879	.0006089	139.529

Internet					
High-income	426	44.21311	34.01286	0.8	96.02286
Upper-middle income	406	22.78703	24.16181	0.5	81.20105
Lower-middle income	370	13.70277	17.96182	.0001113	74
Lower-income	390	4.689112	7.177908	.0000175	38
TFP					
High-income	450	.8612446	.1484321	.508876	1.22886
Upper-middle income	440	.6324319	.1964714	.2530827	1.143904
Lower-middle income	434	.5423953	.2005938	.1254694	1.10942
Lower-income	235	.3365696	.0890791	.1556337	.5653373
Science and technology publications					
High-income	285	70037.76	91813.01	1557.36	433192.3
Upper-middle income	285	29719.91	74960.12	190.17	528263.3
Lower-middle income	285	6238.554	18231.27	5.89	135787.8
Lower-income	285	165.4247	234.6959	3.14	1994.44

Table A. Full sample detailed regression results panel model 1a.

Dependent variable: CO_2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
Technology – Mobile	. .04720*** (9.22)	.00925*** (-2.61)	.000304 (0.13)	-.02094*** (-7.02)	-.01686*** (-8.44)
GDP		.617113*** (20.97)	.256743*** (6.83)	.319516*** (7.48)	.154921** (2.34)
Energy Consumption			.903223*** (25.32)	.829385*** (20.71)	.933625*** (22.67)
Population density				.586699*** (11.06)	.471601*** (10.46)
Exports					.037715 (1.42)

Constant	.543195*** (33.66)	-4.5273*** (-18.87)	-7.8918*** (-50.65)	-10.284*** (-35.18)	-11.688*** (-78.85)
F-test	85.04 (0.000)	1199.12 (0.000)	1393.64 (0.000)	1716.98 (0.000)	1600.09 (0.000)
Observations	1800	1800	1800	1800	1800
Groups	60	60	60	60	60

Note: Driscoll and Kraay's standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

Table B. Full sample detailed regression results panel model 1b.

Dependent variable: CO_2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
Technology – Internet	.0424*** (6.61)	.010519 (4.22)	.00119 (0.66)	-.0181*** (-5.46)	-.0189*** (-5.80)
GDP		.5523*** (11.20)	.2549*** (5.05)	.2663*** (5.53)	.1637*** (2.85)
Energy Consumption			.88767*** (22.71)	.84047*** (24.14)	.9167*** (27.46)
Population density				.61974*** (10.66)	.6326*** (10.14)
Exports					.02572* (0.81)
Constant	.54415*** (26.04)	-4.0128*** (-9.68)	7.7986*** (-29.66)	-10.120*** (-26.54)	-10.464*** (-18.97)
	43.75 (0.000)	114.93 (0.000)	865.41 (0.000)	1237.07 (0.000)	1868.35 (0.000)
Observations	1800	1800	1800	1800	1800
Groups	60	60	60	60	60

Note: Driscoll and Kraay's standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

Table C. Full sample detailed regression results panel model 1c.

Dependent variable: CO_2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
Technology – Patent	.23240*** (7.96)	.10479*** (4.92)	.03328** (2.39)	.00697 (0.63)	.009291 (0.78)
GDP		.59308*** (15.08)	.29664*** (9.35)	.25080*** (7.29)	.19216*** (17.66)
Energy Consumption			.84149*** (19.86)	.83445*** (16.81)	.86201*** (17.66)
Population density				.25193*** (5.50)	.30051*** (4.85)

Exports					-.003307 (-0.11)
Constant	-1.0462*** (-5.70)	-5.0638*** (-22.90)	-8.0452*** (-41.15)	-8.4744*** (-33.21)	-8.2919*** (-25.34)
	63.40 (0.000)	568.15 (0.000)	1269.24 (0.000)	1304.06 (0.000)	1507.26 (0.000)
Observations	1800	1800	1800	1800	1800
Groups	60	60	60	60	60

Note: Driscoll and Kraay's standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

Table D. Full sample detailed regression results panel model 1d.

Dependent variable: CO2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
Technology – R&D	.21292*** (5.72)	.072980** (2.12)	.03230* (1.74)	-.02387 (0.90)	-.021502 (0.86)
GDP		.47588*** (5.66)	.16714** (2.24)	.17163** (2.35)	.15954** (2.56)
Energy Consumption			.89438*** (15.58)	.88262*** (15.59)	.93984*** (20.37)
Population density				.36537*** (5.06)	.43019*** (6.48)
Exports					-.02504 (0.64)
Constant	-3.7978*** (-4.84)	-4.8595*** (-11.96)	-7.7772*** (-23.21)	-8.079*** (-25.56)	-12.969*** (-60.57)
	32.73 (0.000)	97.94 (0.000)	345.29 (0.000)	302.64 (0.000)	425.25 (0.000)
Observations	1800	1800	1800	1800	1800
Groups	60	60	60	60	60

Note: Driscoll and Kraay's standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

Table E. Full sample detailed regression results panel model 1e.

Dependent variable: CO2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
Technology – TFP	.300593*** (3.63)	.06347 (1.23)	.10896** (2.11)	.12426** (2.67)	.14493** (2.60)
GDP		.65009*** (29.14)	.24276*** (11.24)	.15027*** (7.19)	.118187* (1.70)
Energy Consumption			.86363*** (33.15)	.80085*** (27.40)	.90441*** (25.28)
Population density				.36650*** (8.44)	.41710*** (10.72)

Exports					-.01068 (-0.35)
Constant	.944870*** (15.71)	-4.6712*** (-22.19)	-7.3215*** (-35.58)	-7.592*** (-38.46)	-7.7284*** (-19.73)
	13.21 (0.001)	751.84 (0.000)	1113.00 (0.000)	996.27 (0.000)	1571.14 (0.000)
Observations	1800	1800	1800	1800	1800
Groups	60	60	60	60	60

Note: Driscoll and Kraay's standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

Table F. Full sample detailed regression results panel model 1f.

Dependent variable: CO2 emissions					
	Model 1	Model 2	Model 3	Model 4	Model 5
Technology – articles	.19999*** (24.13)	.06719*** (5.06)	.01136 (0.83)	-.03508* (-2.02)	-.03740** (-2.61)
GDP		.56590*** (14.31)	.31004*** (8.71)	.27666*** (7.92)	.07730* (1.68)
Energy Consumption			.90273*** (17.34)	.92307*** (16.99)	1.0339*** (30.37)
Population density				.40093*** (5.83)	.42035*** (6.48)
Exports					.08263** (3.58)
Constant	-.96427*** (-15.04)	-4.6475*** (-18.80)	-8.4643*** (-20.71)	-9.6562*** (-16.35)	-10.861*** (-19.78)
	582.08 (0.000)	772.42 (0.000)	204.51 (0.000)	309.27 (0.000)	220.06 (0.000)
Observations	1800	1800	1800	1800	1800
Groups	60	60	60	60	60

Note: Driscoll and Kraay's standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

IV. The role of green technology in CO2 emissions

The third chapter's results have confirmed the complex relationship between aggregate technology and CO2 emissions. Aggregate technology can either increase or decrease carbon dioxide emissions. This relationship often depends on the characteristic of the technology used, which can be carbon-intensive or carbon-free. After using several indicators of technological progress – such as patents, expenditure on research and development, information and communication technologies, and science and technology publications – Results revealed that ICTs and science and technology publications negatively affect carbon emissions. However, patents and R&D expenditure have a positive but insignificant impact on CO2 emissions in the total sample. In chapter 4, this thesis proposes disaggregating aggregate technology and analyzing the effects of green technology on CO2 emissions. In this chapter, we examine the impact of green technology on the environment where certain indicators of aggregate technology (patent and R&D) have failed to find a significant impact. Renewable energies and environmental-related patents are used as green technology indicators. The second part of chapter 4 is devoted to the reverse causality – CO2 emissions to technological progress. It will be about analyzing how the evolution of carbon emissions and economic growth has affected green technology development in different subsamples.

4.1. Introduction

Global warming is increasingly becoming a major concern for human societies. The greenhouse gases emitted by humans from the pre-industrial period to the current period will persist for centuries and will continue to cause long-term changes in the environment and the climate system, such as ecosystem disruption, ocean level rise, and scarcity of resources (IPCC, 2018). Scientists and policymakers consider many solutions to face environmental degradation. Among the solutions, technological progress is regarded as an important way to achieve the critical transition from fossil fuel energy to renewable energy production. Numerous studies show that the effect of aggregate technology on carbon emissions is either positive, negative, or even inconclusive (Dinda and Coondoo, 2006; Akinlo, 2008; Bosetti et al., 2011, Milindi and Inglesi-Lotz, 2021). This can partially be explained by the fact that most technologies developed since the industrial revolution are not environmentally friendly, and many of them have been designed to accommodate or improve fossil-fuel consumption-based machines or products. There is a consensus that technological progress should be redirected toward developing green products than carbon-intensive ones

(Asongu, Le Roux and Biekpe, 2017; Cheng et al., 2019; Churchil et al., 2019). Although it is theoretically predicted that the higher the number of climate-related technologies and eco-innovations, the better for combating climate change, there is limited empirical evidence to support this (Barbieri et al., 2016; Su and Moniba, 2017).

Green technologies are inventions that reduce the harmful effects of human activity on the environment (Keniel and Gleen, 2012). Green technologies include waste recycling, wastewater treatment, electric vehicle, vertical farming, and renewable energy. Green technologies and eco-innovations are crucial in improving energy efficiency (Lee and Yook, 2015, Zhang et al., 2017; Shahbaz and Sinha, 2018). Advanced green technologies allow the economy to produce a level of output with a lower level of energy. Moreover, green technological innovation could lead to quicker adoption of renewable energy to meet energy demands and change the energy consumption structure (Garrone and Grilli, 2010; Hashmi and Alam, 2012). According to IEA (2018), renewable energies accounted for 16.4 per cent of final energy consumption in the world in 2018. This is about 1 per cent more than in 1990 (15.5 per cent). However, during the same period, carbon emissions increased from 22.5 billion metric tons to 34.2 billion, a rise of 63 per cent (World Bank, 2019). Thus, even if the production of renewable energy has tremendously increased in the last 28 years (more than 200 times for wind and 500 times for solar), fossil fuel energy consumption has also dramatically increased due mainly to its relatively low costs and ease of operation during the same period (BP, 2018). The share of renewable energy in the world energy consumption is still far lower than the share of fossil fuels energy because of the relatively high cost and technological barriers to renewable energy production in many countries (Chen and Lei, 2018; Khan and al., 2020).

Understanding the relationship between green technology production and carbon emissions deserves further investigation for the following reasons. Firstly, some studies suggest that green technology can either increase or decrease carbon emissions under certain conditions (Jaffe et al., 2002; Acemoglu et al., 2009); these conditions are linked to different factors such as income and time. Secondly, the effect of environmental-related technology becomes uncertain in the long run due to the existence of the rebound effect. Thirdly, the impact of green technology on carbon emissions, especially in developing countries, is uncertain due to the lack of environmental regulations and a real cooperation policy of technological transfer with developed countries. The lack of environmental regulations can reduce the diffusion of green technology, resulting in a weak impact of green technology on carbon emissions (Cheng et al., 2019). Fourthly, some studies suggest that many countries have not reached a threshold that represents the level of green technology innovations necessary to start reducing CO2 emissions (Su and Moniba, 2017; Du, Li, and Yan, 2019; Cheng et al., 2019). For instance, despite the increased level of renewable energy consumption, the mitigating effect on CO2 emissions is limited due to the smaller proportion of renewable energy use in the energy mix (Su and Moniba, 2017). Fifthly, investigations of reverse causality from carbon emissions to green technologies are rare in the literature. This is important to investigate if carbon emissions have triggered different responses in terms of technological progress in groups of countries at different development stages.

Therefore, this chapter aims to examine the nature of the relationship between green technology and CO2 emissions and thus contribute to the overall academic debate. To do so, the following research objectives will be answered:

1) What is the impact of green technologies, demonstrated via two different proxies (environmental-related patents and renewable energy consumption) on carbon emissions?
2) Does this impact depend on the level of economic development? Or in other words, does the effect differ in different country income groups?
3) The reverse causality: How do carbon emissions and economic growth affect green and carbon-intensive technology adoption in different country income groups?

Chapter 4 implemented the same methodologies employed in chapter 3 to estimate the results: The fixed effect with Driscoll and Kraay standard errors (1998) and Bruno's (2005) biased-corrected LSDV methodology. The empirical analysis in chapter 4 is carried out on the same sample used in chapter 3. However, the lower-income countries subsample was excluded due to data availability. Thus, the dataset contains 45 countries divided into three groups according to their income level[20]. The study period runs from 1989 to 2018. It is expected that the relationship between green technology and carbon emissions may differ across different country income groups. This is due to differences in terms of financial capacity (Grossman and Krueger, 1995; Dinda and Coondoo, 2006), level of CO2 emissions specific to each group of countries (Hashmi and Alam, 2019), and the presence of stable political institutions and environmental regulations that are stronger and more enforced in some groups of countries than in others (Cheng et al., 2019). Therefore, a comparison of how green technology interacts with climate change in lower-middle, upper-middle, and high-income countries is conducted.

[20] Countries are allocated to their respective income group according to the World Bank classification of income per capita (Lower-middle, \$1026 to \$3995; Upper-middle income, \$3996 to \$12375; High income, \$12376 or more). To constitute our dataset, we have followed the sampling methodology used in the previous chapter.

This chapter contributes to the literature in the following three ways. Firstly, this study is one of the scarce studies that has analyzed the impact of green technologies on carbon emissions in different income-group countries.

Secondly, this chapter uses two indicators of green technology and examines their different impact on carbon emissions in each country's income group. In this chapter, green technology innovation (green patents) and renewable energy production are regarded as "two sides of the same coin," The latter needs to be complemented by the former for countries to fight against climate change successfully. The production of renewable energies can be regarded as a specific objective. Governments and private investors know that they have to invest in energy sources such as solar, wind, and hydro to obtain clean energy. But this is only the "first step." The "second step," which is more diffuse, would be to design or modify machines, devices, or processes predominantly created to be powered by fossil fuel energy and render them compatible with renewable energies. This second step aims to promote the transition from an industry model based on fossil fuel energies to a model based on renewable energies. This step also consists of manufacturing machines and devices that are more efficient, ecological, and less energy-consuming. The second step encompasses green technological innovation, which can be reflected by the number of environmentally-friendly patents recorded by every country each year (Gu et al., 2019). To successfully achieve carbon neutrality, we believe these two stages are linked and constitute "two sides of the same coin." The group of countries that invest massively in renewable energies and technological innovation is more able to reverse the carbon emissions curve. Therefore, this chapter investigates which countries perform better in renewable energy development and eco-friendly innovations.

Thirdly, chapter 4 examines the reverse causality: carbon emission to technology. The analysis in this chapter determines how CO2 emissions influence the development of green technology and carbon-intensive technology. Particularly, this chapter examines countries' reactions in terms of technology used when carbon emissions and GDP increase. How do countries react when carbon emissions and GDP increase? Do they invest in green technology or carbon-intensive technology? This will be interesting to assess, especially for developing countries. When carbon emissions and GDP increase, countries are expected to increase their investment in green technology to fight environmental degradation. This is often relatively easy for high-income countries since they possess the means and capacity to do so. But this is not always the case for lower-income countries, as these countries are often tempted to invest in carbon-intensive technology despite having growing GDPs and carbon emissions. Carbon-intensive technology is relatively cheaper and very widespread compared to green technology. Examining this issue would enable us to draw some important lessons for planning and adopting green energy policy, particularly in developing countries that will face increased energy demands during their development process.

The remainder of this chapter is structured as follows: Section II presents the theoretical model. The methodology and the data set are discussed in section III. In sections IV and V, the econometric results are presented and analyzed. Section VI concludes the chapter.

4.2. Theoretical Framework

The theoretical framework of chapter 4 is based on the following STIRPAT model:

$$\mathrm{lnI_{it}} = \beta_i + \theta \mathrm{lnP_{it}} + \alpha \mathrm{lnA_{it}} + \gamma \mathrm{lnT_{it}} + u_i + v_{it} \quad (1)$$

In equation (1), I represents carbon emissions. P denotes population, represented in this chapter by population density $(\mathrm{POP_{it}})$. A denotes affluence, represented by GDP per capita $(\mathrm{GDP_{it}})$, and T stands for technology represented by green technology $(\mathrm{GTECH_{it}})$. Equation (1) is augmented by adding Terms of trade $(\mathrm{TOT_{it}})$.

Therefore, the final version of our theoretical model can be written as:

$$\mathrm{lnI_{it}} = \beta_i + \theta \mathrm{lnPOP_{it}} + \alpha \mathrm{lnGDP_{it}} + \gamma \mathrm{lnGTECH_{it}} + \omega \mathrm{OTOT_{it}} + u_i + v_{it} \quad (2)$$

Figures 6 and 7 depict a two-way scatter plot of renewable energy and CO2 emissions – environmental patent and CO2 emissions. Figure 6 shows that, in general, lower-middle-income countries have the highest share of renewable energy consumption in total final energy consumption. Figure 7 shows that top emitter countries, mostly high-income countries, also tend to have the highest number of environmentally friendly innovations recorded.

Figure 6

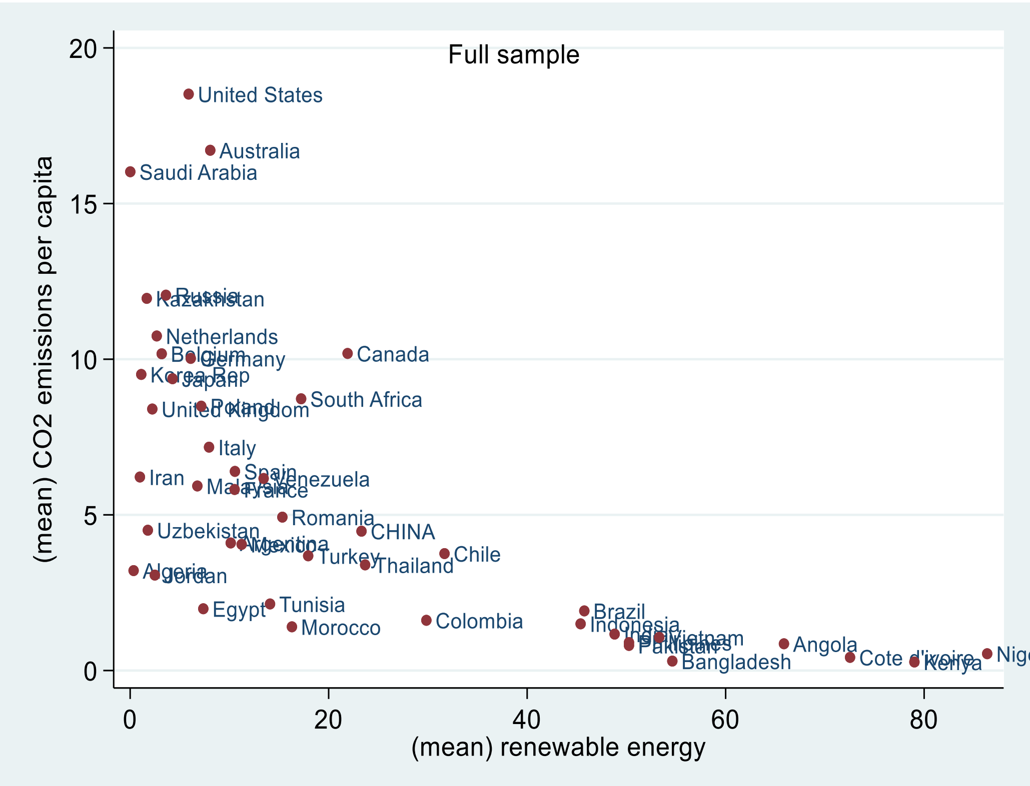


Figure 7

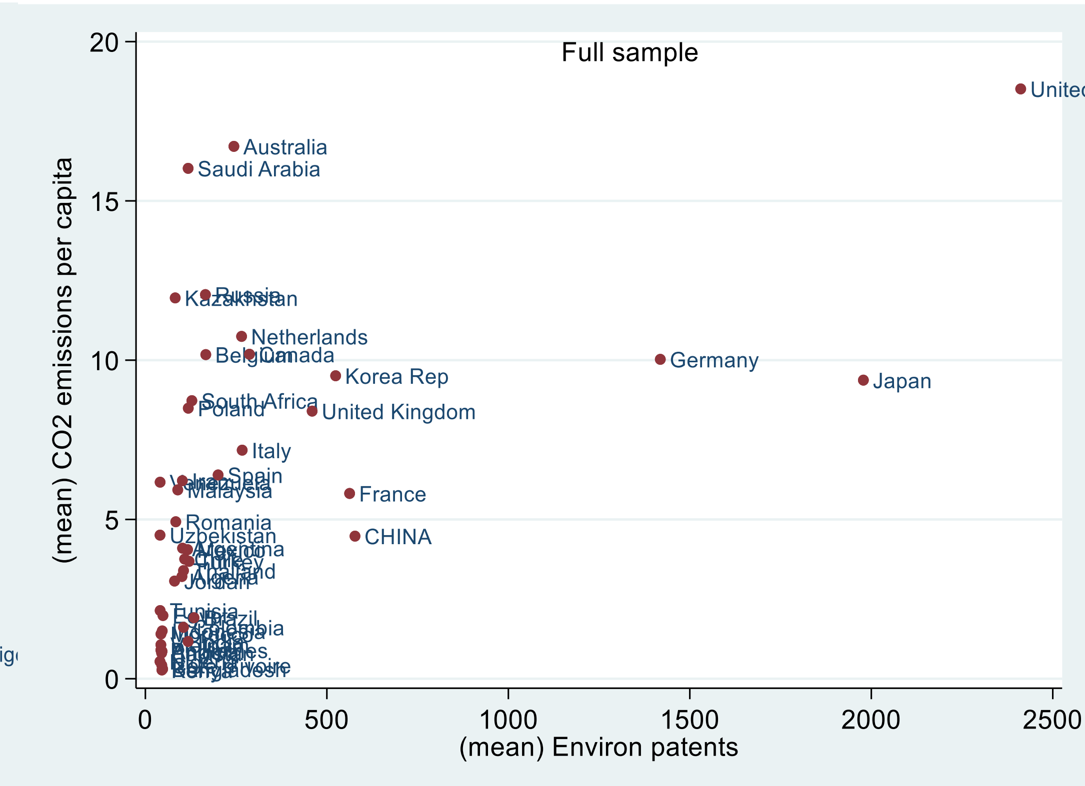


Figure 6. two-way scatter plot of renewable energy consumption (in percentage) and CO_2 emissions (in metric tons per capita).

Figure 7. two-way scatter plot of the number of environmental-related patents and CO_2 emissions.

Source: data used in this chart comes from the World Bank (2019) and the OECD (2020)

4.3. Methodology and Data

4.3.1. Empirical model

Three-panel models are established to estimate the interaction between carbon emissions and green technology. The first panel analyses the impact of green technology on CO2 emissions in the full sample and subsamples. The second model specification is a dynamic panel model, and it is used as a robustness check to verify the results found in the first-panel model. The third-panel model examines the reverse causality; in particular, this chapter analyses how variations in carbon emissions and GDP per capita affect technology adoption in different country income groups.

The first-panel model is specified as follows:

$$\ln CE_{it} = \beta_0 + \ln(GTECH)_{it}\beta_1 + X'_{it}\rho + Y_i + u_{i,t} \quad (3)$$

Where the subscripts i and t refer to countries and time. Y_i is the unobservable country-specific characteristics and $u_{i,t}$ is the i.i.d. disturbance terms. CE_{it} refers to carbon emissions in metric tons per capita. X'_{it} represents a vector of control variables, including GDP per capita, population and terms of trade. $GTECH_{it}$ represents green technology. More specifically, model (3) will be divided into two different sub-models, and each sub-model has its own indicator of green technology:

$$\ln CE_{it} = \beta_0 + \ln(REN)_{it}\beta_1 + X'_{it}\rho + Y_i + u_{i,t} \quad 3(a)$$
$$\ln CE_{it} = \beta_0 + \ln(EPAT)_{it}\beta_1 + X'_{it}\rho + Y_i + u_{i,t} \quad 3(b)$$

In this set of equations, REN_{it} refers to renewable energy consumption. $EPAT_{it}$ refers to environmental-related patents.

When analyzing the impact of green technology in different country income groups, the following submodel will be added to the results table to examine the effect of green technology innovation on CO2 emissions in very high-income countries:

$$\ln CE_{it} = \beta_0 + \ln(VEPAT)_{it}\beta_1 + X'_{it}\rho + Y_i + u_{i,t} \quad 3(c)$$

$VEPAT_{it}$ represent green patents in very high-income countries. Model (3b) and Model (3c) have the same composition in terms of dependent and explanatory variables. However, the sample dataset is different.

The purpose of sub-model (3c) is to investigate the impact of green innovation technology on carbon emissions, specifically in very high-income countries[21]. These are countries that have, on average, during our study period, a GDP per capita greater than 36000$. This distinction is purposely made because green innovation may have a different effect on carbon emissions in a specific income range. Each country is allocated to a particular income category following the World Bank classification of economies. Countries with a GDP per capita greater than 12500$ fall into the high-income category. It is logical to expect that green technology innovation may not have the same influence on CO2 emissions in a country with a GDP per capita of 15000$ compared to a country with a GDP per capita of 40000$, even if they both belong to the high-income category. Thus, we believe a simple distinction between high-income and very high-income countries will bring new insight into the analysis.

Our second empirical specification is a dynamic panel model with a first-order lag term for carbon emissions. The dynamic panel model is as follows:

$$\ln CE_{it} = \beta_0 + \beta_1 \ln CE_{it-1} + \ln(REN)_{it}\beta_2 + X'_{it}\rho + Y_i + u_{i,t} \qquad 4(a)$$

$$\ln CE_{it} = \beta_0 + \beta_1 \ln CE_{it-1} + \ln(EPAT)_{it}\beta_2 + X'_{it}\rho + Y_i + u_{i,t} \qquad 4(b)$$

$$\ln CE_{it} = \beta_0 + \beta_1 \ln CE_{it-1} + \ln(VEPAT)_{it}\beta_2 + X'_{it}\rho + Y_i + u_{i,t} \qquad 4(c)$$

Similar to model 3(c), here model 4(c) examines the relationship between green technology innovation and CO2 emissions only in very high-income countries.

The third-panel model examines the reverse causality from CO2 emissions to technology. The empirical framework of models (5a) and (5b) follows the approach of Sadorsky (2009), and Nguyen and Kakinaka (2019), in which the demand for renewable (5a) and non-renewable energy (5b) depends on real output per capita, oil price, and carbon emissions. Terms of trade and population density are added as additional explanatory variables in our model. In model (5b), this study uses non-renewable energy consumption as a proxy for carbon-intensive technology[22]. Like in previous models (3 and 4), renewable energy consumption is employed as an indicator of green technology development.

[21] Very high income countries include 10 countries: France, United Kingdom, Germany, United States, Netherlands, Canada, Japan, Australia, Italy, and Belgium. These countries have an average GDP per capita greater than 36000$ during our study period.

[22] The evolution of carbon intensive technology (such as number combustion engines vehicles, electricity generation from fossil fuel sources, etc.) has followed similar evolution of non-renewable energy consumption, which in our point of view, makes it a good proxy for carbon intensive technology. More non-renewable energy consumption is also an

The empirical model (5c) follows the approach of Hakimi and Inglezi-Lotz (2019), in which the innovation process, represented by aggregate patent applications, depends on GHG emissions, GDP growth, and population growth. This study uses green patent instead of aggregate patent as the dependent variable in model (5c). In addition to GDP and population, terms of trade and oil price have been added to the model. Oil price is included in model (3c) based on previous studies establishing a causal relationship between oil price and technological innovation (Cheon and Uperlainen, 2012; Guillouzouic-Le Corff, 2018). Cheon and Uperlainen (2012) note that higher oil prices strengthen existing sectoral innovation systems, both economically and politically, thus allowing public policymakers and the private sector to invest in technological innovations profitably. When oil prices increase, public enterprises and the private sector are encouraged to develop new technologies that reduce the cost of energy production (Cheon and Uperlainen, 2012). By regulation and spillover effect, the induced innovation may create the incentive to develop environmentally friendly technologies (Newel, et al., 1999).

Model (5) is established to answer the following question: Does carbon emissions influence the development of green technology and/or carbon-intensive technology? And how the trend to develop green technology and carbon-intensive technology is influenced by the level of carbon emissions in our three groups of countries. When carbon emissions and GDP increase, governments are expected to increase their investment in green technology to fight environmental degradation. This is often relatively easy for high-income countries since they possess the means and capacity to do so. But this is not always the case with low-income countries, as these countries are often tempted to invest in technology that accommodates non-renewable energy despite having growing GDPs and carbon emissions. Models (5) will investigate these hypotheses.

$$\ln REN_{it} = \beta_0 + \ln(CE)_{it}\beta_1 + \ln(GDP)_{it}\beta_2 + \ln(Oilp)_{it}\beta_3 + X'_{it}\rho + Y_i + u_{i,t} \quad (5a)$$

$$\ln NOREN_{it} = \beta_0 + \ln(CE)_{it}\beta_1 + \ln(GDP)_{it}\beta_2 + \ln(Oilp)_{it}\beta_3 + X'_{it}\rho + Y_i + u_{i,t} \quad (5b)$$

$$\ln EPAT_{it} = \beta_0 + \ln(CE)_{it}\beta_1 + \ln(GDP)_{it}\beta_2 + \ln(Oilp)_{it}\beta_3 + X'_{it}\rho + Y_i + u_{i,t} \quad (5c)$$

In the above models, $NOREN_{it}$ represents non-renewable energy consumption, which can also be seen as an indicator of carbon-intensive technology. GDP_{it} refers to GDP per capita. $Oilp_{it}$ refers to the oil price, representing the price of renewable and non-renewable energy. Conversely to the work of Sadorsky (2009)

indication that an economy as a whole invest more in technologies that are fossil-fuel friendly than green energy friendly.

and Nguyen and Kakinaka (2019), the study uses average fuel-pump prices (GIZ data, 2021) instead of a general crude oil price applied to all countries as a proxy for energy price. Fuel-pump price is an end-user price, and it is more specific and realistic in the sense that it reflects the final oil price that consumers face in each country. Oil price is used as a relative price of renewable energy because clean energy contains various energy sources such as hydro, solar, wind, geothermal, and waves, so it is generally difficult to identify the exact price. Although we recognize this issue, we consider oil price as a direct determinant of fossil fuel energy consumption and an indirect determinant of variation in renewable energy consumption. In this regard, it can be expected that an increase in oil price would reduce fossil fuel energy consumption, resulting in higher demand for renewable energy. X_{it} represents two additional regressors: population density and terms of trade.

4.3.2. Econometric methodology

This chapter applies the same mythology used in the previous chapter to estimate the results. The fixed-effect method with Driscoll and Kraay's standards errors is implemented to estimate empirical models (3) and (5). Following the consolidated literature on dynamic panel data models (Kiviet, 1995, 1999; Blundell and Bond, 1998; Bun and Kiviet; 2003, Bruno, 2005), the Bruno’s (2005) biased-corrected LSDV methodology is applied to estimate model specification (4).

4.3.3. Data

This chapter compiles an unbalanced panel dataset covering 45 economies. The data comprises 15 high-income, 15 upper-middle-income, and 15 lower-middle-income countries. The study period runs from 1989 to 2018. This chapter follows the sampling methodology used in the third chapter to constitute the dataset. The study followed the World Bank country classification by income (World Bank, 2020) and selected 15 countries in each income group (high-income, upper-middle-income, and lower-middle-income). The 15 countries chosen per income group are the largest CO2 emitters in their respective income groups.

The variables used in this chapter were collected from different sources. Table 12 shows the descriptions and sources of the data collected. Descriptive statistics for the full sample are presented in table 13.

Table 12. Variables sources and descriptions

Variables	Description	Sources
$\ln CE_{it}$	Carbon dioxide emissions in metric tons per capita. CO2 emissions include the combustion of fossil fuels for electricity generation and heat production (in industries, households, etc.), transportation, and the industrial process, including the manufacture of cement.	WDI (World Bank, 2019)
$\ln REN_{it}$	Renewable energy consumption represents the share of renewable energy in total final energy consumption.	WDI (World Bank, 2019)
$\ln EPAT_{it}$	Environmentally related patents.	OECD (2020)
$\ln NOREN_{it}$	Non-Renewable energy consumption represents the share of fossil fuel energy in total final energy consumption. Fossil fuel comprises coal, oil, petroleum, and natural gas products.	WDI (World Bank, 2019)
$\ln Oilp_{it}$	End-user fuel price in Constant \$. Price of Gasoline 95 octane at petrol stations	GIZ (2018)
$\ln GDP_{it}$	Per capita real gross domestic product in 2010 constant US\$ term.	WDI (World Bank, 2019)
$\ln TOT_{it}$	Terms of Trade (Exports/Imports) in 2010 constant US\$ term	WDI (World Bank, 2019)
$\ln POP_{it}$	Population density per square kilometres	WDI (World Bank, 2019)

Note: all variables are in natural log.

Table 13. Descriptive statistic: full sample

Variables	Observations	Mean	Stand dev	Min	Max
CO2 emissions	1,327	5.647408	4.763908	.133613	20.17875
GDP per capita	1,348	14275.46	16080.63	398.8521	56842.3
Population	1,339	140.9964	184.8893	2.18872	1239.579
Ren. Energy	1,215	22.06828	23.81995	.0059765	88.83185
Env. Patent	1,305	191.6641	624.5274	0	6080.3
Non-renew	1,215	76.80319	21.85675	12.99901	99.99678
Terms of trade	1,283	120.5126	88.73144	39.6998	391.8637

4.4. Empirical results and discussions

4.4.1. Diagnostic testing

Before carrying out estimations, several statistical tests are conducted to ensure the dataset meets the required assumptions and conditions for each model selected. Problems such as serial correlation, heteroscedasticity, and cross-sectional correlation may arise when using panel data. Table 14 summarizes the diagnostic test results for the full and high-income countries samples. Breusch-Pagan's (1980) LM-test and Wald tests confirm the presence of panel effect in the models. The significant p-values from the Wooldridge test and the Pesaran cross-sectional dependence (CD) test indicate the presence of serial correlation and cross-sectional dependence, respectively. The p-value from the Wald test for GroupWise heteroscedasticity is significant, meaning that error term variances vary with explanatory variables in all models specification. In summary, the dataset suffers from heteroscedasticity, serial correlation, and cross-sectional dependence. Therefore, the fixed effect methodology with Driscoll and Kraay standards errors, which is the method proposed in this chapter, turns out to be appropriate for estimating the results.

Table 14. Diagnostic test: serial correlation, heteroscedasticity, cross-sectional dependence, time fixed effect, and panel effect.

			Full sample		
	Model (3a)	Model (3b)	Model (5a)	Model (5b)	Model (5c)
	Statistic	Statistic	Statistic	Statistic	Statistic
Serial correlation	22.19 0.000***	134.9 0.000***	83.19 0.000***	92.01 0.000***	10.734 0.002***
Heteroskedasticity	9348 0.000***	8153 0.000***	27535 0.000***	91548 0.000***	2353.11 0.000***
Pesaran CD	12.71 0.000***	7.251 0.000***	0.011 0.971	-0.423 0.7863	0.1578 0.456
Time fixed effect	0.264 1.000	0.894 0.626	0.472 0.803	0.406 1.000	1.012 0.331
Panel effect	334.3 0.000***	264.1 0.000***	545.1 0.000***	630.35 0.000***	69.5 0.000***
			High-income sample		
	Model (3a)	Model (3b)	Model (5a)	Model (5b)	Model (5c)
	Statistic	Statistic	Statistic	Statistic	Statistic
Serial correlation	8.224 0.012**	93.484 0.000***	47.18 0.000***	17.15 0.000***	10.916 0.005***
Heteroskedasticity	558.29 0.000***	1488.5 0.000***	466.2 0.000***	3101 0.000***	386.07 0.000***
Pesaran CD	10.703 0.000***	5.989 0.000***	33.05 0.000***	-1.897 0.0632*	8.882 0.000***
Time fixed effect	0.280 1.000	0.843 0.698	1.799 0.043**	0.834 0.585	2.337 0.000***
Panel effect	228.60 0.000***	226.45 0.000***	502.4 0.000***	376.1 0.000***	92.91 0.000*

Notes: *(**) [***] indicate rejection of the null hypothesis at a 10(5)[1] % level

4.4.2. Panel unit root test and cointegration

The Im, Pesaran, and Shin (2003) (IPS) and the Maddala-Wu (1999) tests are performed to determine which variables in the data are stationary and which are non-stationary. These two tests are performed because they assumed individual unit root processes for each variable in the empirical models, thus better suited for detecting cross-section heterogeneity in the dataset (Baltagi, 2008). Besides, unlike other unit root tests (such as the Levin-Lin-Chu, and the Harris-Tzavalis), the IPS and Maddala-Wu tests do not require a strongly balanced panel. Table 15 displays unit root test results. In the full sample, per capita GDP, renewable energy, and population density are not stationary, while all other variables are stationary. In the high-income group, CO2 emissions and environmental-related patents are stationary, while all other variables are nonstationary. Unit root test results are more or less similar for other subsamples (upper-middle-income and lower-middle-income countries). Consequently, cointegration tests are necessary to avoid spurious relationships when estimating regressions with non-stationary variables.

Table 15. IPS and Maddala-Wu unit root tests.

Full sample				
Variables	IPS		Maddala-Wu	
	No trend	With Trend	No trend	With Trend
$\ln CE_{it}$	3.7398	3.3439***	129.162***	100.817***
$\ln GDP_{it}$	2.1258	1.7564	47.4603	69.7991
$\ln REN_{it}$	2.0811	-5.1772	96.1296	99.2384
$\ln EPAT_{it}$	-9.7724***	-14.234***	387.291***	572.501***
$\ln Oilp_{it}$	1.8098	-1.9187	11.5311	18.8083
$\ln NOREN_{it}$	-1.5957*	-5.4682***	175.059***	143.879***
$\ln POP_{it}$	9.3182	4.3708	1.12001	1.00833
$\ln TOT_{it}$	0.8517	2.4186**	146.199***	147.364***
High-income sample				
Variables	IPS		Maddala-Wu	
	No trend	With Trend	No trend	With Trend
$\ln CE_{it}$	0.6773	-2.1709**	43.5856**	30.9711
$\ln GDP_{it}$	-0.2042	0.2215	34.3996	19.7541
$\ln REN_{it}$	2.2296	-2.6096***	21.7381	26.6298
$\ln EPAT_{it}$	-4.4290***	-6.3489***	104.180***	143.969***
$\ln Oilp_{it}$	1.8098	-1.9187	11.5311	18.8083
$\ln NOREN_{it}$	4.1973	-0.3212	23.2239	23.2283
$\ln POP_{it}$	1.0146	0.7689	222.873***	36.3132
$\ln TOT_{it}$	0.9944	-1.8555**	19.9640	28.1836

Notes: P-values are in parenthesis. *(**) [***] indicate rejection of the null hypothesis of a unit root at a 10(5)[1] % level.

The cointegration test is performed by using the Westerlund (2005), Pedroni (1999, 2004), and Kao (1999) tests. The Kao and Pedroni tests verify the alternative hypothesis that the variables are cointegrated in all panels, while the Westerlund test verifies the hypothesis that the variables are cointegrated in some or all panels. Cointegration results are presented in Table 16. In the full sample, except for the Dickey-Fuller statistic in panel models (3b) and (5a) and the variance ratio in model (3a), all other statistics are statistically significant, at least at a 10% level. In the high-income sample, the modified Phillips-Perron statistic is insignificant in models (3a) and (5a), but all other statistics are significant at conventional levels of significance. Thus, there is a long-run cointegration relationship in all sample models[23].

Table 16. Cointegration tests results

Full sample					
Cointegration test	Model 3(a)	Model 3(b)	Model 5(a)	Model 5(b)	Model 5(c)
	Statistic	Statistic	Statistic	Statistic	Statistic
Kao test					
Modified Dickey-Fuller t	-1.7473***	1.1883*	-1.3903*	-6.5345***	-1.9914*
Dickey-Fuller t	-1.9149**	0.5027	-1.1461	-5.4770***	-3.6198***
Augmented Dickey-Fuller t	-1.0909*	1.7327**	1.4312*	-5.0021***	1.8431**
Unadjusted modified Dickey-Fuller t	-1.9360**	-1.4778*	-4.6603***	-8.0231***	-7.1113***
Unadjusted Dickey-Fuller t	-2.0236**	-1.5376*	-3.1333***	-6.0135***	-6.2538***
Westerlund test for cointegration					
	Statistic	Statistic	Statistic	Statistic	
Variance ratio	-1.1725	-1.6589**	-3.4502***	-2.6398***	-2.5987***
Pedroni test for cointegration					
	Statistic	Statistic	Statistic	Statistic	
Modified Phillips-Perron	1.9420**	1.6592**	1.9706**	2.3693*	2.3225*
Phillips-Perron t	-6.7723***	-5.1598***	-4.6190***	-3.3583***	-2.6342*
Augmented Dickey-Fuller t	-4.3395***	-3.8971***	-4.2255***	-3.1507***	-3.2659***
High-income sample					
Cointegration test	Model 3(a)	Model 3(b)	Model 5(a)	Model 5(b)	Model 5(c)
	Statistic	Statistic	Statistic	Statistic	Statistic
Kao test					
Modified Dickey-Fuller t	-1.6772***	1.1654*	-1.2084*	-5.2358***	-0.8924
Dickey-Fuller t	-1.8952**	0.4521	-1.1056	-5.8796***	-0.9151
Augmented Dickey-Fuller t	-1.1257*	1.1986*	1.4584*	-5.0653***	1.6485**
Unadjusted modified Dickey-Fuller t	-1.7986**	-1.4546*	-4.5089***	-6.1154***	-2.3502***
Unadjusted Dickey-Fuller t	-2.0236**	-1.5376*	-3.1333***	-6.0135***	-1.7354***
Westerlund test for cointegration					
	Statistic	Statistic	Statistic	Statistic	
Variance ratio	-2.2520**	1.3396*	-1.4577*	-2.6727***	1.6154*
Pedroni test for cointegration					
	Statistic	Statistic	Statistic	Statistic	

[23] Other samples cointegration tests (upper-middle and lower-middle-income samples) also exhibit similar results. Tests tables can be found in the appendix.

Modified Phillips-Perron	0.5853	1.4634*	1.1552	1.7878**	1.6291*
Phillips-Perron t	-4.3750***	-1.6015**	-3.0137***	-1.8351***	-2.0231**
Augmented Dickey-Fuller t	-4.0094***	-1.2839*	-3.8387***	-1.3705*	-0.1538

*(**) [***] indicate rejection of the null hypothesis of no cointegration at a 10(5) [1] % level.

4.4.3. Dumitrescu Hurlin causality test

The Dumitrescu and Hurlin (2012) Granger causality test is employed to verify the causal relationship among panel variables in models (3) and (5). Table 17 reports the Dumitrescu Hurlin causality test results for the full sample. Due to the unbalancedness of our dataset, the study period is restricted from 1999 to 2018. A prerequisite for performing the Ganger Causality test is that the data need to be stationary. The non-stationary series were differenced once before performing the test. Results show that all explanatory variables included in the model (3) and (5) granger cause their respective dependent variables.

Table 17. Dumitrescu Hurlin causality test

Full sample			
Sample: 1999-2018	W-bar	Z-bar	Prob
H0: Variable does not Granger-cause $\ln CE_{it}$ (Model 3a and 3b)			
$\ln REN_{it}$	2.7736	8.4131	0.0000***
$\ln EPAT_{it}$	1.5133	2.4350	0.0149**
$\ln GDP_{it}$	5.1718	19.788	0.0000***
$\ln POP_{it}$	4.6346	17.240	0.0000***
$\ln TOT_{it}$	2.2802	6.0726	0.0034***
H0: Variable does not Granger-cause $\ln REN_{it}$ (Model 5a)			
$\ln CE_{it}$	3.7165	12.885	0.0000***
$\ln GDP_{it}$	2.5852	7.5193	0.0000***
$\ln POP_{it}$	3.4481	11.612	0.0000***
$\ln Oilp_{it}$	2.8963	8.1254	0.0000***
$\ln TOT_{it}$	1.6183	2.9331	0.0034***
H0: Variable does not Granger-cause $\ln NOREN_{it}$. (Model 5b)			
$\ln CE_{it}$	3.3566	11.178	0.0000***
$\ln GDP_{it}$	2.7892	8.4867	0.0000***
$\ln POP_{it}$	4.0651	14.538	0.0000***
$\ln Oilp_{it}$	3.8523	11.589	0.0000***
$\ln TOT_{it}$	1.6327	3.0013	0.0027***
H0: Variable does not Granger-cause $\ln EPAT_{it}$. (Model 5c)			
$\ln CE_{it}$	2.0015	4.7503	0.0000***
$\ln GDP_{it}$	2.4172	6.7224	0.0000***
$\ln POP_{it}$	3.5485	12.0887	0.0000***
$\ln Oilp_{it}$	4.2549	4.6155	0.0012***
$\ln TOT_{it}$	3.4861	5.9534	0.0000***

*(**) [***] indicate rejection of the null hypothesis of no cointegration at a 10(5) [1] % level

4.5. Full sample and subsample analysis

Full sample and subsamples results and discussions are presented in this section. This chapter applies two methods for estimating the regression results: the fixed-effect method with Driscoll and Kraay standard errors and the Bruno LSDVC corrector for robustness check. Our preferred model will be the fixed effect with Driscoll and Kraay standard errors because these standard errors are unbiased and robust in the presence of serial correlation, cross-sectional dependence, and heteroscedasticity in the dataset (Hoechle, 2007).

The section is divided into three subsections. The first subsection examines the relationship between green technology and carbon emissions in the full sample. The study evaluates if the trend in CO2 emissions is responsive to two indicators of green technology: renewable energy and environmental-related patents. The same relationship is analyzed in the second subsection in the different country income groups. Finally, in the third subsection, the study investigates the reverse causality, which is the causality from CO2 emissions to technology.

4.5.1. Full sample analysis

Table 18 presents the full sample results. Overall, results show that renewable energy consumption reduces carbon emissions in both fixed effect and Bruno LSDVC results. The estimated coefficient on $\ln(\mathrm{REN})_{\mathrm{it}}$ is -0.08 in fixed effect, which indicates that a 1 per cent increase in renewable energy consumption decreases carbon emissions by 0.08 per cent, ceteris paribus. The full sample results also show that green technology innovations, represented by green patent applications, do not clearly impact carbon emissions. The result in Model (3b) shows that the coefficient on $\ln(\mathrm{EPAT})_{\mathrm{it}}$ is estimated as 0.009 in fixed effect and 0.004 in Bruno LSDVC. They are both insignificant at the 10% level. Overall, this suggests that we could not find evidence supporting that green technology innovations can effectively curb CO2 emissions in the full sample.

Table 18. Full sample results estimation

Dependent variable: CO2 emissions				
	Fixed effect		LSDVC	
	model (3a)	model (3b)	model (3a)	model (3b)
$\ln(\mathrm{CE})_{\mathrm{it-1}}$			.407745*** (3.84)	.60248*** (6.31)
$\ln(\mathrm{REN})_{\mathrm{it}}$	-.08030*** (-9.61)		-.03429* (-1.97)	
$\ln(\mathrm{EPAT})_{\mathrm{it}}$		.009118 (1.56)		.004835 (1.57)
$\ln\mathrm{GDP}_{\mathrm{it}}$	.55323***	.51069***	.047171	.18784*

	(19.35)	(13.27)	(0.42)	(1.79)
$\ln POP_{it}$	.36595*** (4.25)	.18543*** (1.77)	.38560** (2.57)	.216233 (0.93)
$\ln TOT_{it}$	.06727** (2.35)	.04218 (0.74)	-.00026 (-0.61)	-.05166 (-1.12)
Constant	-4.9993*** (-11.61)	-4.1089*** (-9.90)		
F-test	218.14 (0.000)	89.35 (0.000)	50.87 (0.000)	32.16 (0.000)
Observations	1350	1350	1350	1350
Groups	45	45	45	45

Standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

The coefficient on the lagged dependent variable is positive and statistically significant, confirming that the present value of CO2 emissions is also affected by its past values. Regarding other core drivers of carbon emissions, the results show that GDP per capita, population density, and terms of trade have a positive and statistically significant impact on carbon emissions in both fixed effect and Bruno LSDVC results. These results are consistent with most of the literature that has found a positive relationship between these variables and carbon emissions (see Hu et al., 2005; Wang, 2007; Clarke et al., 2008; Allen, 2012; Bhattacharya et al., 2015).

4.5.2. Subsample analysis

Tables 19 and 20 present the subsample empirical results. Estimated results reveal that renewable energy consumption is negatively associated with carbon emissions in all three groups of countries. A 1 per cent increase in renewable energy consumption decreases carbon emissions by 0.21 per cent in high-income countries, 0.26 per cent in upper-middle-income countries, and 0.36 per cent in lower-middle-income countries. Similar to the full sample results, coefficients on environmental-related patents are positive but statistically insignificant in all three groups of countries. Model (3c) is introduced to investigate the environmental patent coefficient sign further. The purpose of model (3c) is to verify if environmental-related patents will have a different impact on CO2 emissions in very high-income countries compared to high-income countries. Very high-income economies consist of 10 countries with an average per capita income of 36000$ during our study period. Results show that the coefficient on green patents turns out to be negative and statistically significant at a 5 per cent level. These results are similar to those found by Du, Li, and Yan (2019).

Table 19. Subsample results estimation

Dependent variable: Ln CO2 emissions							
Fixed effect with Driscoll and Kraay							
	High income			Upper-middle income		Lower-middle income	
	Model (3a)	Model (3b)	Model (3c)	Model (3a)	Model (3b)	Model (3a)	Model (3b)
$\ln(CE)_{it-1}$							
$\ln(REN)_{it}$	-.2122*** (-16.98)			-.2636** (-6.62)		-.3661*** (-14.68)	
$\ln(EPAT)_{it}$		.0092 (1.08)			-.0196 (-0.82)		.0124 (1.12)
$\ln(VEPAT)_{it}$			-.0217* (-1.96)				
$\ln GDP_{it}$	.5263*** (6.35)	.2436** (2.79)	-.0231 (-0.73)	.4918*** (12.13)	.5915*** (7.46)	.6293*** (12.13)	.7990*** (6.41)
$\ln POP_{it}$	-.1312 (-0.61)	-.4471* (-1.76)	-.2688 (-0.62)	.1498*** (4.67)	.5912** (2.85)	.0296 (0.26)	-.1042 (-0.36)
$\ln TOT_{it}$	0.044 (0.79)	-.1651* (-1.71)	-.2271*** (-3.32)	.0988* (1.92)	.0933* (1.89)	0.0492* (1.96)	.0336 (0.54)
Constant	-2.350*** (-4.06)	2.407* (2.10)	4.913*** (7.18)	-3.294*** (-5.60)	-6.244*** (-4.74)	-1.307** (-2.26)	-5.42*** (-4.97)
F-test	123.48 (0.000)	16.76 (0.000)	14.49 (0.000)	217.32 (0.000)	80.74 (0.000)	338.23 (0.000)	59.58 (0.000)
Observations	450	450	450	450	450	450	450
Groups	15	15	8	15	15	15	15

Note: Driscoll and Kraay Standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

In general, results suggest that green technology innovations, represented in this chapter by environmentally-friendly patents, significantly contribute to carbon reduction only in very high-income countries. In the introduction, we described the production of renewable energies and the development of green innovation technologies as "two sides of the same coin," arguing that their complementarity would allow a country or a group of countries to achieve carbon neutrality more quickly (IRENA, 2019). This chapter's results show that during our study period, only countries with a very high income seem to be on the right track to achieving the complementarity so necessary to reduce CO2 emissions. However, given the low magnitude of the green patents coefficient, we can assume that there is still a lot of effort to be made in terms of green investment and policy incentives in this area, even for these very high-income countries.

Regarding other countries, the level of innovation in green technology seems to have not yet reached a point that allows a significant reduction of carbon emissions. This does not mean that green technology innovations are not present or valuable. It means that they are simply not produced in sufficient quantity to slow down the CO2 emissions curve. The level of green innovation needed to combat global warming is very subjective and depends on one country or group of countries to another. For example, the amount of eco-friendly innovation produced in very high-income countries may not be sufficient for upper-middle-income economies. Therefore, it is important to take into account the characteristics of each country or group of countries to understand the underlying reasons that do not allow better promotion of green technology innovations[24].

Five main reasons can explain the differences in results between the very high-income and upper-middle and lower-middle-income groups. Firstly, environmental issues do not have the same priority in high and low-income countries. In low-income countries, governments and economic actors face more pressing and vital challenges for their people (Akinlo, 2008; Antonakakis, Loannis, Filis, 2017; Adom, 2019). These include poverty, unemployment, infrastructure, and lack of energy. The problems related to the development of green technologies, which will allow the attainment of sustainable development, are instead seen as distant problems which will be solved once an acceptable level of per capita income is reached (Antonakakis, Loannis, Filis, 2017). Secondly, green technology state subsidies are far greater in high-income countries than in lower-income countries. In high-income countries, the government and the financial system support small and medium enterprises, and even individuals, in a common effort to develop and expand the utilization of green technologies and renewable energies (Boutabba, 2014; Kim and Park, 2016). This is critical for industries and companies involved in developing these technologies since producing environmentally friendly technologies is a relatively new field and requires significant financial resources compared to carbon-intensive technologies. According to the International Renewable Energy Agency (IRENA, 2019), the estimated subsidy for renewable energy worldwide was around USD 166 billion in 2017. Subsidies for the generation of renewable energies amounted to 128 billion, and subsidies for transport to

[24] As it can be observed from the patents graph (figure 7), the 10 countries, which are classified in this study as "very high-income countries", have the highest number of patents. The estimations results show that this increasing quantity of green patents coincides with a mitigation of carbon emissions. The quantity of green patents is also indicative of the efforts put in terms of investment in R&D in green technology innovation (Gu et al., 2019). Another aspect which certainly plays an important role in reducing carbon emissions, but which can hardly be proven, is the quality of green technology inventions represented by these patents. It is not enough to have a large number of patents but it is also necessary that these patents are sufficiently valuable to bring a good contribution in reducing the level CO2 emissions (Hall, Jaffe and Trajtenberg, 2005). In view of the results, it seems that high quality inventions are developed in these 10 countries.

38 billion. The European Union constituted 54 per cent of the total share of renewable energy subsidies in 2017, followed by China, with 14 % (23 billion), Japan with 11% (19 billion), the United States with 9 % (16 billion), India with 2 % (4 billion) and the rest of the world with slightly less than 9% (15 billion). These figures show that developing countries still have a long way to go in terms of green technology subsidies.

Thirdly, there is a large difference in the transfer of technology and human resources between high-income countries and other countries (Fu, Kok, Dankbaar, Ligthart, and Van, 2018). Creating green technologies requires a well-qualified workforce capable of producing eco-friendly products and absorbing cutting-edge technological knowledge from the rest of the world. There is often a deficit of high-skilled workers in low-income countries compared to developed countries. In addition, low-income countries are often victims of brain drain, which may hinder the development of local green industries (Docquier, Lohest, and Marfouk 2007; Varma and Kapur2013). According to a joint paper released by the OECD, World Bank, and ILO (2015), the number of highly skilled migrants coming to work in Europe has constantly increased in recent years. In 2010-2011, nearly a fifth of highly skilled migrants came from developing countries like China, India, and the Philippines (Bailey and Clara H. Mulder, 2017).

Table 20. Subsample results estimation (renewable energy and green patents)

Bruno LSDVC							
	High income			Upper-middle income		Lower-middle income	
	Model (3a)	Model (3b)	Model (3c)	Model (3a)	Model (3b)	Model (3a)	Model (3b)
$\ln(CE)_{it-1}$	.7635*** (24.45)	.9231*** (325.1)		.8030*** (24.16)	.8797*** (35.29)	.7905*** (20.16)	.7861*** (17.39)
$\ln(REN)_{it}$	-.0576*** (-20.40)			-.0326*** (-4.27)		-.1933*** (-3.62)	
$\ln(EPAT)_{it}$		-.0139 (1.45)			.0070 (0.42)		.0073 (1.15)
$\ln(VEPAT)_{it} \times D_1$			-.0147** (-2.25)				
$\ln GDP_{it}$	.1536*** (23.68)	.1012*** (32.24)	-.0845 (-1.44)	.1234*** (8.05)	.0331*** (5.13)	.1230*** (5.30)	.1968*** (3.27)
$\ln POP_{it}$	-.1575*** (-13.42)	-.1073*** (-3.71)	.0088 (0.23)	.0345*** (11.02)	.0225 (0.12)	-.0412 (-1.30)	-.1360 (-1.23)
$\ln TOT_{it}$	-.0172*** (-5.38)	-.0115* (-1.66)	-.0225** (-2.26)	-.0095 (-0.44)	-.0357 (1.06)	.0176* (1.69)	.0134 (0.45)
Groups	15	15	8	15	15	15	15

Standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

Fourthly, trade integration and transfer of technologies are much higher in high-income countries than in low-income countries (Ertugrul, Cetin, Dogan, & Seker, 2016). Despite being the biggest consumers of fossil fuel energy, high-income countries also export more green-friendly products than other countries. They easily exchange amongst themselves and adopt green technologies since they are part of organizations where regional cooperation and the free trade regime are fully implemented. Developed countries have gradually put in place and imposed stringent and more environmentally friendly regulations. Therefore, countries that export their products to high-income countries ensure that their goods comply with environmental regulations. Fifthly, there is better tracking in enforcing environmental laws in high-income countries than in low-income countries (Hertin & Berkhout, 2005). Environmental regulations are laws that are designed to protect the environment. They also aim to promote the design, the production, the distribution, and the use of products with less environmental impact throughout their life cycle; and better inform consumers about the environmental impacts of products (Green peace, 2018). In Europe, bodies designated by the EU (such as the Scientific Committee for Consumer Safety, CSSC) monitor whether manufacturers have incorporated environmental characteristics into the product's design to improve the product's environmental performance throughout its life cycle. From lighting products (fluorescent lamps) to household appliances, the production processes of various devices must integrate environmental characteristics.

The five reasons mentioned above provide some answers to explain why developing countries are less advanced in developing green technology. It can be expected that developing countries will probably beneficiate from technology spillover from very high-income countries. But even when this happens, it will be essential for developing countries to develop a good absorptive capacity that will allow them to acquire and use external green technology (Liu and Guo, 2019). Undeniably, some developing countries are making significant advances in eco-friendly innovations (e.g., China or Brazil). But they are still far from being able to guarantee the achievement of carbon neutrality in the decades to come (Green Peace, 2018).

4.5.3. Reverse causality analysis

This subsection presents the results of the "reverse causality," which is how the increase in CO2 emissions and other factors influence the adoption of green technology represented by renewable energy and environmental patent and the adoption of carbon-intensive technology represented by non-renewable energy consumption. Table 21 shows the estimated long-run elasticities of renewable energy (model 5a), non-renewable energy (model 5b), and environmental patent (model 5c) with regard to carbon emissions, real income per capita, oil price, population density, and terms of trade for each of the three income groups.

Regarding the high-income group, renewable energy is negatively associated with carbon emissions but positively associated with GDP per capita, oil price, and terms of trade, while non-renewable energy is positively associated with carbon emissions and negatively related to GDP per capita, oil price, terms of trade, and population density. Similar to Nguyen and Kakinaka's (2019) findings, the large coefficients of carbon emissions in model (5a) compare to model (5b) suggest that renewable energy is more sensitive to carbon emissions than non-renewable energy. The coefficient on carbon emissions in model (5c) is positive and statistically significant at a 1 per cent level. This means that an increase in carbon emissions triggers a positive and significant response of climate-related patents in high-income countries.

Concerning the upper-middle-income group, renewable energy has a negative relationship with CO2 emissions but a positive relationship with GDP per capita, oil price, and terms of trade, while non-renewable energy positively correlates with carbon emissions and population density. The relationship between non-renewable energy and GDP is negative and significant at 5 per cent level. The magnitude of the coefficient on carbon emissions shows that renewable energy is more sensitive to variations in carbon emissions than non-renewable energy. Findings in model (5c) suggest that carbon emissions do not significantly affect climate-related patents in upper-middle-income countries.

Figure 8. A plot of average values of renewable energy consumption, non-renewable energy consumption, GDP per capita, and CO2 emissions from 1989 to 2015

Figure 8.1

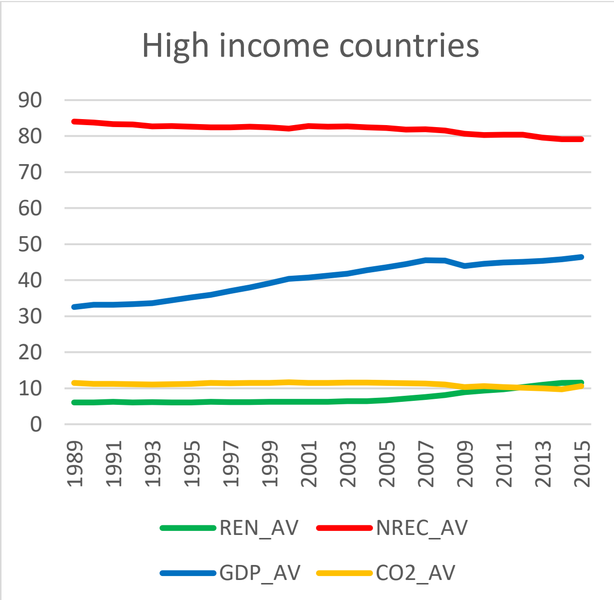


Figure 8.2

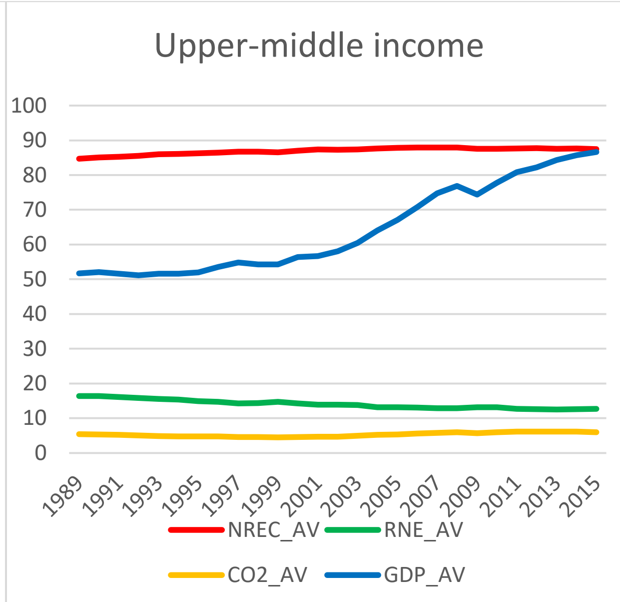
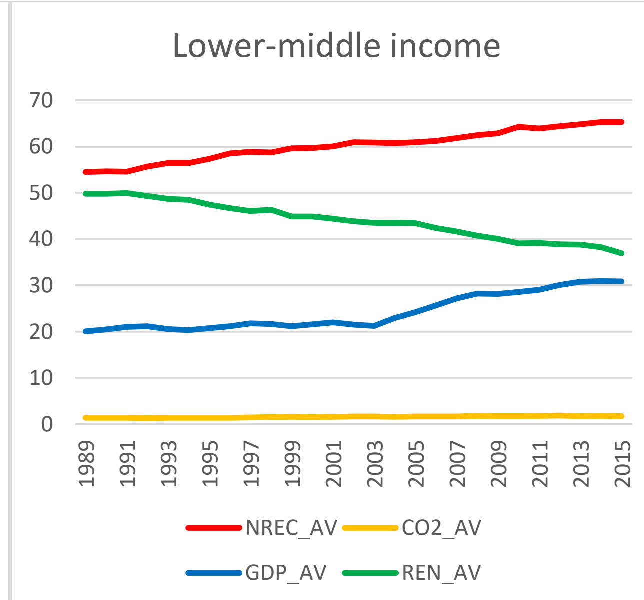


Figure 8.3



Source: data used in these graphs are from the World Bank (2019)

Graphs are used to understand better the coefficient signs of CO2 emissions and GDP per capita in table 21. The study plots average values of four variables[25]: Average renewable energy consumption (REN_AV), average nonrenewable energy consumption (NREC_AV), average GDP per capita (GDP_AV), and average carbon emissions per capita (CO2_AV). Note that, to have a standard scale, the average value of GDP per capita has been divided by 100 in the upper-middle and lower-middle-income figures; and by 1000 in the high-income figure.

[25] For instance, to obtain the average value of renewable energy consumption (REN_AV) for 2005, we sum up renewable energy consumption for that particular year (2005), for all 15 countries and we divide by 15.

Concerning the lower-middle-income group, results show that renewable energy consumption is negatively related to GDP per capita, while non-renewable energy consumption is positively related to GDP per capita and carbon emissions. The relationship between renewable energy and CO2 emissions is negative but not statistically significant at the conventional level of significance. The carbon emissions variable has a positive but no statistically significant coefficient in model (5c), indicating that climate-related technology does not vary with changes in carbon emissions in lower-middle-income countries.

Table 21. Reverse causality analysis

Fixed effect with Driscoll and Kraay									
Dependent variable: (5a) renewable energy, (5b) nonrenewable energy, (5c): environmental-related patents									
	High income			Upper-middle income			Lower-middle income		
	Model (5a)	Model (5b)	Model (5c)	Model (5a)	Model (5b)	Model (5c)	Model (5a)	Model (5b)	Model (5c)
$\ln(CE)_{it}$	-1.667*** (-14.81)	.1542*** (9.87)	.8732*** (2.45)	-.854*** (-6.72)	.1435*** (8.53)	.5656 (0.95)	-.1030 (-0.10)	.0954*** (4.86)	.3114 (1.21)
$\ln GDP_{it}$	.7209*** (5.02)	-.0308* (-1.81)	2.465*** (7.52)	.1300* (1.74)	-.0520** (-2.92)	2.355*** (6.67)	-.401*** (-8.62)	.3553*** (5.63)	1.953** (2.31)
$\ln Oilp_{it}$	.4461*** (10.83)	-.0161* (-1.96)	1.067*** (3.72)	.1918*** (3.27)	-.0032 (-0.49)	.3720*** (3.01)	.2198*** (3.34)	-.101** (-2.93)	-.7812 (-0.86)
$\ln POP_{it}$	.6770** (2.17)	-.1072** (-2.27)	3.099*** (6.30)	-.695*** (-5.25)	.0703*** (6.72)	5.633*** (5.31)	-.364*** (-4.70)	.0413 (0.55)	5.915*** (3.33)
$\ln TOT_{it}$	.4461*** (10.83)	-.0312* (-1.94)	1.067*** (3.72)	.2350* (1.77)	.0191* (1.93)	1.383*** (11.26)	-.068*** (-3.10)	.0015 (0.09)	.2155 (0.41)
Constant	-8.652*** (-4.26)	5.016*** (22.84)	-54.9*** (11.01)	3.358** (2.74)	4.353*** (23.23)	-46.9*** (-7.83)	8.295*** (16.54)	1.302*** (4.41)	-43.71*** (-3.28)
F-test	279.80	90.25	101.77	170.51	209.8	202.47	94	78.82	49.4
Observations	450	450	450	450	450	450	450	450	450
Groups	15	15	15	15	15	15	15	15	15

Standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

Comparing the results between lower-middle, upper-middle, and high-income countries and figure 8 (1-3) displayed above should help us understand the differences in estimated elasticities between these three income groups. First, the study starts by analyzing the relationship between renewable energy and carbon emissions. A common result in all income groups is that renewable energy negatively relates to carbon emissions. Our results showing a negative relationship in high-income countries coincide with the work of Nguyen and Kakinaka (2019). However, this finding contrasts with those of Nguyen and Sadorski (2009), who have found a positive relationship between renewable energy and carbon emissions in lower-income countries. Demonstrating the relationship between renewable energy consumption and carbon emissions is debatable. Because this relation can hardly be explained without referring to both income and the share of non-renewable energy consumption in final energy consumption. From our point of view, a negative relationship between renewable energy and carbon emissions should be expected. This is because the development and expansion of renewable energy mitigate environmental problems of carbon emissions, which implies the negative relationship between carbon emissions and renewable energy. However, as depicted in Figure 8, this relationship has different directions depending on whether we are in a high-income or lower-income group. In the high-income group, as carbon emissions decrease, renewable energy increases. One main reason behind this is the growing share of renewable energy compared to non-renewable energy[26] in the energy mix; this translates into a reduction of carbon emissions per capita, implying a negative relationship between renewable energy and carbon emissions. In lower-income economies, the opposite happens. As carbon emissions increase, renewable energy consumption decreases. This can be explained by the fact that, in the energy mix, the share of non-renewable energy is continuously growing compared to the share of renewable energy[27]. The consequence is higher carbon emissions per capita, implying a negative association between carbon emissions and renewable energy.

Second, this chapter examines the association between renewable energy and GDP per capita. Renewable energy is positively related to GDP per capita in high income (see figure 8.1), but it is negatively associated with GDP per capita in lower-middle-income countries (see Figure 8.3). These results are consistent with Nguyen and Kakinaka's (2019) findings. Explanations of these results are similar to those given in the previous section. The development and expansion of renewable energy are not always among the priorities of the government plan in lower-income countries. Governments often put less priority on environmental issues and focus on other important development goals, such as economic growth, reduction of poverty, infrastructure development, better education, and health system. In addition, there are fewer subsidies for renewable energy production in lower-income economies compared to higher-income economies. Production of renewable energy tends to require advanced technology with relatively high costs. Thus, making it difficult for industries involved in the

[26] Carbon emissions is directly and positively linked to non-renewable energy (Grossman and Krueger, 1995).
[27] This does not mean lower income countries do not invest in renewable energy. It just means that they invest more in fossil fuels energy than green energy.

green energy sector to afford high-cost production, hence being competitive compared to fossil fuels industries. Moreover, environmental laws and policies are better implemented in high-income countries than in lower-income countries (Hashmi and Alam, 2019).

Thirdly, this study analyses the relationship between renewable energy consumption and oil price. The coefficient on the oil price is positively and significantly related to renewable energy consumption in high-income, upper-middle-income, and lower-income countries. These results indicate that a rise in fuel price would imply an increase in renewable energy demand. A high price of fossil fuels encourages investors to invest in renewable energies, especially since these are considered the energies of the future, and see their production cost gradually reduced over the years (IRENA, 2019). The long-run elasticity of renewable energy with respect to oil price is much larger in the high-income group compared to other groups. This result is expected since developed countries are engaged in a much more effective ecological transition than developing countries. Results also show that the coefficient on oil price is negatively and significantly related to nonrenewable energy in high-income and lower-middle-income countries. Higher oil prices imply a decline in nonrenewable energy consumption. The oil price coefficient with respect to nonrenewable energy is larger for the lower-middle-income group than the one for the high-income group. This result is also expected; the demand for nonrenewable energy is more sensitive to price in lower-middle-income countries because of their relatively low purchasing power. Also, when nonrenewable energy price increases, people can still rely on an alternative energy source such as biomass. Another interesting result is that oil price is positively related to green innovation in high-income and upper-middle-income countries. This suggests that an increase in oil price encourages green innovation production and reinforces actual green innovation trajectories in these two groups of countries.

Given that the coefficients on carbon emissions and GDP per capita have similar signs in high-income and upper-middle-income countries for models (5a) and (5b), the comparison of their magnitudes allowed us to identify certain aspects of the results that must be underlined. In high-income countries, the coefficients on carbon emissions and GDP per capita are higher in model (5a) than in model (5b) in absolute value[28]. This indicates that high-income countries tend to invest more in renewable energy and less in non-renewable energy as their carbon emissions and income increase. This result is consistent with the EKC hypothesis, according to which the demand for a cleaner environment grows stronger with higher and higher incomes. In high-income countries, there is gradually an awareness of environmental issues by political and economic actors; but above all, an awareness of the general public on environmental and climatic issues. People who have already reached a high standard of living are

[28] Model (5a) |-1.667| |0.7209| > Model (5b) |0.1542| |-0.308|

becoming more and more environmentalist and find it challenging to endure daily air pollution, sea pollution, large-scale deforestation, and the destruction of biodiversity. Since the political actors depend on their public to be elected or re-elected, they align themselves progressively behind the environmentalist positions of their voters.

To illustrate these results, in 2019, the share of primary energy from renewable energy sources was 12 per cent in France, 17 per cent in Spain, 15 per cent in the UK, 18 per cent in Germany, and 16 per cent in Italy. In 1985, these shares were 7.5 per cent, 9.7 per cent, 1 per cent, 1.5 per cent, and 8.6 per cent (World Bank, 2019). This shows a net increase in green energy investment, which has resulted in a more extensive supply of renewable energy. During the same period, there has also been a slight decrease in the share of fossil fuel energy in total energy consumption. To exemplify this, Germany, whose fossil fuel consumption constituted 87% of final energy consumption in 1989, saw this share drop to 78% in 2015. The UK has gone from 90% of primary energy consumption coming from fossil fuels in 1989 to 80% in 2015, a reduction of 10%. (World Bank, 2019) Some other countries (such as France, Italy and Spain) experienced similar decreases during the same period. This shows that developed countries have diversified their energy sources over the years, especially at the beginning of the 2000s, following a sharp rise in carbon emissions. Thus, the share of renewable energies progressively increased to the detriment of fossil fuels in the production and consumption of final energy. Despite this encouraging trend, much more effort needs to be made if we want to keep temperature growth below 2 degrees Celsius, as stipulated in the Paris Agreement (IPCC, 2018).

In upper-middle-income countries, carbon emissions and GDP per capita coefficients are higher in model (5a) than in model (5b) in absolute value[29]. This indicates that upper-middle-income countries invest more in renewable energy than fossil fuel energy as their GDP per capita and carbon emissions rise. The developing countries have this opportunity to continue their development with a cleaner energy structure. Renewable energy capacities installed in emerging countries (such as China, Brazil, Russia, and South Africa) have increased by roughly 160 per cent over the past decade. This share constitutes 43 per cent of global capacity, according to the International Renewable Energy Agency (IRENA, 2019). China is considered to be the largest green energy market in the world. China is replacing fossil fuels with green energies at an accelerating rate. According to a United Nations report published in 2018, this country invested more than $ 127 billion in 2017, constituting 45 per cent of the global investment in green energy (UN, 2018).

In low-income countries, the coefficient on carbon emissions is positive and statistically significant in model (5b) but statistically insignificant in model (5a). The coefficient on GDP is negative and statistically

[29] Model (5a) |-0.854| |0.1300| > Model (5b) |0.1435| |-0.0520|

significant in model (5a), while it is positive and statistically significant in model (5b). This suggests that in lower-income countries, higher carbon emissions and income lead to higher consumption of non-renewable and lower consumption of renewable energy. Lower middle countries are facing major energy challenges. The demand for energy, which continues to increase, is stimulated by constant economic and demographic growth (IRENA, 2019). Therefore low-income countries need a constant increase in energy supply. But unfortunately, fossil fuel energy is preferred to the detriment of renewable energy. Our sample shows that in 1989, the average share of renewable energy in total energy consumption was 49 per cent (see figure 8.3). This share dropped to 36 per cent in 2015. During the same period, the share of non-renewable energy increases from 54 per cent to 65 per cent. Unlike the developed economies, low-income economies can pursue sustainable energy development as a basis for long-term prosperity by devoting a large part of their energy mix to renewable energies from the start of their economic growth. However, as revealed by this chapter's results, this did not seem to be the case during our study period.

4.6. Conclusion

Recent studies have found contradictory results when examining the relationship between aggregate technology and CO2 emissions. Some studies have found that aggregate technology increases CO2 emissions (Cheng et al., 2019), while others found that aggregate technology can mitigate CO2 emissions but only under certain conditions[30] (Garrone and Grilli, 2010; Li and Wang, 2017; Churchill et al., 2019). The impact of aggregate technology on CO2 emissions often depends on the counterbalancing effect of carbon-intensive technology and green technology in aggregate technology (Milindi and Inglesi-Lotz, 2021). Therefore, chapter four proposed disaggregating aggregate technology and examining the impact of green technology on CO2 emissions in a sample of 45 countries, divided into three income categories between 1989 and 2018. Chapter four sought to answer three questions:

1) To determine the impact of green technologies on carbon emissions.

This chapter used two indicators of green technology development: renewable energy consumption and environmental-related patents. We regard green technology innovation (environmental-related patents) and renewable energy production as "two sides of the same coin," The latter needs to be complemented by the former for countries to be successful in the transition towards low-carbon economies. After applying the fixed-effect method with Driscoll and Kraay standard errors and complementing the latter with the Bruno (2005) LSDVC methodology as a robustness check, results for

[30] Notably conditions related to the application strong environmental regulations.

the 45 countries showed that renewable energy consumption reduces carbon emissions in both fixed effect and Bruno LSDVC results. However, green technology innovations do not significantly impact carbon emissions. Results also revealed that key determinants of carbon emissions such as GDP per capita, population density, and terms of trade are positively related to carbon emissions in the full sample.

2) Does the impact of green technology (renewable energy and environmental-related patents) on CO2 emissions depend on a country's economic development level?

To answer this question, the full sample was divided into three sub-samples according to their level of income (15 high-income countries, 15 upper-middle-income countries, and 15 lower-middle-income countries). After running estimations models using the fixed effect methodology with Driscoll and Kraay standard errors for the three subsamples, the results reveal that renewable energy consumption significantly reduces CO2 emissions in all three subsamples. However, environmental-related patents significantly lower CO2 emissions only in very high-income countries, a group of 10 countries in our high-income sample, with high CO2 emissions per capita and an average GDP per capita above 36000$.

3) How do increased carbon emissions and economic growth affect green and carbon-intensive technology adoption in different country income groups?

Renewable energy consumption and environmental patents are used as indicators of green technology development, while non-renewable energy consumption is employed as an indicator of carbon-intensive technology. The analysis showed clear differences between the groups of low- and high-income countries. A negative association is found between renewable energy and CO2 emissions in the high-income and upper-middle-income groups. Because higher carbon emissions encourage high-income and upper-middle-income countries to invest in renewable energy, this translates into lower carbon emissions over time. GDP per capita increases renewable consumption in high-income and upper-middle-income countries but decreases renewable energy consumption in lower-income countries. In lower-income countries, an increase in carbon emissions and income are associated with higher consumption of non-renewable and lower consumption of renewable energy. Green patents respond positively and significantly to the rise in carbon emissions only in high-income countries. Results also show that higher oil price promotes the adoption of renewable energy in all group of countries. Population density positively affects renewable energy adoption in high-income economies. However, it negatively affects renewable energy adoption in upper and lower-middle-income countries. Terms of trade are positively associated with renewable energy in high-income and upper-middle-income countries but negatively associated with renewable energy in lower-middle-income countries.

The policy implications drawn from chapter four are as follows: (1) To combat climate change, the government and business sectors should keep promoting the growth and use of renewable energy worldwide. (2) Governments should integrate environmental issues into their top objectives, particularly in emerging nations, realizing that addressing these challenges now will cost less than later. (3) Governments should keep funding and expand their support for energy-saving and renewable energy projects, especially in lower- and upper-middle-income countries. (4) In addition to stepping up their renewable energy spending, countries should not overlook investments in green innovations (such as electric cars, carbon capture technology, efficient machines, lightning, etc.). Together, they would enable a quicker achievement of carbon neutrality. (5) Since low- and upper-middle-income countries seem to be falling behind in developing green innovations, they should at least continue to invest heavily in education to acquire a high-skill labor force that can absorb and adopt external knowledge.

Appendix

A.1. Descriptive statistic: full sample

Variables	Observations	Mean	Stand dev	Min	Max
CO2 emissions	1,327	5.647408	4.763908	.133613	20.17875
GDP per capita	1,348	14275.46	16080.63	398.8521	56842.3
Population	1,339	140.9964	184.8893	2.18872	1239.579
Ren. Energy	1,215	22.06828	23.81995	.0059765	88.83185
Env. Patent	1,305	191.6641	624.5274	0	6080.3
Non-renew	1,215	76.80319	21.85675	12.99901	99.99678
Terms of trade	1,283	120.5126	88.73144	39.6998	391.8637

A.3. Descriptive statistic: subsample

	Observations	Mean value	Standard deviation	Minimum value	Maximum value
			CO2 emissions		
HI	450	10.08686	4.192539	2.321076	20.17875
UPMI	427	5.231199	3.316332	1.308847	17.42437
LMI	450	1.602891	1.642865	.133613	7.701744
			GDP capita		
HI	449	33700.83	13617.77	5510.662	56842.3
UPMI	449	6682.485	2793.98	712.1154	15068.98
LMI	450	2469.366	2871.945	398.8521	14920.45
			Population density		
HI	439	179.0955	165.0725	2.18872	529.6521
UPMI	450	54.81616	41.2086	5.503698	148.3488
LMI	450	190.0089	249.634	9.188078	1239.579
			Renewable energy		
HI	405	8.22135	8.437722	.0059765	38.61766
UPMI	405	14.0214	12.86628	.0589587	49.86467
LMI	450	43.96209	27.02946	1.17316	88.83185
			Nonrenewable energy		
HI	405	83.30612	11.64692	46.22592	99.99678
UPMI	405	86.91605	11.93449	49.83301	99.97792
LMI	405	60.18739	27.12474	12.99901	99.15938
			Environmental patents		
HI	435	526.0195	983.9253	0	6080.3
UPMI	435	42.38092	185.2354	0	1958.5
LMI	435	6.591954	27.58999	0	218

Terms of trade					
HI	433	111.0557	39.76975	58.15106	391.8637
UPMI	446	126.6229	50.14804	52.3171	327.1472
LMI	404	123.9027	142.915	39.6998	244.376

B.1. Unit root tests

Upper-middle income				
Variables	IPS		Maddala and Wu	
	No trend	With Trend	No trend	With Trend
$\ln CE_{it}$	-1.4325*	-2.7712***	51.3306***	34.0458
$\ln GDP_{it}$	4.5047	-2.5900	8.7345	33.4160
$\ln REN_{it}$	-0.9556	-3.1160***	37.6770	34.8558
$\ln EPAT_{it}$	-4.7196		141.7187	121.9777***
$\ln NOREN_{it}$	-3.1103***	-3.9949***	108.5398***	96.2430***
$\ln POP_{it}$	-6.5801***	0.3186	334.6625	247.0399
$\ln OPN_{it}$	-1.5589*	-4.1564***	66.3456***	61.1706***

Lower-middle income				
Variables	IPS		Maddala and Wu	
	No trend	With Trend	No trend	With Trend
$\ln CE_{it}$	0.0805	-2.6567*	34.2467	35.8010
$\ln GDP_{it}$	10.9629	2.2293	4.3263	16.6289
$\ln REN_{it}$	4.1162	-1.6561**	28.3819	26.7581
$\ln EPAT_{it}$			121.3722***	110.4952***
$\ln NOREN_{it}$	-2.1093**	-3.5219***	65.2369***	44.9853**
$\ln POP_{it}$	-6.7815***	1.8775	440.583***	122.6552***
$\ln OPN_{it}$	-2.5631***	-4.4139***	59.8896***	58.0106***

B.2. Diagnostic tests

Upper-middle income				
	Model (3a)	Model (3b)	Model (5a)	Model (5b)
	Statistic	Statistic	Statistic	Statistic
Serial correlation	29.656 0.000***	15.952 0.000***	4.386 0.054*	43.109 0.000***
Heteroskedasticity	7616.12 0.000***	1187.12 0.000***	99618.5 0.000***	2502.75 0.000***
Pesaran CD	0.386 0.699	-0.743 0.000***	1.909 0.0563*	-1.877 0.0947*
Time fixed effect	0.796 0.754	-0.743 0.4575	0.946 0.544	0.253 1.000
Panel effect	417.25 0.000***	512.22 0.000***	111.67 0.000***	165.87 0.000***

Lower-middle income				
	Model (3a)	Model (3b)	Model (5a)	Model (5b)
	Statistic	Statistic	Statistic	Statistic

Serial correlation	9.091 0.009***	39.388 0.000***	11.961 0.003***	12.398 0.000***
Heteroskedasticity	2661.24 0.000***	1534.84 0.000***	13018.82 0.000***	32854.85 0.000***
Pesaran CD	3.376 0.000***	3.151 0.000***	3.196 0.001***	-2.604 0.009***
Time fixed effect	0.215 1.000	0.651 0.907	0.164 1.000	1.841 0.008***
Panel effect	213.74 0.000***	186.16 0.000***	42.95 0.000***	67.19 0.000***

V. The role of technological progress on sectoral carbon emissions

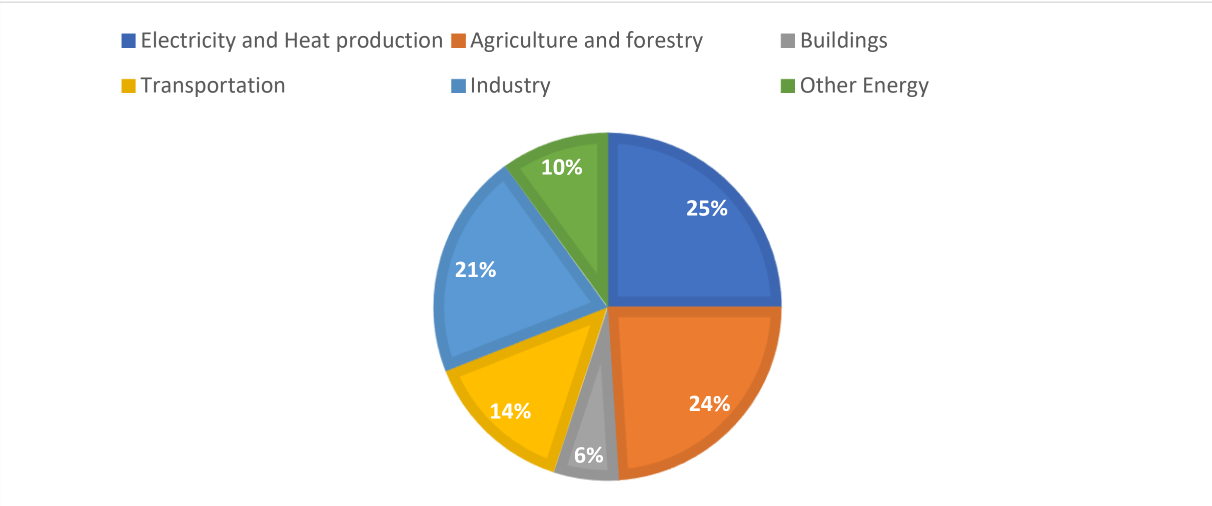
5.1. Introduction

In recent years, the impact of technological progress on the environment and the climate has received increasing attention in the literature (Asongu, Le Roux, and Biekpe, 2017; Cheng et al., 2019; Churchil et al., 2019; Milindi and Inglesi-Lotz, 2021). While some studies suggest that technology reduces overall CO2 emissions by reducing energy intensity, others are concerned about the positive effect of technological progress on energy consumption and economic growth, which translates to higher carbon emissions. The data can also support this intense debate. According to a 2015 report by the Global e-Sustainability Initiative (GeSI, 2015), mobile communications technology and the internet are making a considerable contribution to action on climate change. Analyses revealed that mobile phones and other telecommunications devices save more than 180 million tons of CO2 emissions per year in the U.S. and Europe. This amount of carbon emissions is more than the one produced annually by the Netherland (GeSI, 2015). The negative association between CO2 emissions and ICT was also found in the third chapter of this thesis. The positive impact of technology on CO2 emissions can be illustrated by the boom in shale oil production in the 2000s in the United States. The US became a net exporter of oil in November 2019 - a startling turnaround for a country that had imported more than 10 million barrels per day ten years earlier (Our world in data, 2019). The high oil production in the U.S. is mainly due to improved techniques and technologies for drilling shale oil (Strauss Center, 2018). While this has allowed the U.S. to have some energy independence, it has come at the cost of more carbon emissions, notably in the petroleum sector (EDGAR, 2021).

Given the methods and results obtained by studies that have examined the relationship between carbon emissions and technological progress, several important points can be underlined. First, as discussed above, in general, a clear consensus on the effect of technological progress on CO2 emissions has not yet been reached. This is due to several reasons, such as the differences in terms of sampling, study periods, or the methods used to estimate the results. The definition and quantification of technological progress also constitute a major obstacle that does not allow having refined results. Most studies used only one aggregate or green technology indicator (Du and Li, 2017; Gu et al., 2019). However, as demonstrated in this study's third and fourth chapter, a single indicator can often reveal only a few facets of this complex relationship (Milindi and Inglesi-Lotz, 2021). Second, most of these studies are conducted on carbon emissions emitted at the country level. Still, the effects of technological progress on carbon emissions from different economic sectors are not very discussed in the literature. This chapter argues that as all sectors do not contribute to CO2 emissions at the same level, the impact of aggregate or green technology on carbon emissions might vary significantly across sectors. Some energy sectors may be more sensitive to technological advancement than others, possibly due to differences observed in their production process, financial capacities to induce and spread innovations, their vulnerability to the rebound effect, and their compliance with strict environmental laws (Milindi and Inglezi-Lotz, 2021; Alatas, 2021).

Not all economic sectors contribute to carbon dioxide emissions at the same level. The 2014 IPCC report (IPCC, 2014) shows the contribution of various global sectors to total carbon dioxide emissions in figure 9. According to the IPCC (2014), the electricity from burning oil, coal, and natural gas is the largest source of greenhouse emissions (25 per cent). Agricultural activities and deforestation are the second-largest sources of greenhouse gas emissions (24 per cent). Twenty-one per cent of total emissions come from the industry sector. The transportation sector (road, air, rail, and maritime transportation) and the building sector (energy serves to supply heating and air conditioning systems for buildings and food cooking in homes) constitute 14 per cent and 6 per cent of total greenhouse gas emissions, respectively.

Figure 9. World GHG emissions by economic sectors



Source: IPCC (2014) (2010 global emissions per sector)

Therefore, this chapter aims to examine the nature of the relationship between technology and sectoral CO2 emissions and thus contribute to the overall academic debate. The following research question will be answered:

1) What is the impact of aggregate and green technology on sectoral CO2 emissions? Does this impact differ across income-group countries?

To answer this question, chapter 5 uses the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) theoretical framework with sectoral carbon emissions as the dependent variable and technology, GDP per capita, urbanization, and financial development as explanatory variables. Five energy sectors are selected: The power, manufacturing, transport, petrol, and building sectors. These five energy sectors accounted for 75 per cent of total green gas emissions in 2014 (IPCC, 2014). This fifth chapter employs two methodologies to estimate the results: the two steps DIF-GMM estimator (1991) and the Feasible Generalized Least Square methodology (FGLS). The research is carried out on the same sample used in chapter 4. The study period runs from 1999 to 2018.

The contribution of this chapter to the literature is threefold. Firstly, to the best of our knowledge, no other studies have examined the relationship between carbon emissions, aggregate technology, and green technology in more than one sector. This allowed us to determine which sector aggregate technology and green technology significantly impact CO2 emissions and the reasons that can explain such impact. It will also help policy-makers identify the sector where more efforts must be made in terms of technological advancement to curb the CO2 emissions curve. Secondly, this thesis constructed a composite indicator of aggregate technology from four direct and indirect indicators of technological progress: R&D expenditure, patents, ICT, Science and technology publications (direct indicators), manufacturing value-added, and education level (indirect indicators). The composite indicator contains most of the information comprised in the six variables and is constructed using principal component analysis techniques. Creating an index reduces the number of technical indicators while preserving as much information as possible, thus allowing a global view of the effects of technology on carbon emissions in each sector and each country's income group. Thirdly, like in chapters 3 and 4, chapter 5 analyzed the relationship between technological progress and sectoral carbon emissions in different income-group countries.

The remainder of this chapter is structured as follows: Section II presents the theoretical model. Section III describes technology's influence on carbon emissions in each energy sector selected in this chapter. PCA estimation and methodology and the dataset are presented in section IV. In section V, the econometric results are presented and analyzed. Section VI concludes the chapter.

5.2. Theoretical Framework

The theoretical framework of chapter 5 is based on the following STIRPAT model:

$$\ln I_{it} = \beta_i + \theta \ln P_{it} + \alpha \ln A_{it} + \gamma \ln T_{it} + u_i + v_{it} \quad (1)$$

In equation (1), I represents carbon emissions. P denotes population, represented in this chapter by urbanization (URB_{it}). A denotes affluence, represented by GDP per capita (GDP_{it}), and T stands for technology represented by aggregate and green technology (TECH_{it}). We augment model (5) by adding another important factor that can explain variations in carbon emissions: financial development(FIN_DEV_{it}). In addition, a quadratic term (GDP_{it}^{2}) is added to account for the potential non-linearity association between carbon emission and GDP postulated by the Environmental Kuznets Curve (EKC) (Borghesi, 1999). Therefore, the final version of our theoretical model can be written as:

$$\ln I_{it} = \beta_i + \theta \ln URB_{it} + \alpha \ln GDP_{it} + \gamma \ln TECH_{it} + \omega FIN\_DEV_{it} + \vartheta GDP_{it}^{2} + u_i + v_{it} \qquad (2)$$

5.3. Overview of technological progress in each energy sector

This subsection describes the influence technology has on carbon emissions in each energy sector selected in this chapter. Technology is an instrument that can be used to protect or damage the environment. So, we describe some channels by which technological development increases or decreases carbon emissions. The long-run impact of technology on CO2 emissions often depends on balancing the technology's positive and negative effects (Milindi & Inglesi-Lotz, 2021).

5.3.1. Power sector

The way technology positively affects power sector carbon emissions can be split into two stages. The first stage is the generation of electricity. Most electricity generation technologies have been designed and constructed to produce electricity from fossil fuels (Hoffman, 2019). This is the case in coal-fired or oil and gas-fired power plants. Burning fossil fuels to satisfy the growing electricity demand of economies produces significant greenhouse gas emissions (IPCC, 2014). The second stage is the utilization of electricity. Boosted by an increasing population and GDP, energy consumption continues to rise. A high standard of living translates into the acquisition of energy-intensive home appliances. In general, the richer and more developed people in a country are, the more emissions their lifestyle produces (Dietz & Rosa, 1997). So, on the one hand, technology raises CO2 emissions, but, on the other hand, technology can also serve as a tool to lower CO2 emissions. It can negatively impact carbon emissions in the power sector through renewable energy development and the promotion of energy efficiency (IEA and IRENA, 2017). On one side, green technology's development allows for gradually replacing fossil fuel energies with clean energies such as solar, wind, hydraulic energy, and nuclear. On the other side, energy efficiency brings energy savings by eliminating energy consumption waste (Hashmi and Alam, 2019; Gu et al., 2019). In the power sector, this mainly involves improving household appliances and the heating system, improving different devices used in the house, and upgrading interior and exterior lighting systems. Therefore, in the power sector, technology can increase carbon emissions through the proliferation of fossil fuel power plants to meet the ever-increasing power sector energy demand. Technology can also lower CO2 emissions through the expansion of renewable energies and the promotion of energy efficiency.

5.3.2. Manufacture sector

Figure 11 shows that the manufacturing sector is the sector that emits the most carbon emissions in upper-middle and lower-middle-income countries. This is not surprising because these economies are emerging, and their industries need energy to expand their activities. The relationship between technology and manufacturing sector carbon emissions is similar to the one described in the power sector. Technology has a double effect on manufacturing sector emissions. First, the technology can increase CO2 emissions in industries if most of the energy used in the production processes comes from fossil fuels. Second, technology can reduce carbon emissions if industries decide to cut fossil fuel energy supply progressively and increase clean energy usage. Industries can also embark on energy efficiency by identifying ways to use less energy to light and heat factories or run the equipment. Using natural gas instead of coal to run machinery, the former emits less CO2 than the latter (IPCC, 2014). Industries can also manufacture recycled materials rather than produce new products from raw materials (IPCC, 2014).

5.3.3. Transport sector

In 2018, the road sector accounted for 89% of energy consumption in transport in IEA countries (IEA, 2018). The air, water, and rail sectors accounted for 7%, 2%, and 2%, respectively (IEA, 2018). Petroleum is the primary energy source for transportation globally because the means used to transport people are vehicles, which are carbon-intensive machines primarily built to be fueled by petrol. Internal combustion engine vehicles are still mainly produced globally compared to less polluting vehicles like battery electric vehicles. Electric cars accounted for only 2.6% of global car sales and about 1% of global car stock in 2019 (IEA, 2020). Therefore, it is expected that the more vehicles on the road, the more carbon dioxide is emitted into the atmosphere. Technology can mitigate carbon emissions in the automotive industry by developing and adopting less polluting cars such as electric or hydrogen vehicles. For the technology to have an optimal impact in this sector, it will also be essential to ensure that electric vehicle batteries are initially not recharged with electricity from fossil fuels but rather from renewable energies (Milindi and Inglesi-Lots, 2022). The invention of more efficient combustion engines may also negatively affect carbon emissions in the transport sector. However, Harris and Brown (2015) noted that this negative effect is marginal compared to the one brought by electric vehicles. The government also has a vital role to play, particularly in public transport, by investing in acquiring public buses fueled by compressed natural gas rather than gasoline or diesel. Also, ensuring that electric locomotive trains are driven by electricity from renewable energy and not fossil fuels (Alatas, 2021).

5.3.4. Petrol sector

Technology also plays a double role in the petroleum sector. Hydraulic fracturing[31] , combined with horizontal drilling techniques, illustrates the positive influence technology exerts on petrol carbon emissions. These technics have enabled the U.S. to significantly increase its oil and gas production by producing shale oil during the last decade (Strauss Center, 2018). U.S. oil production doubled from 2008 to 2018, from 302 million to 671 million tons (BP, 2021). Technology allows the petroleum industry to stay afloat by reducing production costs and boosting production (Strauss Center, 2018). Other examples of technology that foster the expansion of petrol extraction are Seismic, gravity, and geomagnetic surveys to find petrol and gas underground more quickly (Havard, 2013). These technologies have considerably evolved over the years. Seismic surveys send high-energy sound waves into the ground to see how long it takes for them to reflect the surface (Havard, 2013). This information can be used to determine the location of the seeps underground. These technologies save time, workforce, and money, as they can successfully locate resources before drilling. While the seismic survey technology allows finding the petrol deposit more quickly, this technology also helps preserve the environment. The seismic surveys used today use big thumpers to make the sound waves; in the past, explosives were used to make the sound waves with devastating environmental impact (Havard, 2013).

5.3.5. Building sector

Apart from construction operations, carbon emissions in the building sector are emitted through the heating, cooling, and lighting system (Bowen, 2021). These systems require a lot of energy to function. This situation can be improved using smart building technology and the internet of things which mitigate the amount of energy consumed (Bowen, 2021). The digital landscape is constantly changing, and this change also affects the building sector. This sector has benefited greatly from digital and technical developments over the last few decades (Ahmed & Ridzuan, 2013). Several examples can be given to illustrate this. For instance, smart devices and sensors, which all share data and can be controlled from a central platform, can help determine when to increase or decrease power consumption and reduce the building's carbon footprint (UK Connect, 2021). An IoT platform provides the necessary energy-consumption analytics on use and overuse and the indicators of where

[31] Hydraulic fracturing consist of injecting a mixture of pressurized liquid containing water, chemicals, and a proppant inside a well to create cracks in the rock formation, allowing oil and natural gas to flow more freely. Hydraulic fracturing has been controversial due to the nature of the technology and its environmental impact, including water depletion and contamination, increased surface pollution, and the potential for induced earthquakes.

adjustments are needed to save energy (Jones, 2020). Therefore, like in all other sectors, technology can increase or decrease energy consumption in the building sector.

5.4. Methodology and Data

5.4.1. PCA estimation

This chapter constructs an index for aggregate technological progress using principal component analysis. In a similar fashion to the paper by Gupta and Modise (2012), using factor analysis, we extract one common factor from four indicators of technological progress, namely, patent applications, R&D expenditure, ICT, and science and technology publications. As shown in the correlation matrix presented in Table 22, these four variables are highly correlated, and extracting a common factor allows for solving the multicollinearity issue that may arise when all proxies of technology are included in the model (Jolliffe, 2002). Moreover, having one indicator of technological progress that encompasses most of the characteristics of several indicators will reduce the data's dimensionality, making the data analysis much easier and faster (Jolliffe, 2002). Many studies have shown that the quality and the diffusion of technology in a country greatly rely on the quantity of a skilled labour force (Messinis and Ahmed, 2009; Toner, 2011). Achieving high academic standards for the largest proportion of school students within a country creates a workforce with greater potential to engage productively with innovation (Toner, 2011). To this end, the level of educational achievement is added to the index construction to reflect the quality of some technological proxies used in the chapter[32]. In addition, we use manufacturing value-added as a share of GDP to reflect the level of industrialization. We argue that the more a country is industrialized, the more technology is needed, utilized, and spread. Therefore, the technological index will be a function of the following factors:

$$\mathrm{Tech\_index_{it}} = \mathrm{f(ICT_{it}, PAT_{it}, RD_{it}, Scien\_tech_{it}, Educ_{it}, MVA_{it})} \qquad (5)$$

ICT_{it} denotes information and communication technology represented in this chapter by internet users per 100 people, PAT_{it} represent the number of patent applications per 1000 people, RD_{it} stands for Research & Development expenditure as a percentage of GDP, $Scien\_tech_{it}$ represent science and technology publication per 1000 people, $Educ_{it}$ represent the enrolment ratio in tertiary education, MVA_{it} stands for the manufacturing value-added as a percentage of GDP. The PCA procedure consists

[32] For instance, the quality of patent application, and science and technology publication greatly dependent on the level of school education in a country (Milindi & Inglesi-Lotz, 2021).

of five steps[33] . An orthogonal transformation is performed to convert the set of technical indicators correlated into a set of values of linearly uncorrelated variables (Jolliffe, 2002).

Table 22. Correlation table of technological indicators.

	ICT_{it}	PAT_{it}	RD_{it}	$Scien\_tech_{it}$	$Educ_{it}$	MVA_{it}
ICT_{it}	1					
PAT_{it}	0.5916	1				
RD_{it}	0.5236	0.7863	1			
$Scien\_tech_{it}$	0.6196	0.8552	0.8872	1		
$Educ_{it}$	0.6757	0.6101	0.6246	0.6751	1	
MVA_{it}	0.5299	0.5653	0.7242	0.6490	0.7136	1

The PCA estimation procedure puts the maximum possible information in the first principal component, followed by the second, the third, etc. In this chapter, we choose the first principal component (pc1) because it contains 76 per cent of information carried in the six indicators of technological progress.

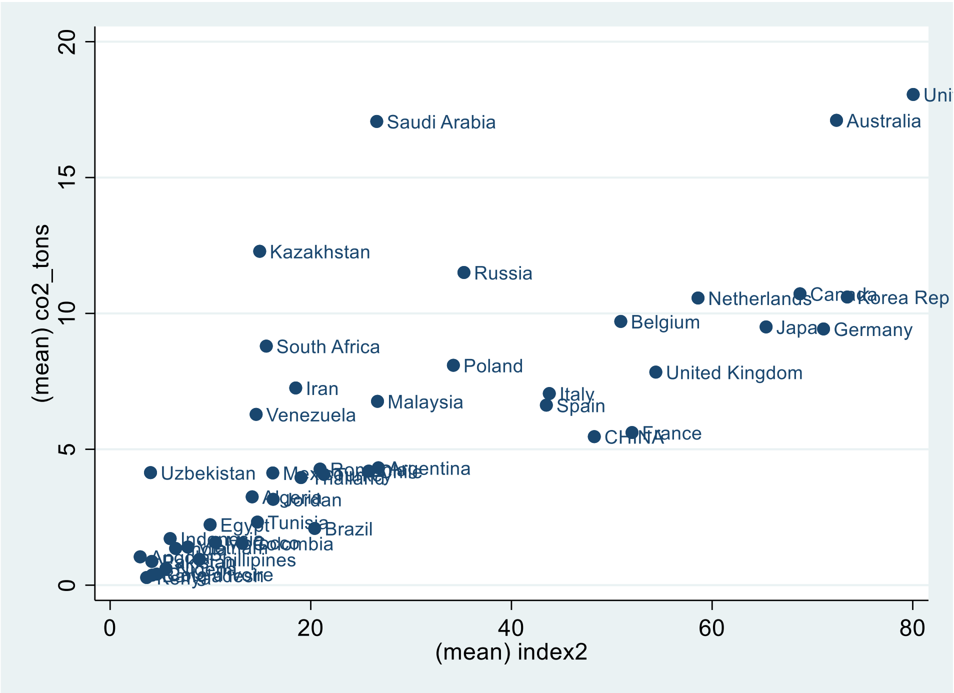
The following mathematical formula is employed to set the index between 0 and 1:

$$\text{Index} = [\text{pc1} - \min(\text{pc1})]/[\max(\text{pc1}) - \min(\text{pc1})] \quad (6)$$

Figure 10 displays the mean value of the technological index on the vertical axes and the mean value of total carbon emissions on the vertical axes from 1999 to 2018. As expected, high-income countries are more advanced in technology than upper-middle-income and lower-middle-income countries. In our sample, the US, South Korea, Australia, Germany, Canada, Japan, and the Netherlands have the highest average technological index of 80, 73, 72, 71, 68, 65, and 58, respectively.

[33] First, the dataset is standardized so that each variable contributes equally to the analysis. Second, the covariance matrix is calculated for the whole dataset. The third step consist of calculating eigenvalues and eigenvectors of the covariance matrix. The number of eigenvectors is equal to the number of principal components, and the number principal component equals the number of variables included in the PCA estimation. Fourth, sort eigenvectors and their corresponding eigenvalues by ascended order, the highest to the lowest. In the fifth and last step, we multiply the original matrix dataset (the dataset that contains technological proxies) with the eigenvectors matrix to obtain the transformed matrix which constitute the matrix of index.

Figure 10. Two-way scatter plot of Aggregate technological index and CO2 emissions



Source: Own estimation

5.4.2. Empirical model

A dynamic panel data approach is adopted in this chapter to examine how aggregate and green technology impact sectoral CO2 emissions. The first-panel model looks at the effect of the aggregate technological index, obtained by summarising the information in equation (5) on sectoral CO2 emissions.

The first-panel model is as follows:

$$\ln SCE_{it} = \ln(SCE_{it-1})\delta + \ln(TECH)_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \qquad (7)$$

Where the subscripts i and t refer to countries and time. u_i is the unobservable country-specific characteristics and $v_{i,t}$ is the i.i.d. disturbance terms. SCE_{it} refers to sectoral carbon emissions in metric tons per year. Sectoral carbon emissions from the power sector $(Power_{it})$, the manufacturing sector $(Manuf_{it})$, the transport sector $(Transp_{it})$, the petrol sector $(Petrol_{it})$, and the building sector $(Building_{it})$. X'_{it} represents a vector of control variables, including GDP per capita (GDP_{it}), GDP per capita square (GDP^2_{it}), urbanization rate (URB_{it}) and financial development (FIN_DEV_{it}). $TECH_{it}$ represents the aggregate technological index. Following the number of sectors, model (7) will be divided into five different sub-models:

$$\ln \mathrm{Power}_{it} = \ln(\mathrm{Power}_{it-1})\delta + \ln(\mathrm{TECH})_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \tag{7a}$$

$$\ln \mathrm{Manuf}_{it} = \ln(\mathrm{Manuf}_{it-1})\delta + \ln(\mathrm{TECH})_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \tag{7b}$$

$$\ln \mathrm{transport}_{it} = \ln(\mathrm{Transp}_{it-1})\delta + \ln(\mathrm{TECH})_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \tag{7c}$$

$$\ln \mathrm{Petrol}_{it} = \ln(\mathrm{Petrol}_{it-1})\delta + \ln(\mathrm{TECH})_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \tag{7d}$$

$$\ln \mathrm{building}_{it} = \ln(\mathrm{Building}_{it-1})\delta + \ln(\mathrm{TECH})_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \tag{7e}$$

The second-panel model will investigate the influence of green technology represented by renewable energy on sectoral CO2 emissions:

$$\ln \mathrm{SCE}_{it} = \ln(\mathrm{GTECH}_{it-1})\delta + \ln(\mathrm{TECH})_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \tag{8}$$

Where $\ln(\mathrm{GTECH})_{it}$ denotes green technology.

5.4.3. Econometric Methodology

This chapter applies two steps generalized method of moments (GMM) with orthogonal deviations to estimate the results. The GMM transforms the data and corrects for endogeneity by eliminating the Nickell bias inherent to dynamic panel models (Arrelano & Bond, 1991). This chapter also employs the Feasible Generalised Least Square (FGLS) to deal with different econometric issues and ensure robust results.

When a lagged dependent variable is included among the regressors, the Nickell (1981) biased will arise as a possible violation of the classical assumptions. We will have an endogeneity problem since SCE_{it-1} is correlated with the unobserved heterogeneity u_i. This chapter uses the DIFF-GMM methodology that Arellano and Bond (1991) proposed to estimate the results and eliminate the Nickell bias. The GMM method corrects the alleged endogeneity bias by using lags, in levels, as instruments for the first-differenced model. Differencing the model eliminates individual effects and endogeneity due to the correlation between individual effects and right-hand side regressors. The starting point of the Arellano and Bond estimator (1991) is given by the following first-differencing the equation:

$$\Delta \mathrm{SCE}_{i,t} = \textstyle\sum_{s=1}^{S} \delta_s \Delta \mathrm{SCE}_{i,t-s} + (\Delta \mathrm{TECH})_{i,t}\beta + \Delta X'_{i,t}\rho + \Delta v_{i,t} \tag{9}$$

This process allows eliminating the individual effect u_i but the differenced lag dependent variable is still correlated with the error terms due to $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ and the existence of $v_{i,t-1}$ in $\Delta v_{i,t} = v_{i,t} - v_{i,t-1}$ (Baltagi, 2008). To solve this problem, Arellano and Bond (1991), suggest the use of lags as an instrument for each forward period so that for period T, the set of valid instruments for the lag dependent variable becomes $(y_{i,1}, y_{i,2}, y_{i,3}, \ldots, y_{i,T-2})$. The suggested advantage of the GMM procedure compared to other types of similar methods, such as the Anderson and Hsiao (1982) estimator, is the use of orthogonality conditions existing between lagged values of $y_{i,t}$ and disturbances $v_{i,t}$ that are the imposed moment conditions.

$$\mathrm{E}\left[\mathrm{SCE}_{\mathrm{i,t-j}}\Delta \mathrm{v}_{\mathrm{i,t}}\right] = 0 \ \text{ and } \ \mathrm{E}\left[\mathrm{X}_{\mathrm{i,t-j}}\Delta \mathrm{v}_{\mathrm{i,t}}\right] = 0 \qquad (10)$$

$$for\ t = s + 2, \dots, j \geq s + 1$$

This chapter uses the two-step DIFF-GMM estimator to account for the variance-covariance of the differenced error terms. The standard covariance matrix is robust to panel-specific autocorrelation and heteroscedasticity (Van Eyden, Gupta, Difeto, & Wohar, 2019). To verify the consistency of the GMM estimator, Arellano and Bond propose a serial correlation test. The test checks the presence of first-order and second-order serial correlation in the disturbances of the first differenced equation. There are two null hypotheses; the first is that there is no first-order serial correlation in the disturbances. The second null hypothesis is that there is no second-order serial correlation in the error terms of the first differenced equation. One should reject the null of no 1st order serial correlation and fail to reject the null hypothesis of second-order serial correlation[34]. Arellano and Bond suggest the use of Sargan's test of overidentifying restrictions. It is essential to check if moment conditions, or instruments, are not correlated with the disturbance terms in the first differenced equation. The null hypothesis of the Sargan test states that instruments are not correlated with disturbances. The test statistic is χ^2_q distributed, with q the number of instruments. The Hansen test of overidentifying restrictions can also be performed. This test is robust to heteroscedasticity and serial correlation. The null hypothesis of Hansen is that over-identification restrictions are valid.

As mentioned above, the FGLS is performed to test the robustness of the DIFF-GMM results. This chapter implements feasible generalized least squares (FGLS), which controls for cross-sectional dependence, heteroscedasticity, and serial correlation in the dataset (Bai, Hoon Choi, & Liao, 2021).

5.4.4. Data

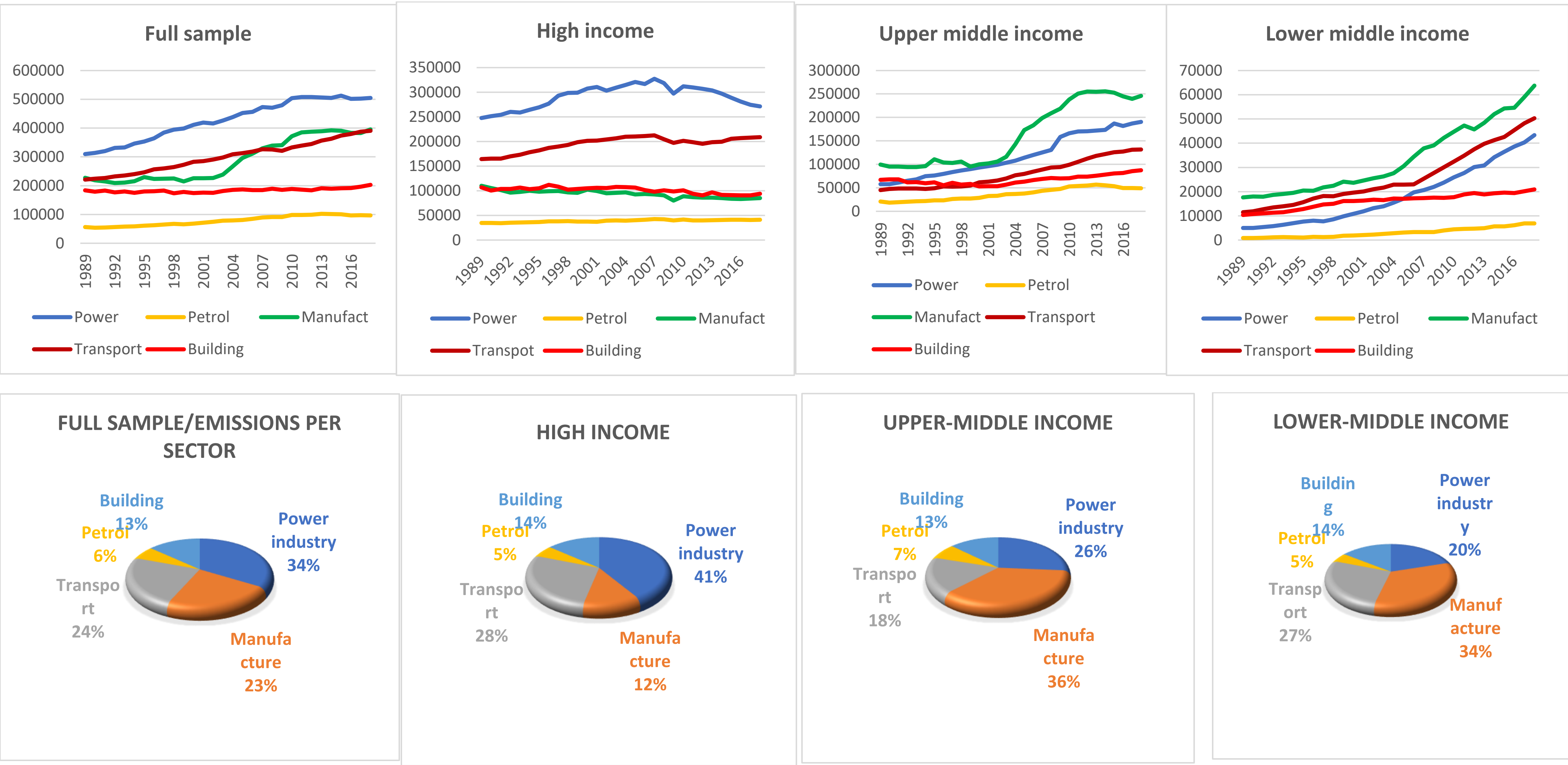
The fifth chapter uses the same dataset employed in the fourth chapter. The dataset provides a period of 20 years, from 1999 to 2018. Due to the lack of data, particularly for lower-middle-income countries, the thesis could not use the same sample period as in the third and fourth chapters. The descriptive statistics table for the full sample is presented in the Appendix. Data on sectoral CO2 emissions comes

[34] Because the consistency of GMM estimator relies on $E(\Delta v_{i,t}\Delta v_{i,t-2}) = 0$; with $\Delta v_{i,t} = (\Delta v_{i,t} - \Delta v_{i,t-1})$ and $\Delta v_{i,t-1} = (\Delta v_{i,t-1} - \Delta v_{i,t-2})$ it is clear that 1st order serial correlation is expected, but not 2nd order.

from Emissions Database for Global Atmospheric Research (EDGAR, 2021). EDGARD estimates sectoral carbon emissions according to the classification guidelines proposed by the (IPCC, 2006) for national greenhouse gas inventories. GDP per capita (in constant 2010 US$), renewable energy consumption (percentage of total energy consumption), financial development (represented by the domestic credit to the private sector as a percentage of GDP), and urbanization (percentage of the total population) were drawn from the World Bank's Development Indicators (World Bank, 2019).

Figure 11. shows the evolution of sectoral carbon emissions across income-group countries from 1989 to 2018 and the share of each sectoral carbon emission in total carbon emissions. The power industry is the first source of emissions in the full sample and in the high-income countries sample. It can also be observed that emissions from the power, manufacturing, and building sectors are decreasing. In contrast, in high-income countries, emissions from the transport sector are pretty stable after 2009. The manufacturing industry is the first source of emissions in upper-middle-income and lower-middle-income countries. CO2 emissions from all sectors are rising in these two groups of countries. However, it is important to note that emissions from lower-middle-income countries have the steepest positive slope. It means the rate at which emissions increase is higher in lower-middle-income countries than in upper-middle-income countries.

Figure 11. Evolution of sectoral carbon emissions from 1989 to 2018 and share of emissions per sector in total CO2 emissions



Sources: Data used in this graph comes from EDGARD (2021).

5.5. Empirical results and discussion

This chapter employs the following empirical strategy to check the dataset and estimate the results: First, we determine the order of integration of each variable included in our empirical model with different panel unit root tests proposed by Im, Pesaran, and Shin (IPS) (2003), Fisher-ADF (Augmented Dickey-Fuller) (Choi, 2001), and Fisher-PP (Phillips-Perron). Second, this chapter investigates the presence of cointegration in our model, using panel cointegration tests proposed by Johansen (1999) and Pedroni (1999). Also, we check the existence of cross-sectional dependence using a Pesaran (CD) (2004), Frees (1995), and Friedman (1937) CD test. Third, this chapter uses an estimation technique that is more appropriate for short-period dynamic panel models with a high number of cross-sectional observations, namely the GMM methodology (Judson & Owen, 1999). The study employs the FGLS methodology for robustness check, which allows controlling for heteroscedasticity, serial correlation, and cross-sectional dependence in data (Bai, Hoon Choi, & Liao, 2021).

5.5.1. Panel unit root, cointegration, and cross-sectional dependence test

The Im, Pesaran, and Shin (Im, Pesaran, & Shin, 2003) (IPS), the Fisher-ADF (Augmented Dickey-Fuller) (Choi, 2001), and the Fisher-PP (Phillips-Perron) tests are performed to investigate the univariate characteristics of each variable. These three tests are employed because they assume individual unit root processes for each variable in the empirical models, thus better suited for detecting cross-section heterogeneity in the dataset (Baltagi, 2008). Besides, unlike other unit root tests (such as the Levin-Lin-Chu, and the Breitung's tests), the IPS and the fisher-type tests do not require a strongly balanced panel. We subtract cross-sectional means by demeaning the series to assist with cross-sectional correlation and cross-sectional dependence. We use the AIC information criteria and set the lags at 1.

Table 23. IPS, Fisher-ADF, and Fisher-PP unit root tests.

Full sample						
Variables	IPS		Fisher-ADF		Fisher-PP	
	With trend	Differenced	With trend	Differenced	With trend	Differenced
$\ln CE_{it}$	1.5606	-4.3002***	95.2055	83.3279***	100.77	155.66***
$\ln PWR\_IND_{it}$	2.1271	-4.5643***	73.8950	90.1828***	124.79***	128.89***
$\ln MANUF\_IND_{it}$	-0.1792	-6.0138***	115.672*	105.299**	99.6745	161.84***
$\ln TRANSP\_IND_{it}$	5.1396	-1.9741***	70.8309	89.2264***	71.2893	92.631***
$\ln PETRO\_IND_{it}$	1.5244	-5.0025***	98.9253	75.5956***	119.41**	153.02***
$\ln BUILD\_IND_{it}$	1.3362*	-5.0649***	87.7577*	131.16***	121.83**	215.91***
$\ln GDP_{it}$	3.6098	1.4042**	109.907	55.5775***	173.651	48.306***
$\ln FIN\_DEV_{it}$	3.6072	6.4215***	2.8497**	9.87895***	8.75931	11.251***
$\ln URB_{it}$	6.3822	6.8864***	19.4804	28.1855***	58.8921	30.8353**
$\ln REN_{it}$	4.6751*	-2.7984***	84.7386	69.1020***	85.2476**	103.870**
$INDEX_{it}$	3.2451	3.6955***	111.636	76.6753***	96.2049	33.5493***

Notes: P-values are in parenthesis. *(**) [***] indicate rejection of the null hypothesis of a unit root at a 10(5)[1] % level.

Unit root test results are displayed in table 23. Results show that for at least two types of unit root tests, we fail to reject the null hypothesis of unit root for all variables, except renewable energy consumption and building sector carbon emissions. After differencing variables that are not stationary to eliminate the non-stationary trend, the results show that the null hypothesis of unit root is rejected at a 5 per cent level. Thus, it can be concluded that all variables are integrated of order one.

Table 24. Cointegration tests results

Full sample					
Cointegration test	Model 7(a)	Model 7(b)	Model 7(c)	Model 7(d)	Model 7 (e)
	Statistic	Statistic	Statistic	Statistic	Statistic
Kao test					
Modified Dickey-Fuller t	-1.7473***	1.1883*	-1.3903*	-6.5345***	-1.9914*
Dickey-Fuller t	-1.9149**	0.5027	-1.1461	-5.4770***	-3.6198***
Augmented Dickey-Fuller t	-1.0909*	1.7327**	1.4312*	-5.0021***	1.8431**
Unadjusted modified Dickey-Fuller t	-1.9360**	-1.4778*	-4.6603***	-8.0231***	-7.1113***
Unadjusted Dickey-Fuller t	-2.0236**	-1.5376*	-3.1333***	-6.0135***	-6.2538***
Westerlund test for cointegration					
	Statistic	Statistic	Statistic	Statistic	
Variance ratio	-1.1725	-1.6589**	-3.4502***	-2.6398***	-2.5987***
Pedroni test for cointegration					
	Statistic	Statistic	Statistic	Statistic	
Modified Phillips-Perron	1.9420**	1.6592**	1.9706**	2.3693*	2.3225*
Phillips-Perron t	-6.7723***	-5.1598***	-4.6190***	-3.3583***	-2.6342*
Augmented Dickey-Fuller t	-4.3395***	-3.8971***	-4.2255***	-3.1507***	-3.2659***

*(**) [***] indicate rejection of the null hypothesis of no cointegration at a 10(5) [1] % level.

Similar to previous chapters, the cointegration test is performed by using the Westerlund (Westerlund, 2005), Pedroni (1999, 2004), and Kao (1999) tests. Cointegration results are presented in Table 24. In the full sample, except for the Dickey-Fuller t-statistic in panel models 7(b) and 7(c) and the variance ratio in model 7(a), all other t-statistics are statistically significant at least at a 10% level.

Table 25. Cross-sectional dependence test

Full sample					
	Model (7a)	Model (7b)	Model (7c)	Model (7d)	Model (7e)
	Statistic	Statistic	Statistic	Statistic	Statistic
Pesaran $\boldsymbol{Z}$	2.547**	1.472**	1.202	0.765	0.815**
Frees $\boldsymbol{Q}$	8.422***	2.485***	8.442***	4.137***	5.566***
Friedman χ^2	5.680	18.333	10.020	5.880	7.107

This chapter applies three different tests procedure to test the presence of cross-sectional correlation in the dataset, namely the Pesaran (2004), Frees (1995), and Friedman (1937) CD test. These tests are more adapted to detect the presence of cross-sectional dependence in panels with many cross-sectional units and few time-series observations (De Hoyos & Sarafidis, 2006). Table 25 reports the results of the cross-sectional dependence test. The Frees test indicates the presence of cross-sectional dependence in all empirical equations. However, the Pesaran detects cross-sectional dependence only in model (7a), (7b), and (7e). De Oyo and Sarafidis (2006) argue that Pesaran's test remains valid in dynamic panels under various estimation methods, including fixed and random effects (even if the estimated parameters are biased). Therefore, it may be the preferred choice since the properties of the other cross-sectional dependence tests in dynamic panels are not yet known.

5.5.2. Empirical results

This section estimates and discusses the impact of aggregate and green technology on sectoral carbon emissions. Aggregate technology is represented by a composite technological index developed in this chapter, following Higon, Gholami, and Shirazi's (2017) approach. Green technology is proxied by renewable energy following the approach of Nguyen and Kakinaka (2019); Milindi and Inglesi-Lotz, (2022). We apply the two steps DIFF-GMM, considered in this chapter as the benchmark model, because this methodology eliminates the Nickell bias. It is more appropriate for the short-period panel dynamic model (Judson & Owen, 1999). The section is divided into three subsections. The first subsection examines the relationship between aggregate technology and sectoral carbon emissions in the full sample and the three subsamples. We evaluate if the composite technological index influences the trend in CO2 emissions in the power, manufacturing, transport, petrol, and building sector. In the second subsection, we examine the effect of green technology on sectoral $C0_2$ emissions in the different country income groups. The last subsection performs a robustness check of the results found in the first subsections, using the FGLS methodology.

5.5.3. Aggregate technology and sectoral carbon emissions

a) Power sector

The results from the two steps GMM estimator reported in table 26 show that, in the full sample, aggregate technology increases carbon emissions in the power sector. A 1 per cent increase in technology increases CO2 emissions by 0.011 per cent in the GMM model. The results are statistically significant at a 10 per cent level. It is not surprising that technology increases CO2 emissions in the power sector globally. Fossil fuels are the largest source of energy for electricity generation (IEA, 2020b). In 2018, electricity generation from fossil fuels accounted for 65 per cent of total electricity generation (IEA, 2020b). The remaining 35 per cent belongs to nuclear and renewable energy. Even if there is a gradual decrease in the share of fossil fuels in the production of electricity in developed economies, many emerging countries continue to invest heavily in these energies to produce electricity (IEA, 2020b). And this is facilitated by the evolution of technology. Another important reason that can explain the positive association between aggregate technology and power sector CO2 emissions is the lack of a competitive electricity market in the electricity sector. In many countries, notably in developing economies, electricity generation is entrusted to a state-owned company that has a monopoly on the production and distribution of electricity. The prevalence of state-owned companies in electricity production is based on the principle that energy is primarily a public good. As such, its management cannot remain in the hands of private companies. Other reasons for monopoly presence in electricity production are the high initial costs of producing electricity on a regional or national scale and the need to find a "fair" price for consumers. However, several studies have shown that promoting competition in the electricity sector can be beneficial for reducing electricity costs and prices. It is also beneficial for the environment by promoting energy efficiency (Hibbard, Tierney, & Franklin, 2017).

In the GMM model, technology increases power sector carbon emissions in upper-middle and lower-middle-income countries. However, it does not have a significant effect in high-income countries. The nonsignificant impact of technology on carbon emissions in the high-income countries' power sector can be explained by the considerable disparity in the evolution of fossil fuel shares in electricity generation across countries. Some countries associate their technological advancement with a greater investment in fossil fuels for electricity generation, while others favour renewable energies. During the previous decade, countries such as UK and Spain have sensibly reduced their dependence on electricity from fossil fuels. From 2008 to 2018, the share of fossil fuel electricity dropped from 80% to 47% in the UK and1% to 41% in Spain (BP, 2021). Other high-income countries such as Germany and Italy have also experienced similar changes in their energy mix.

On the contrary, some countries have increased their production of fossil-fuel electricity. This share rose from 64% to 75% in Japan from 2008 to 2018. South Korea's share increased from 64% to 73% during the same period. Regarding other high-income countries selected in this thesis (e.g., France, Canada, Belgium, and Saudi Arabia), the share of fossil-fuel electricity has remained more or less stable during our study period (BP, 2021). The intuition behind all these figures is that, in the electricity sector, technology development has been at the same time used to increase the exploitation of fossil fuel energy for electricity generation and to expand the development of renewable energy. So we have both a positive and a negative effect of the technology on the CO2 emissions in this sector. This balancing effect has resulted in an insignificant impact of technology on sectoral carbon emissions from the power sector. The two effects seem to have the same magnitude and cancel each other out.

Results also indicate that technology increases carbon emissions from the power sector in upper-middle and Lower-middle income countries. These countries invested more in fossil fuel-based electricity than green electricity during our study period. Take the example of electricity from coal. Asia (continent in which two major coal producers are located: China and India) has increased its coal-based electricity from 12 474 Twh of electricity in 1999 to 33 300 Twh in 2014, a rise of nearly 268 per cent (BP, 2021). Forty per cent of electricity produced in Africa came from gas in 2018; this share was only 20 per cent 20 years ago (IEA, 2018). Because the increase in fossil-fuel-based electricity seems to outweigh the rise in electricity from renewable energy, it can be intuitively deduced that technology has played a more positive role in increasing the power sector carbon emissions in developing countries.

Table 26. DIF-GMM results estimations (technological progress index)

Two-Step DIFF-GMM with orthogonal deviations Dependent variable: sectoral carbon emissions										
	Full sample					High-income sample				
	Power (7a)	Manuf(7b)	Transp (7c)	Petrol (7d)	Building (7e)	Power (7a)	Manuf (7b)	Transp (7c)	Petrol (7d)	Building (7e)
Lag term	.2617*** (14.73)	.5591*** (16.91)	.0319** (2.55)	.3840*** (12.80)	-.0601*** (-3.22)	.7806*** (7.31)	.5172*** (3.38)	.2288** (2.78)	.6492** (2.88)	.6503*** (7.78)
GDP	1.893*** (3.16)	1.638*** (4.44)	1.361** (2.59)	1.113** (2.35)	1.450*** (3.84)	-.0791 (-0.24)	-.0444 (-0.77)	.5188** (2.42)	-.2884 (-0.83)	.1242** (2.49)
GDP_SQ	-.1012*** (-3.20)	-.0843*** (-4.11)	-.0479 (-1.60)	-.0537 (-1.55)	-.0735*** (-2.93)					
Urbanization	1.819*** (6.59)	.9209*** (8.86)	1.470*** (4.70)	.5524*** (4.67)	.3089* (1.86)	-2.057 (-0.83)	-3.826 (-1.07)	-1.894* (-1.82)	-1.365** (-2.19)	.1847 (0.17)
Fin_Dev	-.0186 (-0.88)	.0726** (2.66)	.0408** (2.44)	.1559*** (7.02)	.0267* (1.84)	.1658* (1.90)	.1084 (0.95)	.2062** (2.86)	.0823** (2.72)	.1389* (1.97)
Index1	.0117*** (4.26)	.0036*** (-4.32)	.0025** (2.30)	.0040** (2.18)	-.0004 (-0.43)	.0029 (0.43)	**-.0037**** **(2.48)**	.0006 (1.13)	.0109* (1.95)	**-.0044**** **(-2.62)**
AB(1) Pr > z	0.051	0.003	0.082	0.004	0.062	0.019	0.052	0.086	0.043	0.012
AB(2) Pr > z	0.878	0.762	0.443	0.737	0.398	0.370	0.703	0.434	0.816	0.995
Sargan Pr > χ^2	0.069	0.998	0.000	0.987	0.045	0.500	0.557	0.301	0.001	0.212
Hansen's Pr >χ^2	0.722	0.823	0.313	0.888	0.820	1.000	1.000	1.000	1.000	1.000
Turning point	11 530	16569	-	-	19225					
	Upper-middle income sample					Lower-middle income sample				
Lag term	.0552 (066)	.0422 (0.43)	.0885* (1.71)	.5982*** (5.17)	.1905*** (3.01)	.3290*** (4.52)	.0749 (0.77)	.3797*** (4.17)	.2407 (1.26)	.3265*** (3.13)
GDP	.5865** (2.42)	.6901** (2.23)	.2893* (2.00)	-.5479 (-1.59)	.3147** (2.15)	.5927* (2.01)	.8834** (2.53)	.1195 (0.45)	.4718* (1.76)	.1672 (0.96)
Urbanization	3.288* (1.79)	.9356 (0.64)	1.1198** (2.17)	2.805* (1.72)	.1687** (2.21)	1.247** (2.37)	1.881 (1.51)	1.067 (1.05)	1.735* (1.77)	.9826* (1.69)
Fin_Dev	.2974*** (3.41)	.0858** (2.30)	.1227* (1.89)	.0555 (0.33)	.0840** (2.69)	-.3589 (-1.07)	.1152 (0.57)	-.0802 (-0.68)	-.2690 (-1.32)	-.2627** (-2.21)
Index1	.0183** (2.74)	-.0025 (-0.23)	.0163* (1.73)	-.0052 (-0.52)	.0024 (0.31)	.0231** (2.69)	.0142* (1.86)	.0266** (2.51)	.0042 (0.60)	.0118* (1.73)
AB(1) Pr > z	0.078	0.091	0.690	0.080	0.081	0.048	0.083	0.040	0.065	0.095
AB(2) Pr > z	0.668	0.683	0.418	0.347	0.201	0.542	0.349	0.432	0.356	0.879
Sargan Pr > χ^2	0.001	0.226	0.777	0.851	1.000	0.596	0.399	0.767	0.955	0.681
Hansen's Pr >χ^2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

b) The manufacturing sectors

Results show that technology increases CO2 emissions from the manufacturing sector in the full sample and the upper-middle-income countries but decreases CO2 emissions in high-income countries. The industrial sector requires a lot of energy, particularly in developing countries that have seen their energy demand explode in recent decades. Three main reasons explain technology's positive coefficient in the full sample. First, the growing energy demand from manufacturing industries in developing countries. Second, the reliance on fossil fuel energy to power these industries. The last main reason is the weak impact of measures taken by the industrial sector to lower energy consumption and reduce carbon emissions (Khoshnevis & Dariani , 2019).

Regarding high-income countries, technology turns out to have a negative impact on carbon emissions. High-income countries are progressively diversifying their energy supplies by increasing the share of renewable energies in the energy mix. The industrial sector seems to take advantage of this energy mix by favouring the supply of renewable energy instead of fossil fuel energy. Also, industrial equipment and machinery are constantly improved to make them more efficient. Promoting energy efficiency leads to identifying procedures and techniques that reduce energy consumption[35]. Therefore, it seems that in high-income countries, the negative effect of technology on carbon emissions has outweighed its positive impact, resulting in a negative relationship between technology and CO2.

c) The transport sector

Technology is positively related to carbon emissions in the transport sector in the full sample and upper-middle and lower-middle-income countries. The relationship between aggregate technology and transport sector carbon emissions is negative but statistically insignificant in high-income countries. We consider that the main reason for this positive relationship is the insufficient stock of low carbon vehicles (electric vehicles, hydrogen vehicles, etc.) globally. The stock of electric vehicles in the world is far too low to affect carbon emissions significantly. In 2018, electric cars accounted for only 1 per cent of global car stock (IEA, 2020). Another reason is that energy consumption in the transport sector continues to increase despite technological innovations implemented to save energy and reduce combustion engines' carbon footprint. A typical illustration of this is the continued popularity of Sport Utility Vehicles (SUVs), offsetting some of the benefits of increased electric vehicles in the last decade (IEA, 2021a). The IEA (2021a) notes that despite the increased availability of electric SUV models and

[35] Identifying the ways that manufactures can use less energy to light and heat factories or to run equipment. Industries can also switch to fuels that result in less CO2 emissions but the same amount of energy, when combusted (e.g. using natural gas instead of coal to run machinery).

improved fuel efficiency in new SUV models, an average SUV still consumes around 20% more energy than medium-sized vehicles. This implies more carbon emissions as the sale of SUVs is on the rise worldwide[36].

d) Petrol sector

There is a positive and significant relationship between technology and petrol sector carbon emissions in the full and upper-middle-income samples. This relationship is also positive in high-income and lower-middle-income countries but is not statistically significant. The petroleum industry is the sector that supplies other sectors with fossil fuel energy; unsurprisingly, technologies used in this sector are mostly directed towards the discovery of new oil and gas fields[37], hence expanding petrol and gas production[38]. Green technologies used in this sector can only have a limited impact on CO2 emissions. A promising technology that can allow extracting petrol or gas while not sending carbon emissions into the atmosphere is carbon capture and storage technology (Beuttler, Charles, & Wurzbacher, 2019). There is still the challenge of developing this costly technology on a large scale to impact the petrol sector's carbon emissions significantly. Stopping routine flaring in the petrol sector is another important measure that should be implemented in the petroleum and gas extraction industries. Masnadi et al. (2018) noted that burning unwanted gas associated with oil production - called flaring - remains the most carbon-intensive part of producing oil. According to Masnadi et al. (2018), eliminating routine flaring and cutting methane leaks and venting could cut as much as 700 megatons of emissions from the oil sector's annual carbon footprint - a reduction of roughly 43 per cent.

e) Building sector

Aggregate technology significantly reduces carbon emissions in the building sector only in high-income countries. The relationship between aggregate technology and carbon emissions is statistically insignificant in all other samples. Some of the main reasons that decrease energy consumption and thus carbon emissions in the building sector are as follows. Firstly, the growth rate of urbanization is relatively lower than other income groups, allowing the construction sector to also focus on building smart cities and on the renovation and refurbishment of existing buildings with more efficient systems that can significantly reduce energy consumption. Secondly, energy-consuming building systems such as heating, cooling, and lighting systems in private homes, office buildings, and public buildings (schools,

[36] The share of SUVs in total passenger car sales was around 40% in US, 20% in Europe, 30% in China, 25% in South Africa, and 30% globally (IEA, 2021a).
[37] The proved oil reserved in the world increased from 1277 billion of barrel in 1999 to 1736 in 2018.
[38] Oil production increased from 3448 millions of tons in 1999 to 4500 tons in 2018. An increase of 30 per cent. Gas production went from 2310 billion cubic meters in 1999 to 3857 billion of cubic meters in 2018.

hospitals, campuses, etc.) are becoming more efficient with technological advancement. Thirdly, energy efficiency investment in buildings has constantly increased in high-income countries over the past decade. From 2015 to 2020, efficiency investment in Europe and the US building increases from USD 100 billion to USD 130 billion (IEA, 2021a).

f) Consistency of estimates and other key drivers

Regarding the consistency of the GMM estimator and the validity of instruments, the Arellano and Bond serial correlation test confirms the consistency of the GMM estimator as the test confirms the presence of first-order serial correlation but could not reject the null hypothesis of the second-order serial in all models. Two tests of over-identification restriction are reported: the Sargan and Hansen test (robust to heteroskedasticity and autocorrelation). Both tests confirm the validity of instruments, as they fail to reject the null hypothesis of no over-identification restriction in most models.

Concerning other key drivers of sectoral carbon emissions, generally, GDP per capita elevate sectoral carbon emissions in all samples. Urbanization is positively related to sectoral carbon emissions in upper-middle and lower-middle-income countries. These results are consistent with Wu et al. (2016), who have demonstrated that a higher urbanization rate leads to higher carbon emissions in developing countries. In high-income countries, urbanization reduces sectoral CO2 emissions. As Wang et al. (2021) noted, high-income countries progressively diversify and expand urban public transport, reducing the number of vehicles on the roads. The construction of smart cities also brings optimal use of energy sources. Efficiency and economy of scale in public infrastructure and well-functioning waste management create a better environment (Moreno and Lee-Gosselin, 2011).

Financial development leads to higher carbon emissions in all samples, except the lower-middle-income sample. In lower-middle-income countries, financial development seems negatively related to sectoral carbon emissions. However, this negative relationship is only statistically significant in the building sectors. Overall, the sign of lagged CO2 emissions is positive and statistically significant across sectors, suggesting that the dependent variable has a causal effect on itself over time.

Regarding the presence of an inverted U-shape relationship between sectoral CO2 emissions and GDP per capita in the full sample, the coefficients on GDP per capita and GDP per capita squared have the expected signs in the power, manufacturing, and building sector. Thus, supporting the presence of an Environmental Kuznets Curve in these three sectors. This study could not find evidence of EKC in the transport and petrol sectors. As mentioned above in the transport sector and petrol sector results' subsections, we argue that the lack of EKC evidence in these two sectors is probably related to their nature. The petrol sector is primarily a carbon-intensive sector, and the transport sector dramatically relies on the consumer's individual choice of the type of vehicle to purchase. Although GDP per capita is increasing worldwide, electric vehicles are still expensive to attract middle-class consumers. In the petrol sector, promising solutions for carbon reduction are still expensive or at an early stage of development. Therefore, we think EKC will probably be detected in the near future thanks to technological advancements that will bring game-changing solutions such as large-scale carbon capture storage in the petrol sector and cost-cutting technologies for electric vehicles.

5.5.4. Green technology and sectoral carbon emissions

Table 27 reports the GMM estimation results for model (4). Results reveal that renewable energy is associated with a decline in CO2 emissions in all sectors except the petrol sector for the full sample. Subsample results estimation also reveals similar findings. Thereby endorsing the findings of Saidi and Omri (2020), Akram et al. (2020), and Dogan et al. (2021). The effect of renewable energy on sectoral carbon emissions is negative but becomes nonsignificant in many sectors in upper-middle and lower-middle-income countries. In general, there is a nonsignificant relationship between renewable energy consumption and petrol sector CO2 emissions in all samples. This result can be explained by the fact that the petrol sector is primarily carbon-intensive; fossil fuels come from this sector. Also, as noted by the IEA (2020), carbon emissions from the petrol sector have been dramatically increasing over the past decades despite renewable energy development. While some regions have experienced a significant decline in oil extraction investments (e.g., Europe); other regions have increased their investments in gas extraction over the past decades (e.g., shale gas in the USA, gas extraction in Russia) (Azam, Rafiq, Shafique, Zhang, & Yuan, 2021). Gas is considered less polluting than other fossil fuels – such as oil and coal - (Zárante, Barros, & Sodré, 2009). So this suggests that the development of renewable energies has, for the moment, little influence on carbon emissions from the oil sector, which continues to develop, particularly with natural gas exploitation.

Table 27. DIF-GMM results estimations (Green technology)

Two-Step DIFF-GMM with orthogonal deviations Dependent variable: sectoral carbon emissions										
	Full sample					High-income sample				
	Power (7a)	Manuf(7b)	Transp (7c)	Petrol (7d)	Building (7e)	Power (7a)	Manuf (7b)	Transp (7c)	Petrol (7d)	Building (7e)
Lag term	.3522*** (35.96)	.2526*** (14.62)	.3864*** (19.78)	.3746*** (13.41)	.4144*** (23.58)	.3103** (2.59)	.1693* (1.78)	.1476* (1.82)	.3996** (2.90)	.3906*** (4.42)
GDP	1.963*** (2.00)	1.594*** (10.37)	1.4893*** (3.12)	1.0495 (0.11)	1.267*** (4.94)	.5650 (0.51)	.6004** (2.60)	.5276*** (7.79)	.2501** (2.33)	0.133** (2.24)
GDP_SQ	-.1033*** (-2.78)	-.0828*** (-10.21)	-.0086 (-0.96))	.0222 (0.90)	-.0645*** (-5.07)					
Urbanization	1.988*** (15.49)	1.187*** (10.18)	1.085*** (9.96)	1.016*** (16.84)	1.043*** (14.47)	1.4760 (0.22)	-1.7457* (-1.78)	-1.3881 (-0.60)	-1.9206* (-1.66)	-.7718* (-1.89)
Fin_Dev	.0460** (2.44)	.0287** (2.16)	.1077** (13.13)	.1923*** (12.22)	.0140* (1.82)	.1023* (1.66)	.1350 (0.83)	.1647** (8.87)	.1151** (2.06)	.1728*** (3.05)
renewable	-.1494*** (-7.22)	-.1807*** (-9.94)	-.0868 (1.04)	-.0038 (-0.37)	-.1608*** (-12.88)	-.1793*** (-2.96)	-.2469*** (-4.56)	-.0850* (-1.97)	-.0357 (-0.55)	-.1133** (-4.50)
AB(1) Pr > z	0.145	0.004	0.055	0.011	0.005	0.178	0.100	0.692	0.027	0.013
AB(2) Pr > z	0.827	0.601	0.607	0.817	0.562	0.931	0.688	0.445	0.627	0.986
Sargan Pr > χ^2	0.772	0.279	1.000	1.000	0.958	1.000	0.996	1.000	1.000	1.000
Hansen's Pr > χ^2	0.481	0.380	0.413	0.502	0.673	1.000	1.000	1.000	1.000	1.000
Turning point	13 379	15 148	-	-	18 429					
	Upper-middle income sample					Lower-middle income sample				
Lag term	.5517*** (6.12)	.4022*** (3.62)	.4447*** (3.37)	.3736*** (5.30)	.2767** (2.13)	.3462*** (3.74)	.0568 (0.29)	.4613*** (4.53)	.1230 (0.41)	.3715*** (4.17)
GDP	.2248* (1.98)	.4388** (2.14)	.6041*** (3.85)	.1740 (0.48)	.5927** (2.76)	.3905*** (3.32)	1.030*** (3.13)	.0526 (0.17)	.7448* (1.81)	.4097*** (2.99)
Urbanization	2.324** (2.74)	.1841 (0.38)	.4776 (0.67)	2.352*** (4.91)	.4143** (2.67)	.6221 (0.68)	1.475* (2.03)	1.930** (2.15)	2.125** (2.13)	1.910*** (3.77)
Fin_Dev	.1564* (1.94)	.1499* (1.95)	-.1176 (-1.67)	-.1192 (-0.57)	.0831* (1.80)	.2576** (2.76)	.3761** (2.21)	.0649 (0.45)	.2960* (1.69)	-.0257 (-1.06)
renewable	-.0372** (-2.25)	-.1353* (-1.77)	-.0695* (-1.73)	.0265 (0.22)	-.2222** (-2.58)	.4824 (0.86)	-1.137* (-2.87)	-.2921** (-1.83)	-.4512*** (-3.79)	-.2178* (-1.91)
AB(1) Pr > z	0.025	0.067	0.041	0.072	0.131	0.412	0.416	0.060	0.061	0.097
AB(2) Pr > z	0.184	0.351	0.696	0.311	0.241	0.371	0.335	0.706	0.562	0.769
Sargan Pr > χ^2	0.564	0.221	0.322	0.623	0.911	0.645	0.565	0.742	0.957	0.990
Hansen's Pr > χ^2	0.632	0.453	0.356	0.781	0.812	0.423	0.902	0.501	0.568	0.845

Standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

5.5.5. Robustness check and extension

a) FGLS methodology

The FGLS results are reported in Table A2 in the Appendix. According to the diagnostic test results, problems of cross-sectional dependence are found in the dataset. The FGLS methodology allows controlling for cross-sectional dependence. In addition, it also deals with heteroscedasticity and serial correlation (Bai, Hoon Choi, & Liao, 2021). The results reported by FGLS are generally similar to those obtained with GMM. Generally, aggregate technological progress positively influences carbon emissions in all energy sectors, and green technology reduces carbon emissions (see table A2). FGLS also confirms that the technological index is negatively related to CO2 emissions in high-income countries' manufacturing and building sectors.

However, unlike the GMM, FGLS results suggest that Aggregate technology increases carbon emissions in the power sector in high-income countries. The turning point estimate in the FGLS model (4) is higher in the building sector compared to the power and manufacturing sectors. It is not surprising that the power and the manufacturing sector's carbon emissions would be reduced prior to the building sector emissions as income increases. The power and the manufacturing sectors have more tools in terms of finance and energy policies to develop energy-efficient technologies (Erdogan, 2021). The turning point stands at 14363$, 15870$, and 20768$ for the power, manufacture, and building sectors. Data descriptive statistics presented in the Appendix (chapter 4) show that upper-middle and lower-middle-income countries' average GDP per capita is 6680$ and 2470$, respectively. Also, the income distribution is skewed toward zero. Thus, the majority of the population in our sample has not yet passed the turning points estimated in this chapter, making higher global carbon emissions the likely outcome of economic growth. However, there is hope that these turning points will be reduced thanks to technological progress.

b) Extensions

In this subsection, we analyze further the results obtained in the high-income country's sample. Findings indicate that the technological index developed in this chapter decreases carbon emissions in the manufacturing and building sectors. These two sectors together account for more than a third of total carbon emissions, and most companies that operate in these two sectors belong to the private sector. From the result obtained in table 28, it can intuitively be deduced that enterprises take climate change challenges into account in their expansion strategies. They use the skills acquired through investing in technological progress to decarbonize the production process of goods and services. Model

(8) is established to check this hypothesis. Model (8) aims to provide empirical evidence of the effects of business R&D expenditure on the manufacture and the building sector CO2 emissions in high-income countries. R&D expenditure is considered an essential upstream technology push instrument that helps develop, design, and enhance companies' products, technologies, and processes.

$$\ln \mathrm{Man}_{it} = \ln(\mathrm{Man}_{it-1})\delta + \ln(\mathrm{RD\_Man})_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \tag{8a}$$

$$\ln \mathrm{Build}_{it} = \ln(\mathrm{Build}_{it-1})\delta + \ln(\mathrm{RD\_Build})_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \tag{8b}$$

Model (8a) investigates the effect of manufacturing R&D expenditure on manufacturing carbon emissions, and model (8b) examines the influence of construction R&D expenditure on building sector carbon emissions. Data of these two distinct types of R&D expenditure comes from the OECD. Period (a) refers to the full period (1999-2018), and period (b) refers to a twelve-year period (2007-2018).

Table 28. Manufacture and building sector R&D results.

Two-Step DIFF-GMM with orthogonal deviations Dependent variable: sectoral carbon emissions				
High-income sample				
	Period (a)		Period (b)	
	Manuf (7a)	Building (7e)	Manuf (7a)	Building (7e)
Lag term	.4202*** (8.64)	.6165*** (12.63)	.4838*** (18.7)	.5207*** (10.32)
GDP	.2507 (1.22)	.0931** (2054)	.5051*** (3.14)	.1136** (2.39)
Urbanization	-.3635 (-1.20)	-.5082** (-2.13)	-.2334** (-2.22)	-2.757** (-2.13)
Fin_Dev	.2614 (1.55)	.1538 (0.66)	.4303** (2.30)	.0358 (0.45)
R&D Man	-.1093** (-2.08)		-.2271*** (-12.65)	
R&D BUILD		-.0159*** (-3.02)		-.0201** (-2.45)

*(**) [***] indicate the level of significance at a 10(5) [1] % level.

Table 28 shows that a 1 per cent increase in manufacturing R&D spending decreases manufacturing carbon emissions by 0.10 per cent. When taking the period 2004-2018, this reduction increases from 0.10 to 0.22 per cent. On the other side, a 1 per cent increase in construction sector R&D reduces building sector CO2 emissions by 0.01 per cent from 1999-2018 and by 0.02 from 2004-2018.

This result demonstrates how the private sector is a key player in climate mitigation and the transition to a low-carbon world. These findings suggest that companies are progressively integrating climate change and market opportunities that may arise from it among their priorities. The manufacturing sector is done by gradually decarbonizing production and supply chain processes. Also, by replacing the supply of fossil fuels with renewable energies, encouraging energy efficiency, and implementing a circular economy that aims to optimize the use of materials and energy. Companies are seizing colossal investment opportunities to construct green buildings and smart cities in partnership with the public sector. Green buildings impact climate change and people's lives by reducing energy bills through innovative technics and technologies, such as solar panels and insulation. The Environmental Protection Agency (EPA) estimates that homeowners in the US can save an average of 18% on heating and cooling costs by making proper home insulation (EPA, 2021). Companies can contribute to change through their actions and by encouraging governments to follow the example of the private sector and pass laws that provide the right framework for companies to progress. The public sector can also provide strategic opportunities for target setting and collaboration to support the private sector. The Sustainable Development Goals are a good example of the opportunity for the private sector to formulate long-term goals and partnerships that will help achieve sustainable development for all.

5.6. Conclusion

A growing number of existing studies in the broader literature have examined the relationship between technology and CO2 emissions. However, these studies have generally neglected differences in carbon emissions per energy sector. We argue that because each sector's contribution to total carbon emissions varies, the environmental impact of technological advancement may also differ across sectors.

The research purpose of chapter five was to investigate the heterogeneous effects of aggregate and green technology on sectoral CO2 emissions in 45 countries, divided into three income categories (High-income, upper-middle, and lower-middle-income). The study period ran from 1999 to 2018. The fifth chapter used the STIRPAT model as the theoretical framework with sectoral carbon emissions as the dependent variable and technology, GDP per capita, urbanization, and financial development as explanatory variables. Five energy sectors are selected: the power, manufacturing, transport, petrol, and building sector. These five sectors generally account for more than 75% of carbon emissions across countries (IEA, 2020). Chapter five contributed to the literature by determining which economic sector is positively or negatively impacted by aggregate and green technology. The chapter employed principal component analysis to construct an aggregate technology index from four usual technological progress indicators (Patents, R&D expenditure, ICT, and science and technology publications). Renewable energy consumption is employed as an indicator of green technology development. This study has adopted dynamic panel models and implemented two econometrics methodologies to empirically estimate the results: DIFF-GMM and the Feasible Generalized Least Square (FGLS) methodology.

The full sample results indicated that, on the one hand, aggregate technology increases carbon emissions in the power sector, manufacturing sector, transport sector, and petrol sector. However, aggregate technology fails to affect the building sector's CO2 emissions. On the other hand, renewable energy significantly lowers emissions in all sectors, except the petrol sector. Findings also suggest that urbanization and financial development generally lead to higher carbon emissions in all sectors in the full sample. Results from subsamples indicated that, generally, aggregate technology is positively associated with carbon emissions in all sectors in upper-middle-income and lower-middle-income countries. However, Aggregate technology is negatively related to carbon emissions in high-income countries' manufacturing and building sectors. The study further demonstrated that technological progress induced by the private sector plays a significant role in reducing CO2 emissions in these two sectors.

Regarding the control variables, it is concluded that income and financial development lead to more air pollution and environmental degradation in all samples. However, urbanization is positively related to CO2 emissions in lower-middle-income countries but negatively associated with carbon emissions in high-income countries. These findings are similar to several studies that have found that urbanization can **negatively influence** the ecosystem (deforestation, air pollution, waste management, etc.) (Liddle, 2014; Wu et al., 2016; Khoshnevis and Dariani, 2019). Urbanization can also positively affect the environment by promoting public transport and reducing traffic congestion (Pachauri and Jiang, 2008; Barla, Moreno, and Lee-Gosselin, 2011).

This chapter also investigated the presence of EKC in sectoral carbon emissions in the full sample. We wanted to check if sectoral CO2 emissions decline after reaching a certain income level. This study found evidence of EKC in the power, manufacturing, and building sector. However, the study could not find evidence of EKC in the transport and petrol sector.

Some important policy implications can be drawn from these empirical findings. First, the study's findings indicate that, in most industries, technological advancement benefits carbon emissions. It is a sign that current efforts to decarbonize technology are insufficient. The Paris Agreement's goals must be attained by quicker and increased effort. Many energy-saving techniques and carbon-neutral technologies are either not yet widely used or are still in the early stages of development. In addition, these technologies are usually more expensive than traditional technologies (Hashmi and Alam, 2019). It will require a significant investment in research and development, including pilot projects and large-scale demonstration installations, for these technologies to be competitive and useable on a large scale.

(1) Concerning the power sector, the authorities should liberalize the electricity sector in addition to massive investments in renewable energies. This should be done especially in low-income countries, which often fail to meet the energy needs of their economies. Liberalizing the electricity sector will bring competition, encouraging the acquisition and adoption of innovative technologies and thus increasing energy efficiency in the power sector.
(2) Regarding the transport sector, the major solution is the development and deployment of electric vehicles. Even though the electric car market is rapidly expanding in high-income countries, it is still underdeveloped in the rest of the world. In general, one of the significant challenges in the transportation sector is the cost of buying an electric vehicle. The price of an electric vehicle is still much higher than a combustion engine vehicle. These challenges can only be met through a collaborative effort between governments and industries. The government could adopt a set of incentive policies. Measures such as reducing taxes for the production of electric cars and – primarily purchase subsidies and/or vehicle purchase and registration tax rebates for consumers. Another major challenge for all countries is to invest in a solid network of charging stations and ensure that this network is powered by renewable energy.

(3) Carbon capture storage technologies (CCS) constitute a promising solution to reduce CO2 emissions in the petrol sector. However, CCS projects require a lot of capital and a highly skilled workforce. Oil and gas companies, as well as other large emitters, will not invest in these projects if they significantly impact the profitability of their operations. It is also worth noting that many CCS technologies are either new or are not yet commercially viable. Public R&D funding for emerging CCS technologies can help strengthen CCS development across countries and contribute to developing important future technologies. Governments should seek to strike the right balance between early-stage public investment in CCS projects and better regulation, with the ultimate goal of encouraging increasingly market-oriented CCS investment.

Secondly, the fact that technology reduces carbon emissions in the industrial and building sector in high-income countries indicates gradual decarbonization of industrial processes and a trend towards building more energy-efficient homes. The private sector that owns most companies in these two sectors plays a critical role in the energy transition. Given this fact, policymakers can encourage manufacturers in high-income countries to continue to engage in the energy transition. This requires intensifying incentive measures to enable companies to use green energy, produce eco-friendly goods, and disseminate the acquired "green knowledge" to other industries through cooperation and spillover effects.

Thirdly, implementing effective emissions trading systems (such as the European Union Emissions Trading System (EU ETS) across countries will also help to boost the competitiveness of carbon-neutral technologies compared to traditional technologies. A system where CO2-intensive generation will gradually become more expensive due to the rising cost of emissions. This system will strongly encourage incentives for energy-intensive industries to shift to low-carbon technologies to remain competitive in the future.

Fourth, our research found that rising carbon emissions are typically associated with financial development. This exemplifies how the current financial system typically allocates savings to the most profitable enterprises without considering environmental issues when investing. As a result, it is critical to encourage and promote green finance, which aids the energy transition by funding environmentally friendly businesses and enabling the growth of a sustainable economy.

Appendix

A.1. Descriptive statistic: full sample

Variables	Observations	Mean	Stand dev	Min	Max
GDP per capita	899	15502.76	17088.77	508.3852	56842.3
Financial credit	854	69.27214	48.66821	5.388089	221.2885
Urbanization	900	64.95143	19.54564	19.55	98.001
Index	895	27.41512	23.84828	0.988715	100

A.2. Descriptive statistic: subsample

	Observations	Mean value	Standard deviation	Minimum value	Maximum value
Index					
High-income	296	54.97329	19.30987	13.53428	100
Upper-middle income	300	20.35527	9.652052	4.510289	57.29239
Lower-middle income	299	7.216899	5.45532	0.988715	23.09999

A.2. FGLS estimation (Aggregate technology)

FGLS										
Dependent variable: sectoral carbon emissions										
	Full sample					High-income sample				
	Power (7a)	Manuf(7b)	Transp (7c)	Petrol (7d)	Building (7e)	Power (7a)	Manuf (7b)	Transp (7c)	Petrol (7d)	Building (7e)
Lag term	.9597*** (7.40)	.9728*** (7.38)	.9701*** (6.82)	.9745*** (9.28)	.9747*** (3.63)	.8972*** (3.66)	.9196*** (8.18)	.9462*** (7.88)	.9364*** (5.79)	.8883*** (7.44)
GDP	1.388** (2.21)	1.505*** (2.47)	1.282*** (3.40)	.4977 (1.51)	1.014** (2.15)	.3124** (2.15)	.2201 (1.03)	.2271 (1.21)	.2268** (2.17)	.2630** (2.31)
GDP_SQ	-.0725** (-2.13)	-.0778* (-1.86)	-.0153 (-0.54)	-.0257 (-0.50)	-.0510** (-2.23)					
Urbanization	1.227*** (2.87)	1.0965* (1.83)	1.366* (1.89)	.5294** (2.07)	.3515 (1.25)	-1.9895*** (-4.61)	-1.401*** (-4.24)	-1.284*** (-2.77)	-1.297** (-2.30)	-.7078*** (-3.41)
Fin_Dev	.0189* (1.81)	.0697* (1.84)	.0487 (1.29)	-.1137 (-1.02)	.0209 (0.10)	.0957*** (2.70)	.0138 (0.65)	.2338* (1.86)	.0847** (2.43)	.1780** (2.09)
Index	.0115* (1.70)	.0030** (1.96)	.0021*** (3.27)	.0309 (1.52)	.0033 (1.09)	**.0025*** **(1.77)**	**-.0020***** **(-3.64)**	.0008** (2.13)	.0116** (2.12)	**-.0024**** **(-2.16)**
Constant	-.5872 (-1.01)	.3915 (1.00)	.9701*** (6.82)	-1.560*** (-3.43)	.4074 (1.09)	4.909*** (4.90)	2.218*** (4.34)	1.367*** (3.55)	1.364*** (2.78)	3.179*** (3.64)
Turning point	14 363	15 870	-	-	20 768					
	Upper-middle income sample					Lower-middle income sample				
Lag term	.9521*** (4.48)	.9636*** (3.00)	.9626*** (5.16)	.9704*** (5.54)	.9770*** (7.90)	.9650*** (7.31)	.9631*** (6.08)	.9540*** (6.67)	.9663*** (7.95)	.9502*** (8.19)
GDP	.5537** (2.13)	.6238* (1.76)	.2175** (2.43)	.1149** (2.24)	.4213 (0.30)	-.0265 (-0.45)	.8344* (1.73)	.2625*** (3.98)	.4829** (2.26)	.1227 (0.36)
Urbanization	-1.1741 (-1.30)	1.012 (0.13)	1.044** (2.68)	2.117** (2.18)	.2042** (2.36)	1.107 (0.75)	1.358** (2.18)	1.451** (3.98)	1.317** (1.98)	.9868** (2.40)
Fin_Dev	.2843** (2.14)	.0803 (0.02)	.1172* (1.68)	.0346** (2.91)	.0878** (2.21)	-.0153 (-0.46)	.0217 (0.66)	.0322* (1.66)	.0589* (1.79)	.0086 (0.28)
Index	.0159* (1.82)	.0034* (1.81)	.0026* (1.69)	.0003 (0.23)	.0035** (2.17)	.0080* (1.69)	-.0012 (-0.22)	.0241*** (3.77)	.0066* (1.61)	.0036** (2.74)
Constant	1.099 (1.46)	.0634 (0.11)	.2283 (0.54)	-.1136 (-0.25)	.2066 (0.56)	.9629*** (2.60)	.6519* (1.65)	.1038 (0.36)	.2168 (0.83)	.9529*** (2.82)

VI. Summary of key findings and policies recommendations

6.1. Overview of the thesis

Climate change poses a serious threat to our ecosystem and our society. In many countries, the priority of policymakers is to reduce carbon emissions without reducing economic growth. Despite general awareness and commitments by countries to reduce greenhouse gases, emissions levels continue to increase, reaching high recorded levels in recent years. Many scientists, political and economic leaders believe that technological progress is a game-changer and will play a vital role in the low carbon path for both developed and developing economies. However, it would be interesting to determine whether technological progress has reduced carbon emissions over the past decades. Hence the purpose of this thesis. This thesis aimed to achieve a comprehensive analysis of the relationship between technological progress and CO2 emissions. The main contribution of this thesis is provided by its multidimensional approach to technological progress and by the evaluation of its connection with CO2 emissions in each income group countries.

In order to reach its research purpose, this thesis was divided into three different parts. In the first part, the thesis started by examining the effect of aggregate technology on CO2 emissions. This was achieved by disaggregating technological progress using various technological measures and evaluating their effects on CO2 emissions in a panel of 60 countries divided into four income groups. This task included: i) a review of different aggregate technological indicators employed in the literature ii) a review of major drivers of CO2 emissions iii) A discussion on the limitations of each proxy representing technological progress iv) an empirical estimation of the effect of the selected technology measures on CO2 emissions in the full sample and subsamples. The thesis also considers the rebound effect and examines how technological progress affects carbon emissions through energy consumption. This is achieved by determining whether the rebound effect of energy consumption is higher or smaller than energy savings caused by technological progress. The thesis applied the fixed-effect method and the Bruno LSDVC methodology to estimate the results.

In the second part, the thesis analyzed the impact of green technology on carbon emissions. This task included: i) a review of different green technological indicators employed in the literature, ii) an empirical estimation of the green technology - carbon emissions nexus in the full sample and subsamples, and iii) Determining how climate change influences green technology development – Like in the first part, empirical results have been estimated with the fixed effect and the Bruno LSDVC methodology.

In the third part, the thesis assessed how aggregate and green technology affect sectoral CO2 emissions in five major energy sectors – Power, manufacture, transport, petrol, and building sector - This was achieved in the same sample of countries used in the first and second part. The thesis employed technological proxies used in the first part to construct an aggregate index of technological progress. Some sectors can make better use of technological advances to increase their production and gradually decarbonize their productive activities. The third part of this thesis verified this hypothesis. Empirical results in the third part have been estimated with the Generalized Method of Moment method and the Feasible generalized Least Square methodology.

6.2. Summary of key findings in response to the main research objectives and questions

6.2.1. What is the impact of Aggregate technological progress on CO2 emissions? Does this impact differ across country income groups? (Four groups of countries: low, lower-middle, upper-middle- and high-income countries).

After the thesis' topic introduction in chapter 1 and a comprehensive literature review in chapter 2, the third chapter (first paper) focused on evaluating the impact of various indicators of technological progress on carbon emissions in a full sample of 60 countries and in subsamples of different income categories. The full sample was divided into four income groups (15 high-income, 15 upper-middle-income, 15 lower-middle-income, and 15 lower-income countries), and the third chapter investigated how the relationship between technological progress and CO2 emissions changes across income groups. The study period runs from 1989 to 2018. Technology is a broad concept, and a single indicator can hardly represent it. Therefore, instead of using one indicator of technology as in most papers in the literature, chapter 3 uses six indicators of technological progress and assesses their impact on carbon emissions. ICT, R&D expenditure, patents, science and technology publications, and TFP are the technological progress indicators employed in the third chapter.

Regarding the full sample, this thesis found that ICT represented by mobile cellular subscriptions per 100 people and individuals using the internet (percentage of the population) reduced CO2 emissions over the study period. ICT lowers carbon emissions via three main[39] channels: increasing energy efficiency, decreasing the cost of renewable energy adoption, and reducing travel-related CO2

[39] Many other channels exist. Higon et al. (2017) note that ICT can also foster the development of smarter cities, electrical grids, transportation system and industrial processes.

emissions. This negative impact seems to outweigh ICT's positive impact on carbon emissions as a result of also contributing to the increase in GDP. Science and technology publications are negatively related to CO_2 emissions. Since global warming is increasingly becoming a subject of great concern, scientific debates are gradually more directed toward fostering green economic transformation across countries. Scientific discussions also help raise the awareness of governments, businesses, and the general public. Patent and R&D spending do not have a clear impact on CO_2 emissions. A possible explanation is the dual effect of these two technology measures on carbon emissions. R&D expenditure and patents may increase or decrease carbon emissions, depending on whether they are environmentally friendly or not. The two effects tend to cancel each other out, resulting in an insignificant impact on CO_2 emissions. TFP increases CO_2 emissions in the full sample, suggesting that, in general, taking all its different aspects together, technological progress would increase carbon emissions.

The subsample analysis suggests that ICT reduces CO_2 emissions in all four income groups. Science and technology publications negatively affect CO_2 emissions only in high-income and upper-middle-income countries. Conversely to full sample findings, patent, and R&D spending exhibit statistically significant results in some income groups. Patents increase CO_2 in all income groups, except in upper-middle-income countries. R&D expenditure increases CO_2 emissions only in lower-middle-income countries. R&D spending seems to have a nonsignificant impact on emissions levels in all other groups. The results of R&D spending can be explained as follows: In Lower-income countries, R&D spending is very low and insufficient to significantly impact CO_2 emissions. Lower-middle-income countries wishing to join the group of high-income countries pay little attention to the carbon footprint of funded projects, leading to an increase in CO_2 due to R&D spending. High-income and upper-middle-income countries are reaching a point where the gains from energy savings due to R&D spending equal the rise of energy consumption due to R&D spending, hence leading to an insignificant impact on carbon emissions. TFP positively affects emissions in all income groups. The third chapter also considers the rebound effect by interacting technological progress with energy consumption and assessing their common effects on carbon emissions. Results reveal that carbon emissions decrease despite the rebound effect for all joint interactions. There is an inverted U shape relationship between energy consumption and carbon emissions across technological progress. It suggests that as technology increases, the impact of energy consumption on carbon emission turns from positive to negative because of the energy efficiency induced by technology and the increasing share of green energy in the energy mix.

Regarding other important drivers of carbon emissions, GDP per capita and energy consumption are generally associated with high carbon emissions in the full sample and across all income groups. Export decreases CO_2 emissions in high-income and upper-middle-income countries but increases emissions levels in lower-middle and lower-income countries.

6.2.2. What is the effect of Green technology on CO2 emissions? Does this impact differ across country income groups?

In the fourth chapter (second paper), this thesis proposed to continue the analysis started in the previous chapter by examining the impact of green technology on CO2 emissions. Green technology is a component of aggregate technology, and theoretically, it should have a negative effect on CO2 emissions. Chapter four used the same sample employed in the third chapter; however, the lower-income countries have been excluded due to data availability constraints. Thus, the fourth chapter's empirical analysis was done on a full sample of 45 countries divided into three income groups (15 high-income, 15 upper-middle-income, and 15 lower-middle-income countries). Renewable energy and environmental-related patents have been used as indicators of green technology development. The thesis considered the production of renewable energies and the development of eco-friendly technologies as two complementary conditions for significantly impacting carbon emissions. It is not enough to produce renewable energies, but replacing existing fossil fuels-based technologies with eco-friendly technologies is also necessary. The number of environmental-related patents can, to some extent, show us the production level of a variety of eco-friendly innovations.

In the full sample results, renewable energy consumption reduced CO2 emissions. However, environmental-related patents do not have a significant impact on CO2 emissions. Similar results are found in all three income groups. The thesis did not find evidence supporting that eco-friendly innovation represented by environmentally friendly patents can effectively curb CO2 emissions in the full sample and in all three subsamples. However, findings suggest that eco-friendly innovations significantly contribute to carbon reduction only in very high-income countries[40]. In the other groups of countries, the level of innovation in green technology seems to have not yet reached a point that allows a significant reduction of carbon emissions. This does not mean that eco-friendly innovations are not present or valuable. It means that they are simply not produced in sufficient quantity to slow down the curve of CO2 emissions. Very high-income countries are the only group that achieves carbon reduction through renewable energy and eco-friendly innovations.

Chapter four has also investigated how higher carbon emissions and economic growth affect green and carbon-intensive technology adoption in different country income groups. Chapter four employed non-renewable energy as a proxy for carbon-intensive technology. Findings suggest that as CO2 emissions

[40] Very high-income economies consist of 10 countries that have an average per capita income of 36000$ during our study period

increase, high-income and upper-middle-income countries tend to invest more in renewable energy and less in non-renewable energy. However, lower-middle-income countries invest more in non-renewable energy and less in renewable energy. Findings also show that green patents respond positively and significantly to the increase in carbon emissions only in high-income countries. In other words, high carbon emissions push high-income countries to invest in green technology innovation.

Results also show that higher oil price promotes the adoption of renewable energy in all group of countries. Population density positively affects renewable energy adoption in high-income economies. However, it negatively affects renewable energy adoption in upper and lower-middle-income countries. Terms of trade is positively associated with renewable energy in high-income and upper-middle-income countries but negatively related to renewable energy in lower-middle-income countries.

6.2.3. What is the impact of aggregate and green technology on sectoral CO2 emissions? Emissions from five energy sectors: Power, manufacture, transportation, petrol, and building sectors

Through the fifth chapter (third paper), in pursuit of gaining a deeper understanding of the role of technology in climate change, the thesis investigated the effect of technology on CO2 emissions in five important energy sectors: Power, manufacture, transport, petrol, and building sector. The objective was to identify which sector technological progress is positively or negatively associated with carbon emissions. We argue that because each sector's contribution to total carbon emissions varies, the environmental impact of technological advancement may also differ across sectors. Chapter five used the same sample employed in the fourth chapter. The causal dynamics were studied using the GMM methodology from 1999 to 2018. The thesis developed an aggregate technological index using technology indicators employed in chapter three. Findings in the full sample analysis showed that, on the one hand, aggregate technology increases carbon emissions in all sectors except the building sector. On the other hand, renewable energy significantly lowers emissions in all sectors, except the petrol sector. Sub-sample findings indicate that aggregate technology is generally positively associated with carbon emissions across sectors in upper-middle-income and lower-middle-income countries. However, it is negatively related to carbon emissions from the manufacturing and building sector in high-income countries. The share of renewable energies in the energy mix is constantly increasing in higher-income countries. The industrial sector seems to take advantage of this energy mix by favouring the supply of renewable energy instead of fossil fuel energy. Also, there is a constant efficiency improvement in industrial equipment and machinery. Promoting energy efficiency leads to identifying procedures and techniques that reduce energy consumption in the production process. Results also confirm that the private sector plays an important role in reducing manufacturing and building sector CO2 emissions in high-income countries. Private R&D expenditure in these two sectors negatively affects CO2 emissions.

The fifth chapter also found that financial development leads to more air pollution and environmental degradation in all samples. However, urbanization is positively related to sectoral CO2 emissions in lower-middle-income countries but negatively associated with sectoral carbon emissions in high-income countries.

In conclusion, the findings of this thesis have confirmed that the relationship between technological progress and CO2 emissions is complex. This thesis allowed us to determine the dynamics between the different dimensions of technological progress and CO2 emissions. It can be concluded that, overall, aggregate technology seems to have a positive effect on CO2 emissions. But certain dimensions of technology have desirable effects on CO2 emissions—dimensions such as ICTs tools and scientific debate – renewable energy, and green innovations. ICT tools help in reducing CO2 emissions. Scientific debates reflected through science and technology publications encourage optimal and efficient energy use, leading to carbon abatement. This thesis also showed that R&D spending differently affects CO2. R&D can have a positive or insignificant impact on CO2 emissions depending on the country's income group. R&D spending, an upstream technology push instrument, is employed to fund both carbon-intensive and lower carbon-intensive projects, resulting in uncertain environmental impacts. Overall, the thesis shows that total patent increases CO2 emissions, suggesting that most innovations recorded during our study period did not sufficiently consider the environmental dimension in their innovation processes. This thesis also confirmed that renewable energy consumption reduces CO2 emissions. It has also demonstrated that high-income countries are more likely to achieve carbon neutrality quickly. It is the only group that successfully reduces carbon emissions through renewable energy development and eco-friendly innovations. Finally, the thesis showed that technological progress reduces sectoral carbon emissions in high-income countries' manufacturing and building sectors. The private sector plays a key role in achieving this result.

6.3. Policy recommendations and possible extensions

Climate change requires a collective effort from all stakeholders, particularly governments, businesses, and households, to limit the average temperature increase below 1.5 degrees by 2100, as stated in the Paris agreement (2015). To achieve the goals set by the Paris agreements, the world needs a massive and rapid reorientation of technology towards sustainable development.

The policy implications drawn from this thesis are as follows:

i. Regarding the impact of aggregate on CO2 emissions

(1) ICT can be used as an instrument to reduce carbon emissions. Efficient and responsible development and expansion of ICTs should be encouraged. For example, the use of smartphones helps to decrease carbon emissions by encouraging behaviours such as reducing the movement of people using cars[41], the increasing use of public transport, expansion of mobile money (notably in Africa), and the use of remote control for home heating and other connected devices. The benefits associated with ICTs were even more felt during the Covid 19 pandemic that hit the planet in 2020[42]. (2) Governments worldwide should have a common agreement to encourage green patent applications and intensify policies that will encourage firms and industries to produce lower carbon products. (3) Public R&D expenditure should be more directed towards projects that will produce lower carbon products and technologies. (4) Science and technology publication should be promoted as it fosters the debate on reaching green and sustainable development solutions.

ii. Regarding the effect of green technology on CO2 emissions

The policy implications drawn from chapter four are as follows: (1) government and industries should continue to promote the development and expansion of renewable energy around the world to fight climate change. Here, it is important to note that lower-income countries do not necessarily have to reinvent new technologies. They can borrow and adapt to their own situation technologies already created in developed countries to reduce carbon emissions. Some strategies for promoting clean energy are worth considering by policy-makers. This includes demand-focused strategies and supply-oriented strategies. Strategies based on the demand side are those which increase the ability of consumers to buy clean energies. This may assume the form of government vouchers or in-cash assistance to consumers. Supply-oriented strategies include the use of market mechanisms such as

[41] Most cars need fuel to move. Smartphones also help in reducing movement of people through online shopping.

[42] There has been a sharp decline of CO2 emissions between March and June in 2020 due to the lockdown regulations put in place in most countries around the world. Working from home is believed to have significantly contributed to this decline.

subsidies, tax reductions, or direct subsidies to companies engaged in the energy transition. Policymakers need to understand that any strategy must aim to reduce the cost of renewable energy to make it affordable for consumers (Njoh, 2021). (2) Policymakers in lower-income countries should continue to strengthen their cooperation with developing countries in the context of technology transfer. This will help lower-income countries to master the use of green technologies and thus be a major contributor to the global energy transition. (3) For all countries, it is important to ensure that the development of green technologies is linked to the firms' profits. Thus, the production of green energies should not constitute an additional cost for companies but rather an opportunity to create high incomes and participate in the advent of a green economy. (4) Environmental issues must be fully integrated among the top priorities of governments, especially in developing countries which should realize that it will cost less to deal with these issues now than in the future. Good management of environmental and natural resources must be considered no longer an obstacle to development but as its precondition and constitutes a key element of any program intended to improve the living conditions of the populations. (5) Governments, especially those in low- and upper-middle-income countries, should continue increasing their subsidies to projects that save energy and use renewable energy. (6) Besides intensifying investments in renewable energies, countries should not neglect investments in eco-friendly innovations (such as electric cars, carbon capture technology, efficient machines, lightning, etc.). The two go together and will allow achieving carbon neutrality more quickly. A more profound global technology transfer and collaboration efforts are critical to facilitating low-carbon technology development and deployment. (7) Since low- and upper-middle-income countries seem to be lagging behind in producing green innovations, they should at least continue to invest heavily in education to acquire a high-skill labour force that can absorb and exploit external knowledge in terms of innovation in green technologies.

iii. Regarding the impact of aggregate and green technology on sectoral carbon emissions

Some important policy implications can be drawn from the fifth chapter's results. First, the findings of this thesis clearly indicate that, generally, technological progress favours carbon emissions in the majority of sectors. It suggests that the efforts made so far to decarbonize technology are not enough. Many carbon-neutral technologies and energy-efficient procedures are not yet produced on a large scale or are still at a relatively early stage of development. In addition, these technologies are often costly compared to traditional technologies (Hashmi and Alam, 2019). For these technologies to be usable on a large scale and competitive, heavy investment in research and development will be necessary, including pilot projects and large-scale demonstration installations.

Secondly, the fact that technology reduces carbon emissions in the industrial and building sector in high-income countries indicates gradual decarbonization of industrial processes and a trend towards building more energy-efficient homes. The private sector that owns most companies in these two sectors plays a critical role in the energy transition. The private sector is more flexible than the state sector and can gradually and much more quickly replace fossil fuel technologies with environmentally friendly ones. From this perspective, it can be suggested that the increase in green technologies and their competitiveness compared to traditional technologies will more likely come from the industrial sector. This could thus disseminate in other sectors and other countries through technology transfer and spillover effects.

Thirdly, this thesis showed that, generally, financial deepening is related to higher carbon emissions. This shows that the traditional financial system usually directs savings towards the most profitable projects without considering the environmental aspects of the investments made. States should continue encouraging the financial sector to participate in developing a green economy. It is about reorienting fossil fuels exploration and extraction funding to renewable energy development and energy efficiency projects[43]. Banks can support renewable energy and green technology projects and prevent the construction of new high-emitting units. This can also help to reduce the high installation costs of renewable energies.

In developing countries, political risks (political instability, war, etc.), economic risks (corruption, inflation, solvency of consumers), and the lack of power infrastructure often prevent international private investors from investing massively in renewable energies and green technologies. International financial organizations can support investors through mechanisms such as risk-mitigation, credit-enhancement tools, and direct financing to cover the country's risk faced by international energy companies and institutional investors (Hafner, Tagliapietra, & De Strasser, 2018).

These policy recommendations listed above may not succeed if there are no solid environmental regulations and a clear commitment from governments to fight climate change by integrating carbon mitigation policies into their sustainable development objective. Policy-makers should set ambitious policies that help find the right balance between economic growth and the need to protect the environment and the planet.

[43] To enable the transition to a low-carbon economy compatible with the Paris agreement objective of limiting the increase of a global temperature below 1.5 degrees by 2100, the International Energy Agency (IEA) estimates that around 3.5 trillion dollars investment will be required annually between 2016 and 2050 (IEA and IRENA, 2017).

Future research

Data availability was one of this thesis's limitations. The thesis could not conduct a more in-depth analysis due to a lack of data, particularly on the impact of green technologies on CO2 emissions levels. For example, data on green R&D spending for most countries used in this thesis were unavailable. The lack of data also prevented this dissertation from expanding its sampling and including a large number of countries. This thesis could also not assess the quality of technological progress and its impact on CO2 emissions. This thesis mostly adopted a quantitative approach to technology, but technology also has a qualitative dimension that must be measured accurately. This should provide pertinent information and shed additional light on the relationship between technology and climate change.

This thesis aimed to examine technological progress's impact on carbon emissions. Broad indicators of "aggregate and green technology" have been used in this thesis. Given the diversified nature of the different technologies developed, it would have been interesting to assess the impact of a particular aspect of technological progress (carbon capture storage, electric vehicle, green hydrogen) on carbon emissions. Unfortunately, the data availability of these particular aspects of technological progress is limited.

- Future research can evaluate the effect of specific technologies on the environment. For example, analyzing the effects of different types of patents and R&D spending on the environment. Investigating the relationship between a particular type of patent and climate change. Many inventions are recorded in different patent families. Patents related to the energy sector, the transport, or the manufacturing sector.
- Future research can also investigate how specific green technologies affect the environment, such as solar panels, wind turbines, direct air capture, electric vehicles, Long-term storage batteries, plastic recycling, and LED light efficiency.
- Exploring the carbon footprint of futuristic technologies such as artificial intelligence, augmented reality, and 3D printing. The idea is to estimate the extent to which technology or a particularly innovative process affects climate change. This can be assessed on a country or a group of countries, provided data availability.
- The analysis started in the fifth chapter of our thesis can also be extended. Future research can analyze how technological progress induced by the public sector (public R&D spending) and private (private R&D spending) affect sectoral CO2 emissions in the power, petrol, and building sectors.
- Future research can also explore the technological spillover effect through trade and research and development. CO2 emissions levels are not only influenced by technologies produced

locally but there is a significant amount of technology imported into each country. Trying to distinguish local technology from imported technology can be important. Such an analysis will allow a country to better position itself by strengthening its local technology and developing the means to acquire foreign technologies.

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