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Impact of technological progress on carbon emissions in different country income groups

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Abstract

This study examines the complex relationship between carbon emissions and technological progress in a sample of 60 countries, divided into four categories based on their per capita income between the periods of 1989-2018. For robustness purposes and due to the broad definition of technology, we use six different proxies to represent technology; namely: Information and telecommunication technology (ICT); patents; public R&D expenditure; total factor of productivity (TFP); and a number of science and technology publications. After applying the fixed-effect method with Driscoll and Kraay standard errors, for the full sample, the results show that the ICT variables are a good instrument for carbon abatement, while R&D expenditure and patents do not have a clear impact on carbon emissions, TFP increases carbon emissions, and science and technology publications are negatively related to carbon emissions. The impact of the indicators on the various income levels groups of countries vary which has significant policy implications.

Keywords: Technological progress, Income groups, rebound effect, fixed effect methodology with Driscoll and Kraay standards errors.

JEL codes: O30, O32, C23,Q56

1 Introduction

Global warming has been one of the most critical environmental issues of our ages. Over the past few decades, many scientists, researchers, and policymakers have been trying to find ways and means of reducing greenhouse gas (GHG) emissions to alleviate global warming. According to many international organizations such as IPCC (2000), UNFCCC (2006), and IEA (2010); burning fossil fuels such as coal, gas, and oil that come from human activity is the main cause of global warming. The global economy has been growing at a fast pace since the industrial revolution. This has thus led to a significant improvement in the quality of life. The incomes of households have increased - the average GDP

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per capita increased from approximately 500$ in the 1500s to 6000$ in the year 2000 (Maddison Project Database, version 2018). People have increasing access to energy, energy demanded infrastructure has been built, and life expectancy has increased. However, all this improvement comes at a cost: global warming. Now effective measures need to be taken by humanity to protect the earth from climate disaster. The transition from fossil fuel energy (oil, coal, gas, etc.) to renewable energy (solar, hydro, wind, etc.), and the improvement of energy efficiency is considered as the two major solutions to fight global warming (Fare et al., 1994; Li and Lin, 2016). The initial cost of renewable energy implementation and production is still high especially for poor countries. Governments expect a reduction of these initial costs, and one of the major channels by which this can be achieved is through technological progress.

Technologies are a complex socio-technical system (Mooney, 2011). They refer to the whole complex of scientific knowledge, process technologies, engineering practices, product characteristics, infrastructures, tools and machines, skills, and procedures that are used to resolve real-world problems (Mooney, 2011). In recent years, technological progress has been at the forefront of the fourth industrial revolution[1] that has transformed our lives like never before. Although this revolution operates differently, it affects the environment and the entire planet whether you are in a rich country or a poor country. Technology is considered as one of the engines of sustainable economic development (OECD, 2014). Technology plays an important and positive role in the economic development of a country (Solow, 1957; Romer, 1986, 1987, 1990). Amongst other things, it promotes economic growth by improving productivity, 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 show that technological progress has a dual effect on global CO_2 emissions. On the one hand, technology reduces overall CO_2 emissions by reducing energy intensity, adjusting the energy structure, and fostering the diffusion of green technology in industries and countries (Grubb, 2004; Barret, 2006, Edmonds et al., 2007; Bosetti et al., 2009). On the other hand, technology increases CO_2 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 CO_2 emissions have increased dramatically since the industrial revolution (Boden et al., 2015), following the similar evolution of technological progress. Any immense progress in technology not only brings about an improvement in the environment and energy supply but also tremendously stimulates economic development and the consumption of energy on a large scale (Hertin and Berkout, 2005; Herring and Roy, 2007; Sorrell and Dimitropoulos, 2008; Sorrell, Dimitropoulos and Som-

[1] The fourth industrial revolution refers to new information and communication technologies (NICT), and designates the tools born from the combination of IT, telecommunications and audiovisual, such as smartphones, microcomputers, tablets (Arnaud, 2019).

merville, 2009; Hall, 2011; Jin et al, 2017; Cheng et al., 2019).

Measuring technological progress quantitatively is a challenging task, as its representation and realization vary. The interaction between technology and the environment, in general, has been the subject of several studies; but to our knowledge, there has not yet been an analysis of how technology influences CO_2 emissions by assessing various "proxies" of technology since each proxy may yield different results. Moreover, the positive and negative impact of technology on CO_2 emissions have not yet been comprehensively investigated on different "income level" scale. Given that the responses to environmental challenges mostly depend on each country's financial capacity, it is necessary to look at this relationship in countries at all levels of development.

Therefore, this study'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 CO_2 emissions when using various measurements of technology? Notably: R&D expenditure, patents, information and communication technology (ICT), science and technology publications, and Total factor productivity (TFP).
2. Does this impact depend on the level of economic development?

To answer these two questions, this paper will use two methodologies: The fixed effect with Driscoll and Kraay standard errors and the Bruno's (2005) biased-corrected LSDV methodology. The strength and the weaknesses of each proxy in representing technological progress at a country level are also discussed in the paper. This study will be carried out on a panel of 60 countries divided into 4 groups according to their level of income. Thus, we will have 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 will be conducted.

Measuring the responsiveness of GHG emissions to technological progress is important for economic and environmental policies for several reasons Firstly, if the net effect of technological change on carbon emissions is negative; this implies that within our study period, technology has contributed to carbon abatement. Secondly, since technology is complex to quantify, using different indicators of technology will reveal which indicator works best for carbon reduction. For instance, one may find that on one hand, public R&D expenditure positively impacts carbon emissions because they are mostly directed to carbon-intensive projects; and on the other hand, the proliferation of mobile phones (ICT) in countries may reduce the transportation of people from point A to point B[2], thus reducing carbon emissions. In this scenario, the

[2] People can communicate easily via telephones 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 CO_2 emissions.

Government may consider redirecting public R&D expenditure towards environmentally friendly projects and fostering the proliferation of mobile phones to combat climate change. Lastly, the fact that the study will be done on different groups of countries according to their income level has also its importance. Because some measure of technology advancement may work better in reducing carbon emissions in some group of countries than in other. In this regard, high-income countries will particularly be monitored since they are more advanced in terms of R&D expenditure, the number of patent applications, and TFP.

This study contributes to the literature in the following three ways. Firstly, while the majority of papers cited in the literature have used only one proxy to represent technological progress, we employ several proxies to estimate their different impact on climate change. Technology is a complex concept to measure. Patents and ICT cannot have the same impact on CO_2 emissions, but they are both "indicators" of technological progress. Therefore, to have a well-rounded assessment of technology impact on climate change, it is important to have different measurements of technology. Moreover, in most of the sources cited in the literature, the strength and weaknesses of technological indicators used are not discussed. This will be done in this study since each proxy used cannot be considered as a "perfect" indicator of technological progress. Secondly, this study will account for the rebound effect which has been left out in many studies (e.g. Li and Wang, 2017; Higon et al., 2017). They have treated technological progress and energy consumption as general independent variables in CO_2 emissions model estimation, thus neglecting the interaction effect of technological progress and energy consumption on CO_2 emissions. In our paper, we will account for the rebound effect by interacting with technological progress and energy consumption and assess their common impact on carbon emissions. Thirdly, in this paper, we use a panel of 60 countries divided into 4 income groups: high income, upper-middle-income, lower-middle-income, and lower-income countries. Doing so constitutes another novelty of the paper as the majority of papers in the literature only focus on two groups of countries: developed and developing countries. Thus, it will be interesting to assess how technology interacts with the environment in these four groups given their income differences.

The remainder of this paper is structured as follows: Section II contains a brief literature review. Section III presents the theoretical model. The methodology and the data set are discussed in section IV. In section V, the econometric results are presented and analyzed. Section VI concludes the study.

2 Literature review

Over time, an extensive literature has developed on the role played by technological progress in the environment and more particularly in climate change. Existing studies can be divided into 3 categories. The first strand of the literature comprises research that has used R&D expenditure as a proxy for technological progress. The second strand of research has used ICT as a proxy for technological progress. Finally, the third strand of research has employed patents as an indicator of technological progress.

Bosetti et al. (2008, 2009, 2011, and 2015) are among the first stream of research. The authors have published several papers that analyze the relationship between international knowledge spillover and carbon emissions on the one hand; and on the other hand, the relationship between technology and carbon emissions using aggregate R&D as a proxy for technology (Bosetti et al., 2008, 2009, 2011; Bosetti and Tavoni, 2015). Bosetti et al (2009) found that fostering R&D expenditure and de-carbonization of energy is essential to reduce carbon emissions. The authors show 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 et al. (2018) employed Ordinary Least Square (OLS) techniques to analyze the impact of the effort in technological innovation on greenhouse gas emissions in the United States, European Union, and China from the year 1990 to 2013. To this end, a linear regression by OLS has been estimated, having R&D spending and energy consumption as an independent variable and greenhouse gas emissions as a dependent variable. The findings support the hypothesis that government spending in R&D translates to a reduction of greenhouse gas emissions. Unlike Fernandez and Lopez's findings, Garron and Grilli (2010) found that government R&D expenditure fails to have a significant impact on CO_2 emissions reduction in 13 developed countries over the periods of 1980-2004. The authors argue that for R&D spending to mitigate CO_2 emissions, it should be coupled with intensive energy efficiency policy implementations.

Li and Wang (2017) showed that technological progress has a dual effect on the aggregate CO_2 emissions in a panel of 95 countries over the period of 1996 to 2007. On one hand, technology reduces aggregate CO_2 emissions by reducing energy intensity. On the other hand, technology increases CO_2 emissions through increased economic growth. The authors have demonstrated that CO_2 emissions rose with the scale effect of technology change, and previous studies that considered the intensity effect overestimated the impact of technology change on CO_2 emissions. The authors conclude by saying that technological progress through R&D expenditure does not necessarily alleviate global warming.

Churchill et al. (2019) employed panel data techniques to examine the impact of research and development expenditures on carbon emissions in the G-7 countries. The study is particular in the fact it is the first research that analyses this relationship over 145 years, from the period 1870 to 2014. Their results indicate that the relationship between R&D and CO_2 emissions varies over time. The estimated time-varying coefficient function of R&D 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.

Zhang et al. (2017) use panel data techniques to analyze the impact of environmental innovations on reducing carbon emissions of 30 provinces in China. They describe environmental innovations as measures taken by relevant entities (private households, unions, firms) that apply new technology, introduce new energy efficiency processes, and new ideas aiming at contributing to a proper and sustainable 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). The authors show that most of the environmental innovations help in reducing carbon emissions. In particular, R&D expenditure, patent, and energy efficiency help in reducing carbon emissions. They also found that the initial measures taken by China for greenhouse gas emissions reduction are effective. This study is particular in the sense that it uses comprehensive measures of environmental innovation.

The second strand of the literature has used ICTs as a proxy for technological progress to estimate its impact on carbon 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 CO_2 emissions through increased manufacturing production, energy consumption, production of devices and machinery, and recycling of electronic waste. On the other hand, ICTs can lower CO_2 emissions on a global scale through energy savings, smart efficient cities, efficient production processes, and ecological transportation systems and electrical grids. These studies have generally found that the net effect of ICT on CO_2 emissions is negative.

However, the paper by Xiaoyoung et al. (2019) is amongst the studies that have found a positive net effect of ICT on carbon emissions. The authors have explored the extent to which ICTs affect carbon emissions in China. The authors developed and embodied a carbon analysis framework for the ICT sector by integrating input and output analysis approaches. They found that ICTs are far from being environmentally friendly. This is because of the carbon-intensive intermediate inputs used in the production process of ICT items. They show that the ICT sector uses many materials (metal and non-metal, and chemical) that degrade the environment. The paper is one of the scarce studies that assess how ICT drives carbon emissions at sector levels (manufacturing, communication equipment, audio-visual apparatus, electronic component, telecommunication services, and ICT services).

Asongu, Le Roux, and Biekpe (2017) used the Generalized Method of Moment (GMM) approach to examine the effect of information and communication technology on carbon emissions, and how they both impact inclusive human development in 44 sub-Saharan African countries for the period of 2000-2012. ICT is measured with mobile phone penetration and internet penetration. The results show that ICT can be used to dampen the negative impact of carbon emissions on human development. As an illustration, the mobile phone can help in reducing transportation costs; and this can help households to invest more in education or health, and hence improving their quality of life. The findings also indicate a threshold of ICT that allows lowering the negative effect of carbon emissions on human development for all 44 countries.

The third strand of the literature has employed patents as a proxy for technological progress. The paper by Cheng et al. (2019) falls into this category. The researchers investigated the impact of the various variables on CO_2 emissions: renewable energy, foreign direct investment, GDP per capita, environmental patent, and exports. The analysis is done for the BRICS countries and the period runs from 2000 to 2013. The authors emphasize two strategies that are at the center of the BRICS's action against global warming: (**??**) the development of renewable energy sources and (2) the development of energy efficiency technology. The results indicate that environmental patent, exports, and GDP per capita increase carbon emissions while renewable energy and foreign direct investment decrease carbon emissions. The authors explain the positive impact of patents on carbon emissions by the lack of environmental regulation that can allow the diffusion of sophisticated technology in the BRICS countries. Other papers have found similar results for different countries or regions (see Su and Moaniba, 2017; Du, Li, and Yan, 2019).

Hashmi and Alam (2019) estimate the effect of innovation and environmental regulations on carbon emissions in OECD countries from 1999 to 2014. The authors highlighted that the adoption and deployment of eco-friendly technology and stringent environmental regulations are the key factors to fight against global warming. Environmental tax revenue is used as a proxy for environmental regulations. The empirical results show that a 1 per cent increase in technology innovation patent lowers carbon emissions by 0.017 per cent and when environmental tax revenue per capita increases by 1 per cent, carbon emissions decrease by 0.03 per cent in OECD countries.

As mentioned in the introduction, this study uses several indicators of technological progress and assesses their impact on carbon emissions on a full sample panel of 60 countries and subsamples of different income categories. This study also follows the paper by Gu et al. (2019) and analyses the rebound effect by assessing the common impact of technological progress and energy consumption on carbon emissions.

3 Theoretical model

Global warming is a global phenomenon of climate change characterized by a general increase in average temperatures and modifies weather balances and ecosystems (IPCC, 2000). Since the start of the Industrial Revolution, average temperatures on earth have increased regularly (IPCC, 2014). In 2016, the average temperature on planet earth was about $1^o$to 1.5^oC above the average temperatures of the pre-industrial era (before 1850) (IPCC, 2014).

According to the IPCC 2018 report (IPCC, 2018), human activities are estimated to have caused about 1.0^oC of global warming above pre-industrial levels, with a probable of 0.8^oC to 1.2^oC. If human activities continue to increase at the current rate, global warming is likely to reach 1.5^oC between 2030 and 2052 (IPCC, 2018). The greenhouse gases emitted by humans from the pre-industrial period to the current period will persist for centuries and continue to cause a long-term change in the environment and the climate system, such as ecosystems disruption, ocean level rise, scarcity of resources, etc. (IPCC, 2018).

Global warming is a consequence of several factors. Mainly, it is the production of energy (electricity, heating, etc.) and fuel for transport (mainly cars, but also aviation and maritime transport) that cause global warming. Deforestation, large scale agriculture, and the expansion of livestock are also amongst the causes of global warming (IPCC, 2014). Consequently, these root problems are mainly linked to the acceleration of economic growth, energy consumption, population density, and technology advancement since the industrial revolution. Following this theory and based on the literature (see Seldan and Song, 1994; Barbier, 1997; Friedl and Getzner, 2003; Richmond and Kaufmann, 2006; Ang, 2008; Akinlo, 2008; Zhang and Cheng, 2009; Garrone and Grilli, 2010; Shabbaz et al, 2011; Alkhathlan and Javid, 2015; Higon, Gholami, Shirazi, 2017; Antonakakis et al., 2017; Churchill et al, 2019; Gu et al., 2019), this article retains five factors that are often cited as being among the main drivers of carbon emissions: fossil fuel consumption, economic growth; population density, technology, and trade.

Therefore, this study is based on the following theoretical model:

$$CO_2\, emission_{it} = f(GDP_{it} ECONS_{it} POP_{it} EXP_{it} TECH_{it}) \tag{1}$$

3.1 A priori expectations

GDP (+): Many studies show that at the early stages of development, economic growth is associated with an increase in carbon emissions (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 demands of companies, industries, and households. Unfortunately, though, the energy developed and used in the world is largely extracted from our fossil fuels. It is thus expected that economic growth will lead to higher CO_2 emissions. However, for high-income countries, the positive impact of economic growth on carbon emissions might change over time (Seldan and Song, 1994). The enrichment of populations in developed countries is generally accompanied by a demand for a healthier environment. This observation led to the following hypothesis: economic growth would be harmful to the environment in the early stages of development; then, beyond a certain threshold of per capita income, economic growth would lead to an improvement in the quality of the environment. This hypothesis is known as the *Environmental Kuznets Curve*. Thus, according to this hypothesis, the impact of economic growth on carbon emissions depends on the stage of development of a country.

Energy consumption (+): Energy consumption is another well-known driver of carbon emissions (Dimitropoulos and Sommerville, 2009; Hall, 2011; Jin et al, 2017; Cheng et al., 2019). As mentioned above, the recent pace of higher economic growth after the industrial revolution has implied higher fossil fuel energy consumption, (such as oil, coal, and natural gas) which has, in turn, resulted in environmental degradation. The impact of energy consumption on carbon emissions depends on the type of energy used in a country. If the largest part of energy consumption comes from fossil fuels, which is usually the case it can be expected that an increase in energy consumption will also increase carbon emissions.

Population (+): Over the past century, the world's population has increased from 1 billion to 7 billion people (World Bank, 2019). To accommodate this growing population, there was a need for industrialization, urbanization, and transport infrastructure. The rapid transition from agriculture-based development to industrial-based development has required a lot of energy, which led to increased green gas emissions. It is therefore expected that carbon emissions will increase as the population is increasing (Seldan and Song, 1994; Borghesi, 1999; Moyer and Hugues, 2010, Churchill et al., 2019).

Export (+/-): After the industrial revolution, the world has become more and more connected and open to trade. The impact of exports on carbon emissions is inconclusive (Boutabba, 2014; Ertugrul et al., 2016; Shahbaz et al., 2017; Murat, Ecevit, and Yucel, 2018). It 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. Whereas, on the other hand, countries that export cleaner energy or more eco-friendly products will experience fewer carbon emissions.

Technology (+/-): As stated in the introduction, the impact of technology on carbon emissions is complex. This impact depends on the environmental characteristic of the technology used. If the technology used is eco-friendly such as renewable energy technologies and electric vehicles; then a reduction in carbon emissions can be expected. However, technology could increase carbon emissions if the technology developed is not eco-friendly or has been created to facilitate and increase the production of fossil fuels. As an illustration, the boom in shale oil production in the 2000s saw the United States become 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 production of oil in the US is mainly due to improved techniques and technologies for drilling shale oil. While this has allowed the US to have some energy independence, it has come at a cost of more carbon emissions.

4 Methodology and data

This section describes the methodology and the data used in this study. As above- mentioned in the introduction, this paper uses proxies that can represent the level of technological progress reached in each country. In the data section, the strengths and weaknesses of each proxy used are discussed.

4.1 Methodology

In this paper, three-panel models are established to analyze how technological progress affects carbon emissions. The first empirical specification is a static panel model.

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

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 will be replaced by six different proxies of technology. More specifically, model (2) will be divided into six different sub-models and each sub-model has its own proxy of technological progress:

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

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

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

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

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

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

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.

We use a simple fixed effect (within) method to estimate all six equations in the model specification (1). We apply the fixed-effect method because it controls for cross-sectional heterogeneity. 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 the correction of potential endogeneity problems since the within estimator wipes out the individual effects through demeaning and 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 potential problem will be addressed in the results section.

Many studies have shown that most environmental indicators, CO_2 emissions included, are considered to 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. We decided to adopt a one lag model specification to preserve the maximum possible number of freedom available for the estimates.

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

Similar to model (2), $TECH_{it}$ will be successively replaced by six different proxies of technological progress. Therefore, we will have six different sub-models[3].

Following the consolidated literature on dynamic panel data models (Kiviet, 1995, 1999; Blundell and Bond, 1998; Bun and Kiviet; 2003, Bruno 2005), we used Bruno's (2005) biased-corrected LSDV methodology to estimate model specification (2). 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 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). We prefer LSDVC to alternative Nickel biased correction methodology, such as the GMM method because for two reasons.

[3] We will have six different sub models with different proxies: 3(a) - Mobile phone, 3(b) - internet, 3(c) - patents, 3(d) – R&D expenditure, 3(e) - TFP and 3(f) – science and technology publications.

First, Judson and Owen (1999), by performing a Monte Carlo experiment show that for a large period ($T \geq 30$), the LSDVC methods may be outperforming the GMM method in terms of efficiency, bias, and Root Mean Square Error (RMSE). Secondly, 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).

In conclusion, since the two methods have some differences in terms of assumptions, any eventual similarities of the estimates obtained with them would clearly prove the robustness of the findings. The diagnostic test that will be performed in the results section will give us a preference of which method between the two will be more considered in the discussion of our results.

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

$$\begin{aligned} \ln CE_{it} = {} & \beta_0 + \beta_1 lnTECH_{it} + \beta_2 lnECONS_{it} \\ & + \beta_3 lnGDP_{it} + \beta_5 lnPOP_{it} + \beta_6 lnEXP_{it} \\ & + \boldsymbol{\beta_7} \mathbf{lnTECH_{it}} * \mathbf{lnECONS_{it}} + Y_i + u_{i,t} \end{aligned} \tag{4}$$

Here $TECH_{it}$ will also be replaced by six different proxies of technological progress[4]. Empirical specification (4) will also be estimated with the fixed-effect method.

4.2 Data

This study uses a balanced panel dataset of 60 countries that is constituted of 15 high income, 15 upper-middle-income, 15 lower-middle-income, and 15 lower-income economies. The dataset provides a period of 30 years, from 1989 to 2018. The variables used in this study were collected from different sources.

[4] Panel model (**??**) 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.

Table 1 shows the descriptions and sources of the data collected. Tables with descriptive statistics for the full sample and subsamples are presented in the Appendix. Data on CO_2 emissions (metric tons per capita); energy consumption (tons of oil per capita); GDP per capita (in constant 2010 US$); trade (exports in constant 2010 US$); the number of scientific and technical articles and population density were drawn from the World Bank's Development Indicators (WDI) (World Bank, 2019). Two ICT variables are used in this study: mobile cellular subscriptions per 100 people and individuals using the internet (percentage of the population). The ICT variables were also drawn from the WDI (World Bank, 2019). Data on Research and development expenditure (as a percentage of GDP) was collected from the United Nations Educational and Cultural Organization (UNESCO, 2019) and the OECD database, while data on patents was collected from World Intellectual Property Organization (WIPO, 2020).

4.3 Technology indicators discussion

4.3.1 Public R&D expenditure

R&D expenditure is of fundamental importance in the creation of new technology, new knowledge, and new products. It is a usual remedy for knowledge spillovers and for market failure that does not foster innovation in the in-production sector (Churchill et al, 2019). For many Scholars (Solow, 1956; Romer, 1987, 1990, 1994; Jones, 1995; Kohler et al, 2012; Szarowska, 2018), the key to economic development is found in research and development, when companies seek to develop and improve their products, services, technology, and processes. This comes with the creation of new products, the addition of new features to old products, and the creation of new production lines.

The energy sector has experienced and continues to experience rapid development towards low-carbon energy partly because of investment in research and development. Investing in R&D has made it possible to develop and extend the production of renewable energies that feed 10% of the world population today (Our World in data, 2019). The electric cars, which are considered as the solution to face the devastating pollution of the combustion engines, were developed by companies that have invested massively in R&D. Thus, expenditure in R&D may be regarded as an important technology push measure (Garrone & Grilli, 2010). As such, R&D expenditure should be at the centre of government policies for technology improvement.

At the same time, Garron and Grill (2010) argue that considering R&D spending as a climate technology policy towards low carbon energy is sometimes controversial. R&D spending cannot be viewed as a climate technology policy unless there is initially a market for low-carbon and energy-efficient products. Moreover, when funds are spent to finance an R&D project, it does not necessarily mean that project will lead to technological advancement in the short term, as it may be an attempt that will bear fruit only in the long term. Certain R&D projects will never be able to give results because of the corruption and embezzlement of public funds which undermine many of our countries, especially the less developed ones. From an environmental angle, it is important to understand that aggregate R&D is divided into two components: green R&D expenditure and non-green R&D expenditure. It follows from this fact that the final impact of R&D expenditure on carbon emissions is uncertain as the two components clash together. Another limitation of public R&D spending is that it has a limited impact on the effort done by firms to attract and deploy new technologies; as the creation of revolutionary technology and products is done by firms (Sagar and Holdren, 2002; Sagar and Zwaan, 2006). Despite all its limitations, R&D spending remains a good indicator of technological progress in a country.

4.3.2 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 the state grants to its owner to protect his invention and allow him to use and exploit it, by preventing others from using it without his permission (WIPO, 2020). The invention can be a product, software, a new procedure in the production process, or anything technical that is new and has never been created before (WIPO, 2020). If the owner chooses not to exploit his patent, he can sell it or assign the rights to another company to license it. A patent generally lasts for about 20 years (WIPO, 2020).

Patents are good indicators of technical progress because they are often the result of intense research leading to the creation and production 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 or patents. Patents serve to stimulate technical progress and are indicators of the technological level reached by a nation.

The use of patents as a proxy for technology has potential limitations that are important to take note of. Firstly, the number of patents granted in a country does not necessarily reflect the utility or the quality of the inventions created. In most countries, to obtain a patent, the invention must present a novelty, an inventive contribution, and have a utility. 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 such as the invention of a more efficient and non-polluting electric motor, or the invention of drones to help monitor the condition of crops or those that can deliver medical equipment to hard-to-reach areas. Looking at the inventions which have proved less usable (until now), to mention two examples: the "automatic bed maker" (self-maker bed); or the "butter stick" which allows you to butter your toast without having to use the butter knives. It follows from these illustrations that a patent or an invention bears a utility weight that is added to aggregate technology. The utility weight can be higher or smaller depending on the value of different innovations, and it has a different impact on economic growth and the environment. In general, we can safely say that smaller innovations are more numerous than game-changing ones (Cremers et al., 1999; Scherer and Harhoff 2000; Hall, Jaffe and Trajtenberg, 2005). In 2018, China overtook the US in terms of patents granted. This does not automatically mean that China has become more advanced technologically than the US because the value of patents granted is not the same.

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 it will be automatically adopted by the industry or the society.

4.3.3 Science and technology publications

Another potential indicator of technological progress in a country is the number of technical-science and technology publications in a peer-review journal. 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 each context (Monteiro, Devan, Soans, & Jeppu, 2012). Articles published in scientific journals typically have gone through a rigorous screening and validation process known as blind peer review. In this process, independent researchers and experts provide the author with critical commentary and suggestions to improve their final paper, before its publication (Marusic & Marusic, 2009). Science and technology publications allow fostering and increasing genuine human knowledge. Scientific methods are the mean that has allowed the gain of verifiable and applicable knowledge (Marusic & Marusic, 2009). The Scientific knowledge acquired is further transformed into a concrete product or procedure that increases the stock of technology. Science and technology publications are also linked with the improvement of human capital. A country that has a high level of tertiary education attainment is likely to produce more science and technology publications than other countries that have a lower level of 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 concrete product or procedure. Some articles may be published just to criticize or review other articles that have come up with contestable findings. Other articles are published to contribute to the scientific debate between specialists. Secondly, the quality and relevancy of articles published sometimes differ greatly. As explained above, most scientific journals make sure that articles published have a certain standard quality. But scientific journals do not have the same ranking. Some are more prestigious and reliable than others. However, despite these limitations, the number of articles published remains an acceptable indicator of the level of debate, knowledge, and technical progress reach by a country.

4.3.4 Information and communication technologies (ICT)

ICT includes all tools, services, and techniques used for the creation, recording, processing, and transmission of information. It is therefore mainly about computers, the Internet, radio and television, and telecommunications. We also address the new information and communication technologies (NICT) to designate the tools born from the combination of IT, telecommunications, and audiovisual, such as smartphones, microcomputers, tablets. 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).

Many countries including the United States, Japan, UK, Korea, and Germany have experienced significant economic growth due to labour productivity growth in the second half of the 19th century. Several researchers have tried to break down the US labour productivity growth during this period, and have found that ICT has significantly contributed to both labour productivity and total factor productivity (TFP) growth over this period (see Oliner and Sichel, 2000; Gordon, 2000; Bakhshi and Larsen, 2005). In this paper, we use the percentage of internet users and the number of mobile phone users as proxies of ICT development.

Having a high number of mobile phone users does not necessarily mean that the country is technologically advanced[5]. Using the number of mobile phone users as an indicator of technological progress should be taken cautiously. Some countries that have a good number of mobile phone users are not mobile phone producers. This is the case in many less developed countries- these countries adopt this technology but are not producers of this technology. They do not often have high skilled workers, technicians, and high-tech infrastructures to produce smartphones, tablets, computers, and other connected objects. In those countries where mobile phones are 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 to download useful applications and procedures that are going to increase their stock knowledge.

4.3.5 The total factor productivity (TFP)

TFP is the part of economic growth that is unexplained by the accumulation of capital or labour (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 indicate whether output growth is attributed to an increase in the two factors of production or more efficient uses of these two

[5] As an illustration, according to the World Bank database (WDI, 2019), 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).

factors. Solow found that in the United States between the years 1910-1950, the capital increase was able to explain only 12 per cent of the increase in labour productivity (Solow, 1956). In other words, the increase in productivity was due to a more knowledgeable workforce due notably to technological progress (Solow, 1956).

The drawback of TFP as a measure of technological progress comes from its estimation (Hall, Using productivity growth as an innovation indicator, 2011). Generally, to measure TFP, the following standard Cobb Douglas production function is used:

$$Y = A\,K^{\beta}\,L^{1-\beta} \tag{5}$$

Where output is denoted by Y, the level of capital stock is represented by K, and L is labour (and potentially other noncapital inputs)[6]. β and $(1-\beta)$ represent the share of revenue received by capital and labour. A is the overall level of technology that varies across countries. That is, because of differences among countries, in terms of human capital, research, and development, high-tech infrastructures, ICT level, etc. Thus, countries with identical levels of K and L may not be able to achieve the same level of output Y.

For measurement purposes, the logarithm of equation (5) is taken; we then have the growth (Υ) of each variable.

$$\Upsilon_Y = \Upsilon_A + \beta\,\Upsilon_K + (1-\beta)\Upsilon_L \tag{6}$$

Equation (2) yields an expression for total factor productivity:

$$TFP \equiv \Upsilon_A = \Upsilon_Y - \beta\,\Upsilon_K - (1-\beta)\Upsilon_L \tag{7}$$

It follows from equation (5) that measuring TFP requires measures of real output Y, real labour L and real capital stock K (as well as possible other inputs, such as energy and materials) (Hall, 2011). Moreover, one will need to fairly determine the weight of parameters β and $(1-\beta)$. Hall (2011) notes that there are many approaches used by researchers, agencies, or organizations to measure the inputs and outputs factors. Unfortunately, TFP measurement can be greatly impacted by the choices done in these approaches. The difficulty lies in the measurement of real inputs and outputs while holding constant the unit of measure over time. Unlike other proxies that are simply recorded such as R&D expenditure and the number of patents, TFP needs reliable data of labour and capital stock of a given economy to be calculated. Many developing countries lack consistent data on labour and capital stock. TFP measures need to be used carefully, with an understanding of the approach used for deflation and quality adjustment (Hall, 2011). The TFP measure used in this study comes from the Penn World Table. To calculate TFP, they use a procedure where the nominal value of capital is deflated, and the quality of labour is adjusted.

[6] See H.Hall

5 Results estimation and discussions

5.1 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 correctly identify a suitable method for the estimation of the results. In the dataset, we check for the presence of heteroskedasticity; serial correlation; cross-sectional dependence; panel effect; and time fixed effect. Cross-sectional dependence in the dataset is verified with the Pesaran cross-sectional dependence (CD) test (2004). Breusch-Pagan (1980) LM-test and Wald tests are used to check the presence of panel effect and time fixed effect in the model specifications. A modified Wald test for GroupWise heteroskedasticity is performed to check for heteroskedasticity. Serial correlation in the dataset is checked 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 (1) and (3). Bruno's (2005) biased-corrected LSDV methodology is employed to estimate panel model (2).

5.2 Diagnostic test results

Before estimating our models, we start by conducting a basic diagnostic test for the presence of heteroskedasticity, serial correlation, panel fixed effects, and time fixed effect and cross-sectional dependence for all six sub-models in panel model (1). Table 2 shows that we fail to reject the null hypothesis of no cross-sectional dependence, no serial correlation, and no heteroskedasticity in all six sub-models. The diagnostic test also confirms the presence of a panel effect in the data. Regarding the time fixed effect, it is only present in one sub-model. If these diagnostic issues are not addressed, the empirical results might be biased and inconsistent. Thus, this paper considers these issues in the results estimation section.

5.3 Panel unit root test and cointegration results

Before estimating our regressions, we need to define which variables in the data are stationary and which are non-stationary. We use 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. We subtract cross-sectional means by demeaning the series to assist with cross-sectional correlation and cross-sectional dependence. For most variables, we fail to reject the null hypothesis of a unit root and conclude that most series are not stationary. Consequently, cointegration tests are necessary to avoid spurious relationships when estimating regressions with non-stationary variables.

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 4. Except for the Augmented Dickey-Fuller statistic in panel model (2b), (2c), (2d), and (2f); all other statistics are statistically significant' at least at a 10% level. Thus, our study concludes that cointegration exists in all six-panel sub-models.

5.4 Results estimation

In this section, we discuss the results of the impact of technological progress on carbon dioxide emissions. This study 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 heteroskedasticity in the dataset (Hoechle, 2007).

The section is divided into four subsections. In the first subsection, we examine the relationship between technology advancement and carbon emissions in the full sample[7] using the fixed-effect method with Driscoll and Kraay's standard errors. We assess the responsiveness of carbon emissions to six proxies of technological progress (ICT, R&D expenditure, patents, TFP, and science and technology publications). The same relationship is analyzed in the second subsection with the Bruno LSDVC corrector; a dynamic term will be added to the model. In the third subsection, we consider the rebound effect and test 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 $C0_2$ emissions in the different income group levels..

5.4.1 Full sample analysis

Tables A to F in the appendix[8] presents detailed results obtained from the full sample analysis. Table 5 below presents a summary of these results. Table 5 shows the responsiveness of carbon emissions when each variable of technology

[7] For all 60 countries in the dataset

[8] 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.

is included with all other explanatory variables at once[9]. It can be observed from table 5 that a rise in ICTs variables causes a decline in CO_2 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 a 5 and 10 per cent level, 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[10]. Patents and R&D expenditure have opposite signs after including additional explanatory variables, and they are both statistically insignificant at the conventional level of significance (see table 5). 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 number of 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 emissions in all six sub-models. This is in accordance 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). Export is associated with an increase in carbon emissions only in two of the sub-models.

The full sample results confirm the complex relationship between technological progress and carbon emissions stated in the literature. The results show that each indicator of technology may have different impacts on carbon emissions. Our fixed effect results reveal that ICT is a good instrument for carbon abatement. The net effect of ICT (internet and mobile phone subscriptions) on CO_2 emissions 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 the use of mobile phones and other telecommunications devices save more than 180 million tons of CO2 emissions per year in the US and Europe. This amount of carbon emissions is more than the one produced annually by the Netherland. Mobile phones create emissions savings in many different ways across several key categories. As an illustration, communication has succeeded in overcoming 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

[9] Table 5 contains all six "regressions 5" of panel sub model A to F which are presented in the appendix.

[10] Please refer to table C and D in the appendix.

mobile phones. The use of online banking allows reducing the number of people going down to the local bank branch. The transition to cloud computing is one of the main trends in modernization. ICT tools used within companies help streamline business processes and improve energy efficiency. Another example is energy reductions in buildings, which are the result of technologies that improve energy efficiencies, such as building management systems and smart meters.

The negative impact of science and technology publications on CO_2 emissions is an indication that scientific debate and research can progressively foster a green economic transformation across the globe. Since global warming is increasingly becoming a subject of great concern, the scientific debate is gradually becoming more direct towards ensuring economic growth without damaging the environment, and this also helps in raising the awareness of governments, businesses, and the 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 measures of technology 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 above- mentioned in the data section, R&D expenditure and patents data used in this study are in aggregate. This means they are not necessarily green R&D or patents. Another explanation is that during our period of study, R&D expenditure and patents did not increase enough to impact carbon emissions. 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 bring an increase in carbon emissions; while when they exceed a certain turning point[11], R&D expenditure and patents start reducing carbon emissions progressively. If this is the case, then it suggests that in our data and analysis; R&D expenditure and patents have not yet reached the turning point where CO_2 emissions are declining. Further analysis will therefore be necessary to verify these hypotheses.

5.4.2 Bruno LSDVC estimation

The LSDVC is used as a robustness check for results found with the fixed effect methodology. Table 6 shows that ICT variables are still negative and statistically significant at a 1 per cent level of significance. Similar to the fixed effect results, number of science and technology publications has a negative sign whilst 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.

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

As we mentioned earlier, our preferred results are the ones estimated with Driscoll and Kraay standard errors, since they are robust to many types of bias including cross-sectional dependence. As such, this simple fixed-effect model results will only serve the purpose of a benchmark.

5.4.3 The rebound effect

Panel model three introduces an interaction term to account for the rebound effect. When technology is associated with energy consumption, does it increase or decrease CO_2 emissions? In other words, what is the impact of technology on carbon emissions when the rebound effect is taken into consideration?

The results indicate that for two joint interactions, carbon emissions decrease despite the rebound effect. CO_2 emissions decline when energy consumption is associated with ICT variables, and science and technology publications. However, carbon emissions increase when energy consumption is associated with TFP. The joint interactions between energy consumption and R&D expenditure; and energy consumption and patents are positive but statistically insignificant.

5.4.4 Subsample analysis

Table 8 presents the results of the impact of technology advancement on carbon emissions across different income levels using the 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's proxies are negative and significant across all income levels. In high-income and upper-middle-income countries, 1 per cent increase in mobile cellular subscriptions decreases carbon emissions by 0.011 and 0.010 per cent, respectively; and a 1 per cent increase in internet use decreases CO_2 emissions by 0.007 and 0.006 per cent, respectively. The results are not really different in lower-middle-income and lower-income countries. A 1 per cent increase in mobile cellular subscriptions decreases CO_2 emissions by 0.013 per cent in lower-middle-income countries and 0.05 per cent in lower-income countries. Carbon emissions decline by 0.036 and 0.033 per cent when internet connection increases by 1 per cent in lower-middle-income and lower-income countries, respectively. Globally, ICT appears to be a good tool to reduce CO2 emissions.

The coefficient on patents is statistically significant and positively affects carbon emissions in 3 out of the 4 groups of countries. A 1 per cent increase in patent application increases carbon emissions by 0.032 per cent in high-income countries, 0.047 per cent in lower-middle-income countries, and 0.06 per cent in lower-income countries. R&D expenditure causes CO_2 emissions to rise only in lower-middle-income countries by 0.055 per cent. The impact of R&D expenditure on carbon emissions in the other groups of countries is positive but not statistically significant. The number of science and technology publications produced reduces carbon emissions only in high income and upper-middle-income countries. This might be explained by the number of science and technology publications produced in high-income economies compared to lower-income economies. According to data compiled from the World Bank database, on average, science and technology publications produced in high-income countries are 400 hundred times superior to those produced in lower-income countries (World Bank, 2020). 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. Regarding GDP per capita, this variable is statistically significant and positively related to carbon emissions in most of the regressions. Population density appears to be positive and statistically significant in half of the regressions. Population growth has always been considered as one of the major factors of global warming. High population density means more demand for fossil fuels to provide more energy and fuel with an increasingly mechanized lifestyle.

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

5.4.5 Subsample results discussion

In all four groups of countries, mobile cellular subscriptions, and internet connection reduce carbon emissions. This result is in line with what previous papers have found (see Asongu, Roux, and BIekpe, 2017; Anon Higon et al., 2017; Moyer and Hugues, 2012). ICT lowers carbon emissions via two main[12] channels: by increasing energy efficiency and by lowering the cost of renewable energy adoption. This negative impact seems to outweigh the positive impact ICT has on carbon emissions because of also contributing to the increase in GDP. Even though the magnitude of the coefficients of mobile cellular subscriptions and internet connection in the estimation results are not very high, they remain negative and statistically significant across all income levels. Thus, investment in the ICT sector can be recommended as a good policy to combat climate change, especially for lower-income countries since they are at an early stage of development. The number of science and technology publications is associated

[12] 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.

with a decrease in carbon emissions in high-income and upper-middle-income countries. Science and technology publications fail to have a significant impact on carbon emissions in lower-middle and low-income countries. This is not surprising given the huge gap in several scientific publications between high-income countries and low-income countries. According to the World Bank database (2020), 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.

In high-income countries, the number of patents applications is positively and significantly related to carbon emissions. This is an indication 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 each year on average between 2010 and 2018. It seems like patents granted in these countries and more specifically in energy-intensive industries, which have the biggest share in energy used, are not enough environmentally friendly. Therefore, it will be necessary to encourage green patent applications and intensify policies that will encourage firms and industries to produce products that are less damaging 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 level of significance. However, it is worth noting that the positive coefficient of TFP is statistically significant only at the 20 per cent level of significance.

Regarding upper-middle-income countries, the results are not very clear. We 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 used in their respective regressions. However, their coefficients became statistically insignificant as additional explanatory variables were added in the regressions. An explanation might that upper-middle countries (it can also be the case for high-income countries) are reaching a point where the gains from energy savings due to technological improvement equal the increase of energy consumption also 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 is no strong regulation to "force" industries and companies to adopt and use them, then 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 in these countries, public expenditure in R&D is still more directed toward carbon-intensive projects. Also, patents granted in these countries reflect inventions that might be beneficial for households, companies, or industries but damaging for the environment. Another explanation is the limitation of 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 are seeking to expand their economic growth to join other groups of high-level income countries. Therefore, they invest massively in energy-intensive projects which unfortunately do not often consider environmental sustainability. TFP seems to increase carbon emissions in these countries.

Results also confirm that GDP per capita; energy consumption; and population are the key drivers of carbon emissions in each group of countries. The impacts of these three variables are higher than the effect of technology variables in all models and income groups. These results are similar to those found in other studies (see Selden and Song, 1994; Dinda and Coondoo, 2006; Wang et al., 2016; Antonakakis et al., 2017; 2016 Hashmi and Alam, 2019; Cheng, Ren, and Yan, 2019).

6 Conclusion

The relationship between technological change and carbon emissions is complex. Numerous studies show that technological progress has a dual effect on global CO_2 emissions. On the one hand, technology reduces overall CO_2 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 CO_2 emissions by increasing energy consumption and economic growth. The purpose of this study is to reexamine the above relationship in a group of 60 countries divided into four categories based on their per capita income level for the period of 1989-2018.

This paper seeks to answer two questions. The first question is to determine the impact of technological progress on CO_2 emissions when using various measurements of technology. Notably: Information and telecommunication technology (mobile cellular subscription and percentage of internet user); the number of patents; public R&D expenditure; total factor of productivity (TFP); and a number of science and technology publications.

To answer this question, we use the full sample of 60 countries. After applying the fixed-effect method with Driscoll and Kraay standard errors and complement 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 abatement. The net effect of ICT variables on CO_2 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 the number of science and technology publications is negatively related to carbon emissions. We also found that key determinants of carbon emissions such as GDP per capita, energy consumption, population density, and exports are positively related to carbon emissions. This paper also considers the rebound effect by interacting with technological progress and energy consumption and assessing their common impact on carbon emissions. The results indicate that CO_2 emissions are declining when energy consumption is associated with ICT variables, and science and technology publications. However, carbon emissions increase when energy consumption is associated with TFP. The joined interactions between energy consumption and R&D expenditure, and energy consumption and patents are positive but statistically insignificant.

The second question is to determine whether the impact of our measurement of technological progress depends on the level of economic development of a country. To answer this question, the full sample is divided into four sub-samples according to their level of income. 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 reveal that ICT development is associated with a decline in CO_2 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 CO_2 emissions to rise only in lower-middle-income countries but fails to have a significant impact on carbon emissions in high-income countries. The number of science and technology publications is negatively associated with carbon emissions only in high-income and upper-middle-income countries.

Climate change requires a collective effort from governments, businesses, and households if we are to succeed in limiting the increase of a global temperature below 1.5 degrees by 2100 as stated in the Paris agreement (2015). The policy implications that can be drawn from this study are as follows: (1) government and industries should continue to promote the development and expansion of ICTs to fight climate change. For example, the use of smartphones helps in decreasing carbon emissions through encouraging behaviours such as the reduction of movement of people using cars[13], the increasing use of public transport, and the use of remote control for home heating and other connected devices. The benefits associated with ICTs are even more felt during the Covid 19 pandemic that hit the planet in 2020[14]. (2) Governments around the world should have a common agreement to encourage green patent applications and intensify policies that will encourage firms and industries to produce products that are less damaging to the environment. (3) Public R&D expenditure should be more directed

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

[14] 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.

towards projects that will result in the production of environmentally friendly products and technologies. (4) Science and technology publication should be promoted as it fosters the debate on solutions to how to reach green and sustainable development. (5) These policy recommendations may not succeed if there are no strong environmental regulations and a clear commitment from governments to gradually decrease the use of traditional energy and increase the level of renewable energy.

The idea of this paper was to examine the impact of "aggregate" technology on carbon emissions. A broad concept of technology has been used and it was represented by the six proxies employed in this study. There was no distinction between green technology and non-green technology. This paper shows that "aggregate" R&D expenditure and "aggregate" patents fail to have a clear impact on carbon emissions. In terms of future research, it will be interesting to go further and assess the impact of green R&D expenditure and green patents on carbon emissions in different income groups of countries. Future research can also consider the creation of a composite indicator of technological progress in each group of income. The index can be obtained from the synthesis of technical indicators used in this paper.

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Table 1. Variables description

Variables	Description	Sources
$\ln CE_{it}$	Carbon dioxide emissions in metric tons per capita. CO_2 emissions include the combustion of fossil fuels for electricity generation and heat production (in industries, households, etc.), for transportation, and the industrial process including the manufacturer of cement.	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)
$\ln Mob\_cel_{it}$	Two ICT's variables are used in this study: mobile cellular subscriptions per 100 people	WDI (World Bank, 2019)
$\ln Internet_{it}$	Individual using the internet (percentage of the population)	WDI (World Bank, 2019)
$\ln Patent_{it}$	Patent applications filed 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 Nation 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[1]
$\ln Scien\_tech_{it}$	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 kilometres	WDI (World Bank, 2019)

Note: all variables are in natural log.

[1] 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 2. Diagnostic test: serial correlation, heteroskedasticity, 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***
Heteroskedasticity	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

Table 3. IPS unit root tests.

Variables	IPS	
	Specification without trend	Specification trend
$\ln \mathrm{CE}_{it}$	3.7398 (0.999)	3.3439 (0.999)
$\ln\mathrm{GDP}_{it}$	2.1258 (0.983)	1.7564 (0.874)
$\ln\mathrm{ECONS}_{it}$	6.2513 (1.000)	7.9012 (1.000)
$\ln\mathrm{R\&D}_{it}$	0.3586 (0.640)	3.4411 (0.999)
$\ln\mathrm{Patent}_{it}$	-1.5039 (0.066) *	-1.6513 (0.049) *
$\ln\mathrm{Mob\_cel}_{it}$	-2.4299 (0.007) ***	-2.9685 (0.001) ***
$\ln\mathrm{Internet}_{it}$	-3.9694 (0.000) ***	-11.759 (0.000) ***
$\ln\mathrm{Scien\_tech}_{it}$	5.6321 (1.000)	1.6940 (0.954)
$\ln\mathrm{TFP}_{it}$	-2.0377 (0.020) **	-1.1386 (0.127)
$\ln\mathrm{POP}_{it}$	9.3182 (1.000)	4.3708 (1.000)
$\ln\mathrm{EXP}_{it}$	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.

Table 4. 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.

Table 5. Full sample results with all explanatory variables included:

Dependent variable: CO_2 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 standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

Table 6. Panel model (3)

Dependent variable: CO_2 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 level of significance at a 10 (5) [1] %

Table 7. Panel model 4

Dependent variable: CO_2 emissions						
	model (4a)	model (4b)	model (4c)	model (4d)	model (4e)	model (4f)
$lnCons\_Mob\_cel_{it}$	-.00347*** (-8.96)					
$lnCons\_Internet_{it}$		-.00330*** (-5.23)				
$lnCons\_Patent_{it}$			.0019081 (0.24)			
$lnCons\_R\&D_{it}$				.031062 (-1.70)		
$lnCons\_Scien\_tech_{it}$					-.01026** (-4.92)	
$lnCons\_TFP_{it}$						.042138** (2.11)
$lnGDP_{it}$	.19498*** (3.19)	.20044*** (2.97)	.19520*** (2.81)	.25097*** (3.89)	.13454** (2.54)	.09640* (1.75)
$lnECONS_{it}$	.91984*** (27.06)	.92606*** (23.71)	.91086*** (15.51)	1.2233*** (14.35)	1.1475*** (25.92)	.90785*** (25.95)
$lnPOP_{it}$	.62861*** (11.82)	.51605*** (12.94)	.32821*** (5.38)	.48670*** (8.42)	.47934*** (6.70)	.41688*** (10.83)
$lnEXP_{it}$	.03314 (1.05)	.04892* (1.82)	-.00239 (-0.08)	-.02848 (-0.76)	.07737*** (3.62)	-.01208 (-0.41)
Constant	-10.905*** (-17.41)	-10.851*** (-29.08)	-8.6363*** (-22.54)	-9.7125*** (-11.81)	-11.970*** (-17.17)	-7.8264*** (-21.59)
F-test	2687.42 (0.000)	1389.52 (0.000)	1595.99 (0.000)	518.80 (0.000)	242.93 (0.000)	1356.37 (0.000)
Observations	1800	1800	1800	1800	1800	1800
Groups	60	60	60	60	60	60

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

Table 8. Subsample regressions results

Dependent variable: CO_2 emissions								
	Technology – Mobile - cell				***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***	-.01930**	.12222***	-.04810	-.13368***	-.04402**	.05821	.08102

	(-7.25)	(-2.17)	(3.21)	(-0.62)	(-7.61)	(-2.67)	(1.50)	(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 [

Appendix

Table A. 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
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 B. Descriptive statistic: full sample

Variables	Observations	Mean	Stand dev	Min	Max
CO_2 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
Export/GDP	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 article	1140	26540.41	65870.67	3.14	528263.3

Table C. Descriptive statistic: Sub-sample

	Observations	**Mean value**	**Standard deviation**	**Minimum value**	**Maximum value**
CO_2 **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 D. Full sample detailed regression results panel model 1a.

Dependent variable: CO_2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
$\ln Mob\_cel_{it}$	. .04720*** (9.22)	.00925*** (-2.61)	.000304 (0.13)	-.02094*** (-7.02)	-.01686*** (-8.44)
$\ln GDP_{it}$		.617113*** (20.97)	.256743*** (6.83)	.319516*** (7.48)	.154921** (2.34)
$\ln ECONS_{it}$			.903223*** (25.32)	.829385*** (20.71)	.933625*** (22.67)
$\ln POP_{it}$				.586699*** (11.06)	.471601*** (10.46)
$\ln EXP_{it}$					.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 standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

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

Dependent variable: CO_2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
$\ln Internet_{it}$	.042476*** (6.61)	.010519 (4.22)	.001194 (0.66)	-.01817*** (-5.46)	-.01896*** (-5.80)
$\ln GDP_{it}$		.55238*** (11.20)	.25492*** (5.05)	.26636*** (5.53)	.16373*** (2.85)
$\ln ECONS_{it}$			.88767*** (22.71)	.84047*** (24.14)	.91670*** (27.46)
$\ln POP_{it}$				.61974*** (10.66)	.63268*** (10.14)
$\ln EXP_{it}$					.02572* (0.81)
Constant	.544153*** (26.04)	-4.0128*** (-9.68)	7.79863*** (-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 standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

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

Dependent variable: CO_2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
$\ln Patent_{it}$	.23240*** (7.96)	.10479*** (4.92)	.03328** (2.39)	.00697 (0.63)	.009291 (0.78)
$\ln GDP_{it}$		.59308*** (15.08)	.29664*** (9.35)	.25080*** (7.29)	.19216*** (17.66)
$\ln ECONS_{it}$			.84149*** (19.86)	.83445*** (16.81)	.86201*** (17.66)
$\ln POP_{it}$				.25193*** (5.50)	.30051*** (4.85)
$\ln EXP_{it}$					-.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 standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

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

Dependent variable: CO_2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
$\mathrm{lnR\&D_{it}}$	.21292*** (5.72)	.072980** (2.12)	.03230* (1.74)	-.02387 (0.90)	-.021502 (0.86)
$\mathrm{lnGDP_{it}}$		.47588*** (5.66)	.16714** (2.24)	.17163** (2.35)	.15954** (2.56)
$\mathrm{lnECONS_{it}}$			.89438*** (15.58)	.88262*** (15.59)	.93984*** (20.37)
$\mathrm{lnPOP_{it}}$				.36537*** (5.06)	.43019*** (6.48)
$\mathrm{lnEXP_{it}}$					-.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 standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

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

Dependent variable: CO_2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
$\ln TFP_{it}$	.300593*** (3.63)	.06347 (1.23)	.10896** (2.11)	.12426** (2.67)	.14493** (2.60)
$\ln GDP_{it}$		.65009*** (29.14)	.24276*** (11.24)	.15027*** (7.19)	.118187* (1.70)
$\ln ECONS_{it}$			.86363*** (33.15)	.80085*** (27.40)	.90441*** (25.28)
$\ln POP_{it}$				.36650*** (8.44)	.41710*** (10.72)
$\ln EXP_{it}$					-.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 standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %

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

Dependent variable: CO_2 emissions					
	Model 1	Model 2	Model 3	Model 4	Model 5
$\ln Scien\_art_{it}$	.19999*** (24.13)	.06719*** (5.06)	.01136 (0.83)	-.03508* (-2.02)	-.03740** (-2.61)
$\ln GDP_{it}$		.56590*** (14.31)	.31004*** (8.71)	.27666*** (7.92)	.07730* (1.68)
$\ln ECONS_{it}$			.90273*** (17.34)	.92307*** (16.99)	1.0339*** (30.37)
$\ln POP_{it}$				.40093*** (5.83)	.42035*** (6.48)
$\ln EXP_{it}$					.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 standard errors are in parentheses. *(**) [***] indicate the level of significance at a 10 (5) [1] %