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

Chris Belmert Milindi

Department of Economics, University of Pretoria, Pretoria, South Africa

Roula Inglesi-Lotz

Department of Economics, University of Pretoria, Pretoria, South Africa

Abstract

This study examines the complex relationship between carbon emissions and technological progress in a sample of 60 countries divided into four income groups for the period 1989-2018. For robustness purposes and due to the broad definition of technology, we use six different proxies to represent technology: Information and telecommunication technology (ICT), patents, public R&D expenditure, Total factor of productivity (TFP), science and technology publications. After applying the fixed-effect method with Driscoll and Kraay standard errors, ICT variables appear to be good instruments for carbon reduction in the full sample. However, R&D expenditure and patents do not significantly impact carbon emissions. TFP increases carbon emissions, while science and technology publications are negatively related to carbon emissions. The analysis shows mixed results for the various country income groups and all indicators.

Keywords: Technological progress; Income groups; rebound effect; Driscoll and Kraay standards errors.

1. Introduction

Global warming has been one of the most critical environmental issues of our ages. Over the past few decades, scientists, researchers, and policymakers have been trying to find ways and means of reducing greenhouse gas (GHG) emissions to alleviate global warming. Burning coal, gas, and oil to feed human activity is the leading cause of global warming (UNFCCC, 2006; IPCC, 2014). The transition from fossil fuel energy (oil, coal, gas, etc.) to renewable energy (solar, hydro, wind, etc.) and the improvement in energy efficiency are considered as the two major solutions to global warming (Garrone and Grilli, 2010; Fernandez, Lopez, and Bianco, 2018). The initial cost of renewable energy implementation and production is still high, especially for developing countries. Governments expect a reduction of the initial cost of renewable energy technology, and one of the major channels by which it can be done is through technological progress (Churchill et al, 2019).

Technologies refer to the whole complex of scientific knowledge, process technologies, engineering practices, product characteristics, infrastructures, tools and machines, skills, and procedures used to resolve real-world problems (Mooney, 2011). In recent years, technological progress has been at the center of the fourth industrial revolution[1], transforming our lives as never before. Although this revolution operates differently, depending on whether you are in a rich or developing country, it does affect the entire planet and the environment. Technology plays a significant positive role in developing a country (Solow, 1957; Romer, 1986, 1987, 1990). It promotes economic growth by improving productivity and infrastructure, and it increases 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 reveal that technological progress has a dual effect on global CO2 emissions. On the one hand, technology reduces overall CO2 emissions by reducing energy intensity, adjusting the energy structure, and fostering green technology diffusion in industries and countries (Bosetti et al., 2009; Moyer and Hugues, 2012; Higon, Gholami, and Shirazi, 2017). On the other hand, technology increases CO2 emissions by increasing energy consumption and economic growth` (Grossman and Krueger, 1995; Bongo, 2005; Hu, Li and Wang, 2006; Bosetti et al., 2008; Zhang and Cheng, 2009; Garrone and Grilli, 2010; Ghosh, 2010; Gu et

[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).

al., 2019). An obvious fact is that CO2 emissions have increased dramatically since the industrial revolution (Boden, Andres, & Marland, 2015), following the similar evolution of technological progress. Any immense advancement in technology not only brings about an improvement in the environment and energy supply but also tremendously stimulates economic development and energy consumption on a large scale (Hertin and Berkout, 2005; Herring and Roy, 2007; Sorrell and Dimitropoulos, 2008; Sorrell, Dimitropoulos and Sommerville, 2009; Jin et al., 2017; Cheng et al., 2019).

Measuring technological progress quantitatively is challenging as its representation and realization vary. How technology interacts with the environment, in general, has been the subject of several studies (Jin L. , Duan, Shi, & Ju, 2017; Gu, Zhao, Yan, Wang, & Li, 2019; Chen, Gao, Ma, & Song, 2019; Chen, Gao, Mangla, Song, & Wen, 2020; Khan, Raza, Khan, & Ali, 2020) but, to our knowledge, there has not yet been an analysis of how technology influences CO2 emissions by assessing various "proxies" of technology[2] since each proxy may yield different results. Moreover, technology's positive and negative impact on CO2 emissions has not yet been comprehensively investigated on different "income level" scales. Given that the response to the environmental challenges mostly depends on each country's capacity, it is necessary to look at this relationship in countries at all levels of development. The recent literature has focused primarily on single-country analysis to examine the impact of technological progress on emissions, while some other studies have also proceeded with sectoral or regional (provincial) disaggregated research (for example, Khan et al. (2020) conducted a sectoral study for Pakistan and Chen et al. (2020) a regional analysis on 30 provinces in China).

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

This study has been carried out on a panel of 60 countries divided into four groups according to their income level. Thus, we had 15 high-income countries, 15 upper-middle-income countries, 15 lower-middle-

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

income countries, and 15 lower-income countries. The study period runs from 1989 to 2018. A comparison of how technology interacts with climate change in low-income, lower-middle, upper-middle, and high-income countries was conducted.

Measuring the responsiveness of GHG emissions to technological progress is essential for economic and environmental policies for several reasons. First, if the net effect of technological change on carbon emissions is negative, this implies that technology has contributed to carbon reduction within our study period. Secondly, since technology is complex to quantify, using different technology indicators will reveal which indicator works better for carbon reduction. For instance, one may find that, on the one hand, public R&D expenditure impact positively carbon emissions because they are mainly directed to carbon-intensive projects. On the other hand, the proliferation of mobile phones (ICT) in countries may reduce the transportation of people from point A to point B[3], thus reducing carbon emissions. In this scenario, the Government may consider redirecting public R&D expenditure toward environmentally friendly projects and fostering the proliferation of mobile phones to combat climate change. Thirdly, the fact that the study was done on different country's income groups also has its importance. Because some measures of technological advancement may work better in reducing carbon emissions in some groups of countries than in others, in this regard, high-income countries were particularly monitored since they are more advanced in R&D spending, patent applications, and TFP.

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

As an illustration, Gu et al. (2019) used patent application as a technological advancement indicator to investigate the impact of technology on CO2 emissions in China. Garrone and Grilli (2010) employed R&D expenditure as a technology-push instrument to analyze its causality link with carbon emissions in a sample of 13 OECD countries. Higon, Gholami, and Shirazi (2017) utilized ICTs variables as indicators of technology

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

development and examined the same relationship in 142 economies. While there is a growing number of studies examining the interaction between technological progress and climate change, the previous literature does not provide comparable empirical evidence on how various technology measurements may differently affect carbon emissions. Therefore, this study uses six indicators of technological progress and assesses their impact on carbon emissions. We argue that since each indicator capture a particular aspect of technology, their respective impact on CO2 emissions may differ. By doing so, the study will be able to provide specific policy recommendations to promote particular aspects of technology to reduce CO2 emissions. The strengths and weaknesses of all these indicators are also thoroughly discussed – such a detailed comparison will also contribute to future studies' choice of technological progress indicators.

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, Jin et al., 2017; Gu et al., 2019). They have treated technological progress and energy consumption as general independent variables in CO2 model estimation, thus neglecting the interaction effect between technological progress and energy consumption on CO2 emissions. Our paper will account for the rebound effect by interacting technological progress with energy consumption and assessing their joint impact on carbon emissions.

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

The remainder of this paper is structured as follows: Section II contains a brief literature review. Section III present 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.

2. Literature review

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

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

The second strand of the literature has used ICTs as a proxy for technological progress to estimate 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 CO2 emission by increasing manufacturing production, energy consumption, production of devices and machinery, and recycling electronic waste. On the other hand, ICTs can lower CO2 emissions on a global scale through energy savings, smart cities, efficient production processes, ecological transportation systems, and electrical grids. These studies have generally found that the net effect of ICT on CO2 emissions is negative.

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

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

Many studies have emphasized the critical role of governments in fostering the adoption of new technologies for carbon emissions reduction. There is a consensus in the literature that technological progress needs to be coupled with strict environmental regulation, such as carbon tax, to have a significant impact on carbon emissions (Moyer and Hugues, 2012; Hashmi and Alam, 2019; Churchill et al., 2019; Cheng et al., 2019). Mees, Uittenbroek, Hegger, and Driessen (2019) have proposed a “ladder of government participation” to explore the role of local governments in citizens’ initiatives for climate adaptation in the Netherlands. They have found government support in citizens’ climate change initiatives allows raising communities' awareness on the challenges of climate change. Cheng et al. (2021) have investigated the potential role of fiscal expenditure on carbon emissions differences in different provinces of China. The authors argued that modifying the structure and scale of budgetary spending will directly impact GDP as well as energy consumption and CO_2 emissions. Results reveal that fiscal decentralization is a significant driver of provincial CO_2 emissions in China. Reduction of CO_2 emissions can hardly be achieved with an inefficient distribution of expenditure authority between the provincial and the central government. Besides, some scholars investigated how environmental regulation can promote green technology adoption and reduce green gas emissions. Xie, Zhou, and Hui (2022) demonstrated that china's carbon emissions trading-market-system had improved the power generation technology structure.

Marques, Fuinhas, and Tomas (2019) have shown that economic growth increases energy efficiency technology in the European Union. The authors have pointed out the critical role of policymakers in incentivizing green investment and controlling energy pricing.

As mentioned in the introduction, this paper evaluates the impact of various indicators of technological progress on carbon emissions in a full sample of 60 countries and on subsamples of different income categories. Technology is a broad concept, and a single indicator can hardly represent it. Therefore, instead of using one indicator of technology as the majority of papers cited in the literature above, we use six indicators of technological progress and assess their impact on carbon emissions. We argue that since each indicator captures a particular aspect of technology, their respective effect on CO2 emissions may differ. This study also follows Gu et al.'s (2019) paper and analyses the rebound effect by assessing the joint impact of technological progress and energy consumption on carbon emissions.

3. Theoretical model

Global warming is a global phenomenon of climate change characterized by a general increase in average temperatures, which durably modifies weather balances and ecosystems (IPCC, 2000). Global warming is the consequence of several factors. Mainly, the production of energy (electricity, heating, etc.) and fuel for transport (mostly cars and aviation and maritime transport) causes global warming. Deforestation, large-scale agriculture, and the expansion of livestock are also among the causes of global warming (IPCC, 2014). But these root causes are mainly linked to 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; Richmond and Kaufmann, 2006; Akinlo, 2008; Garrone and Grilli, 2010; Shabbaz et al., 2017; Higon, Gholami, Shirazi, 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: energy consumption, economic growth, population density, technology, and trade. Therefore, this study is based on the following theoretical model:

$$CO2\ emission_{it} = f(GDP_{it}, ECONS_{it}, POP_{it}, EXP_{it}, TECH_{it}) \qquad (1)$$

Where GDP_{it} represent GDP per capita and $ECONS_{it}$ refers to energy consumption ($ECONS_{it}$). These two variables are well-known drivers of carbon emissions. We expect positive coefficients from these two regressors. The positive impact of economic growth and energy consumption on carbon emissions has been demonstrated in several studies over the past few decades (Hertin and Berkout, 2005; Bousquet and

Favard, 2005; Sorrell, Dimitropoulos and Sommerville, 2009; Hall, 2011; Jin et al., 2017; Cheng et al., 2019). As long as the energy used to power the economy is based on fossil fuel, it can be expected that the growth in CO2 emissions will be proportional to the continued growth of the world economy. Among the other covariates in this study expected to influence per capita carbon dioxide emissions, we include as suggested by previous literature: population density (POP_{it}) (Seldan and Song, 1994; Borghesi, 1999; Moyer and Hugues, 2010, Churchill et al., 2019) and exports (EXP_{it}) (Boutabba, 2014; Ohlan, 2015; Ertugrul et al., 2016; Shahbaz et al., 2017; Murat, Ecevit and Yucel, 2018).

4. Methodology and data

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

4.1 Methodology

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

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

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

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

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

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

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

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

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

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

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

Similar to model (2), $TECH_{it}$ is successively replaced by six different proxies of technological progress. Therefore, we will have six different sub-models[4].

[4] 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.

Following the consolidated literature on dynamic panel data models (Kiviet, 1995, 1999; Blundell and Bond, 1998; Bun and Kiviet; 2003, Bruno 2005), we used the Bruno's (2005) biased-corrected LSDV methodology to estimate model specification (2). When a lagged dependent variable is included among the regressors, the Nickell biased (1981) 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 (Abrate et al., 2012; Garrone and Grilli, 2010). We prefer LSDVC to alternative Nickel biased correction methodology, such as the GMM method, for two reasons. First, Judson and Owen (1999), by performing a Monte Carlo experiment, show that for a large period (T ≥ 30), 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 large relative 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 prove the robustness of the findings. The diagnostic test performed in the result 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 takes into account the rebound effect, which was 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 improved 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 have to travel long distances to get to work, in the end, energy consumption will keep increasing. Technological progress implies the production of energy-saving technology, which leads to lower carbon emissions, but the energy consumption is stimulated to a certain extent at the same time, which is consistent with the rebound effect (Gu et al., 2019). This shows that the impact of technology on carbon emission emissions is difficult to predict when considering human behavior to new technology. Our paper will account for the rebound effect by interacting technological progress with energy consumption and assessing their common impact on carbon emissions. Therefore, our third empirical specification is a static panel model that includes an interaction term:

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

Here $TECH_{it}$ is also replaced by six different proxies of technological progress[5]. Empirical specification (4) is estimated with the fixed-effect method. β_7 is the coefficient on the interaction term. It determines the impact of technological progress on CO2 emissions through energy consumption. The interaction term only indicates whether the rebound effect of energy consumption is higher or smaller than energy savings caused by technological progress. A positive coefficient on the interaction terms suggests that as technology increases (and therefore energy efficiency), it also increases the positive impact of energy consumption on carbon emissions. Thus, energy savings brought by technological progress is offset by higher energy consumption. A negative coefficient on the interaction term means that as technology increases, it reduces the positive impact of energy consumption on carbon emissions. This can indicate that the rebound effect is offset by energy savings caused by technological progress.

4.2 Data

This study uses a balanced panel dataset of 60 countries, split into 15 high-income, 15 upper-middle-income, 15 lower-middle-income, and 15 lower-income economies. The dataset provides a period of 30 years, from 1989 to 2018. The World Bank classifies countries according to their income level in four income groups (high income, upper-middle-income, lower-middle-income, and low-income countries). Following this classification, we have selected 15 countries in each income group. The 15 countries chosen per income group are the largest CO2 emitters in their respective income groups. To clarify further, the sample was selected based on three criteria. The first criterion is the average level of GDP per capita throughout the study period. When considering the average GDP per capita, each country selected in the sample has always belonged to a specific income group throughout the study period (1989 – 2018)[6]. The second criterion is the national level of carbon emissions. In each income group, we have selected the countries that emitted the most CO2 during the period 2000-2018. The third criterion is the availability of data, particularly data on technological proxies. The combination of these three criteria led to the selection of 15 countries per income group[7]. This way of selecting allows to examine how the CO2 emissions in the top 15 emitting

[5] Panel model (3) 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.

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

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

countries of each income bracket respond to technological progress. In 2016, the 60 countries selected in this study represented 94 per cent of global GDP and 91 per cent of global CO_2 emissions (World Bank, 2019).

The variables used in this study were collected from different sources. Table 1 -Panel A 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$), trade (exports in constant 2010 US$), science and technology publications, and population density were drawn from the World Bank's Development Indicators (WDI, 2019). Two ICT's 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. Data on Research and development expenditure (as a percentage of GDP) was collected from the United Nations Educational and Cultural Organization (UNESCO) and the OECD database, while data on patents was collected from World Intellectual Property Organization (WIPO).

Table 1 Panel B reports the pairwise correlation matrix among variables. The correlation matrix helps in revealing potential multicollinearity problems among variables. It also helps in the choice of relevant variables affecting carbon emissions. It is important to emphasize that the correlation matrix gives a picture of correlation among variables but cannot be considered as a causal relationship (Baltagi, 2008).

Table 1. Variable description and Correlation matrix

Panel 1A: Variable Description		
Variables	Description	Sources
$\ln CE_{it}$	Carbon dioxide emissions in metric tons per capita. CO2 emissions include combustion of fossil fuels for electricity generation and heat production (in industries, households, etc.), transportation, and industrial processes, 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)
$\ln Mob\_cel_{it}$ $\ln Internet_{it}$	Two ICT's variables are used in this study: mobile cellular subscriptions per 100 people and individuals using the internet (percentage of the population)	WDI (World Bank, 2019)
$\ln Patent_{it}$	Patent applications by residents and nonresidents in each country.	WIPO (World Intellectual Property, 2020)
$\ln R\&D_{it}$	Public expenditure in Research and development as a percentage of GDP.	United 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[8]
$\ln Scien\_tech_{it}$	These are scientific articles. They include research published in the following field: energy, physics, chemistry, biology, mathematics, earth and space sciences, biomedical research, engineering, and technology.	WDI (World Bank, 2019)
$\ln EXP_{it}$	Exports in 2010 constant US$ term	WDI (World Bank, 2019)
$\ln POP_{it}$	Population density per square kilometers	WDI (World Bank, 2019)

[8] 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.

Panel 1B: Correlation matrix										
	CO2	GDP	EC	R&D	ICT	PAT	Stech	TFP	POP	EXP
CO2	1									
GDP	0.83*	1								
EC	0.84*	0.58*	1							
R&D	0.63*	0.62*	0.59*	1						
ICT	0.31	0.41*	0.36*	0.23*	1					
PAT	0.64*	0.60*	0.63*	0.59*	0.31*	1				
STech	0.60*	0.62*	0.64*	0.68*	0.44*	0.55*	1			
TFP	0.50*	0.58*	0.50*	0.52*	0.20*	0.37*	0.60*	1		
Pop	0.27*	-0.17	-0.28	0.08*	0.05*	0.02	0.14*	0.08*	1	
EXP	0.69*	0.67*	0.63*	0.58*	0.47*	0.62*	0.61*	0.41*	0.03	1

4.3 Technology indicators discussion

4.3.1 Public R&D expenditure

R&D expenditure is of fundamental importance in creating new technology, new knowledge, and new products. It is a usual remedy for knowledge spillovers and market failure that does not foster innovation in the in-production sector (Churchill et al., 2019). R&D may be regarded as an essential technology push measure (Garrone & Grilli, 2010). However, Garron and Grill (2010) note that considering R&D spending as a climate technology policy towards low carbon energy is sometimes controversial. In reality, R&D spending cannot be viewed as a climate technology policy unless there is initially a market for low-carbon and energy-efficient products. 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; it may be an attempt that will bear fruit only in the long term. Actually, 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 green R&D expenditure and no green R&D expenditure. It follows from this fact that the final impact of R&D expenditure or patents on carbon emission is uncertain as the two components clash together (Sagar and Holdren, 2002; Sagar and Zwaan, 2006). Despite all its limits, R&D spending remains a good indicator of technological progress in a country.

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). Patents are good indicators of technical progress because they are often the result of intense research leading to the manufacture of products or the creation of techniques that bring added value to industries and positively impact economic growth. Patents indicate the existence of output or “finished product,” unlike R&D expenditure which are the inputs that can lead to the creation of new products or patents. Patents serve to stimulate technical progress and indicate the technological progress level reached by a nation. However, the use of patents as a proxy for technology has potential limitations, which are important to note. Firstly, the number of patents granted in a country does not necessarily reflect the utility or the quality of the inventions created. The utility or the quality of patents in terms of "technological contribution" is not the same. Some patents bring a real revolution to the industry, while others have a minor impact instead (Cremers et al., 1999; Scherer and Harhoff 2000; Hall, Jaffe, and Trajtenberg, 2005). Secondly, patents can reflect technological development but cannot represent the situation of technological adoption (Du et al., 2019). A Patent can be created, but it does not necessarily mean that the industry or the society will automatically adopt it.

4.3.3 Science and technology publications

Another potential indicator of technological progress in a country is the number of science and technology publications in peer-review journals. Scientific journals aim to provide information about new research to increase the stock of knowledge and facilitate knowledge transmission. Research results provided must be strong, relevant, reliable, and capable of being replicated in a given context (Monteiro, Devan, Soans, & Jeppu, 2012). The Scientific knowledge acquired is further transformed into a concrete product or procedure that increases technology stock. Science and technology publications are also linked with the improvement in human capital. A country with a high level of tertiary education attainment is likely to produce more science and technology publications than other countries with 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 only to criticize or review other papers 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 sometimes significantly differ. As explained above, most scientific journals ensure 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 science and technology publications remains a good indicator of the level of debate, knowledge, and technical progress reached by a country.

4.3.4 Information and communication technologies (ICT)

ICT includes all tools, services, and techniques used to create, record, process, and transmit information. Therefore, it is mainly about computers, the Internet, radio and television, and telecommunications. There is a common consensus in the literature that the ICT sector contributes to technological progress, productivity, and economic growth (see Wang, 1999; Bongo, 2005; Ahmed and Ridzuan, 2013, Sassi and Goaied, 2013; Niebel, 2018). Having a high number of mobile phone users does not necessarily mean that the country is technologically advanced[9]. Using the number of mobile phone users as an indicator of technological progress should be taken cautiously. Some countries with a high number of mobile phone users are not mobile phone producers. This is the case in many developing countries. These countries adopt this technology but are not producers of this technology. In those countries where mobile phones are not produced, the number of mobile phones or internet users can be seen as an input that boosts technological progress. For example, for students and researchers, a smartphone allows them to acquire new knowledge and information and download valuable applications and procedures that will increase their knowledge.

4.3.5 The total factor productivity (TFP)

TFP is the part of economic growth that is unexplained by the accumulation of capital or labor (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 labor. The model developed by Solow was able to tell whether output growth is attributed to a rise in the two factors of production or to more efficient use of these two factors. Solow found that the capital increase in the United States between 1910 and 1950 could explain only twelve percent of labor 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 B. H., 2011). Measuring TFP requires measures of real output, real labor, and real capital stock (as well as possible other inputs, such as energy and materials). Hall (2011) notes that researchers, agencies, or organizations use many approaches to measure the inputs and outputs. Unfortunately, TFP measurement can be significantly impacted by the choices done in these approaches. The difficulty lies in evaluating real inputs and outputs, holding constant the unit of measures over time. Unlike other recorded proxies, such as R&D expenditure and the number of patents, TFP needs reliable data of labor and capital stock of a given economy to be calculated. Moreover, TFP measures need to be used carefully, with a good understanding

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

of the approach used to deflation and quality adjustment (Hall B. H., 2011). The TFP measure used in this study comes from Penn World Table. To calculate TFP, they use a procedure where the nominal value of capital is deflated, and the quality of labor is adjusted.

5 Results estimation and discussions

5.1 Diagnostic test results

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

Table 2. Serial correlation, heteroscedasticity, cross-sectional dependence, time fixed effect, and panel effect.

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

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

5.2 Panel unit root test and cointegration results

Table 3 shows that we fail to reject the null hypothesis of a unit root for most variables and conclude that most series are not stationary.

Table 3. IPS unit root tests.

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

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

Consequently, cointegration tests (Westerlund (2005), Pedroni (1999, 2004), and Kao (1999) tests) are necessary to avoid spurious relationships when estimating regressions with non-stationary variables. Table 4 shows that 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.

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.

5.3 Results estimation

This section discusses the impact of technological progress on carbon dioxide emissions results. 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 heteroscedasticity in the dataset (Hoechle, 2007).

The section is divided into four subsections. The first subsection examines the relationship between technology advancement and carbon emissions in the full sample[10] 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 C02 emissions at different income group levels[11].

5.3.1 Full sample analysis

Tables A to F in the appendix[12] present detailed results from the full sample analysis. Table 5 below presents a summary of these results. Table 5 shows the responsiveness of carbon emissions when each technology variable is included with all other explanatory variables at once[13]. 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 percent increase in mobile cellular subscriptions and internet use lower carbon emissions by 0.016 and 0.018 percent, respectively. Mobile cellular subscriptions and internet use are significant at 5 and 10 percent 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 percent rise of patents and R&D expenditure, increase carbon emissions by 0.032, and 0.033 percent, respectively[14]. Patents and R&D expenditure have opposite signs after including additional explanatory variables, and they are both statistically insignificant at conventional levels of significance (see table 5). When all explanatory variables are included in the model, the sign of TFP is positive and statistically significant at 5 percent level of significance, while the sign of science and technology publications is negative and statistically significant at 5 percent level of significance. A 1 percent

[10] For all 60 countries in the dataset
[11] We divide the full sample into 4 groups according to their income level: 15 high income, 15 upper-middle income, 15 lower-middle income and 15 lower-income countries.
[12] 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.
[13] Table 5 just contains all six “regressions 5” of panel sub model A to F which are presented in the appendix.
[14] Please refer to table C and D in the appendix.

rise in TFP increases carbon emissions by 0.1449 percent, while a 1 percent increase in science and technology publications reduces carbon emissions by 0.0374 percent.

Regarding other core drivers of carbon emissions, the results show that GDP per capita, energy consumption, and population density have a positive and statistically significant impact on carbon emission in all six sub-models. This result follows the vast majority of literature that has found a positive relationship between these variables and carbon emissions (Selden and Song, 1994; Akinlo, 2008; Bosetti et al. 2009; Hashmi and Alam, 2019; Gu et al., 2019). Export is associated with an increase in carbon emissions only in two sub-models.

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

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

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

R&D expenditure and patents do not have a clear impact on carbon emissions. A possible explanation is the dual effect of these two technology measures on carbon emissions. R&D expenditure and patents may increase or decrease carbon emissions, depending on whether they are environmentally friendly or not. The two effects tend to cancel each other out, resulting in an insignificant impact on CO2 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 study period, 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[15], R&D expenditure and patents start reducing carbon emissions progressively. If this is the case, it suggests that in our data and analysis, R&D expenditure and patents have not yet reached the turning point where CO2 emissions are declining. Further research will therefore be necessary to verify these hypotheses.

5.3.2 Bruno LSDVC estimation

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

Table 6. Panel model (3)

Dependent variable: CO2 emissions						
	model (3a)	model (3b)	model (3c)	model (3d)	model (3e)	model (3f)
$\ln \mathrm{CE}_{it-1}$	.772628*** (253.56)	.75296*** (96.58)	.781399*** (48.42)	.79162*** (195.84)	.74646*** (32.85)	.747742*** (26.15)
$\ln\mathrm{Mob\_cel}_{it}$	-.00194*** (-29.49)					
$\ln\mathrm{Internet}_{it}$		-.0053*** (-4.86)				
$\ln\mathrm{Patent}_{it}$			.0019081 (0.24)			
$\ln\mathrm{R\&D}_{it}$				-.031062* (-1.70)		
$\ln\mathrm{Scien\_tech}_{it}$					-.020659** (-2.00)	
$\ln\mathrm{TFP}_{it}$						.042138** (2.11)

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

$\ln GDP_{it}$	.018423** (2.42)	.046714 (0.77)	.054716** (2.29)	.046240 (1.16)	-.026234 (-0.42)	.031559*** (6.91)
$\ln ECONS_{it}$	.21007*** (9.69)	.214531*** (4.07)	.144765*** (4.12)	.237714*** (17.06)	.337586*** (5.25)	.194748*** (40.35)
$\ln POP_{it}$	.066015** (1.96)	.164314*** (11.02)	.079287 (1.51)	.121199*** (1.40)	.152597*** (5.48)	.11602*** (6.73)
$\ln EXP_{it}$	.019070** (2.38)	.014434 (1.50)	.010548* (1.64)	.007011 (0.66)	.031492 (1.17)	.0057858 (0.60)
Groups	60	60	60	60	60	60

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

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

5.3.3 The rebound effect

Panel model three introduces an interaction term to account for the rebound effect. The coefficient on the interaction term indicates how technological progress affects carbon emissions through energy consumption (Gu et al., 2019). A negative coefficient would suggest that technological progress, through channels, such as energy savings and renewable energy development, attenuates the positive impact of energy consumption on carbon emissions. A positive coefficient would suggest that additional energy savings induced by technological progress are offset by higher energy consumption caused by the rebound effect, thus increasing carbon emissions[16].

Table 7. Panel model 4

Dependent variable: CO2 emissions						
	model (4a)	model (4b)	model (4c)	model (4d)	model (4e)	model (4f)
$\ln Cons\_Mob\_cel_{it}$	-.0169*** (-7.42)					
$\ln Cons\_Internet_{it}$		-.0149*** (-4.66)				
$\ln Cons\_Patent_{it}$			-.0719*** (-10.04)			
$\ln Cons\_R\&D_{it}$				-.0880*** (-11.64)		

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

$lnCons\_Scien\_tech_{it}$					-.0818*** (-10.33)	
$lnCons\_TFP_{it}$						-.2429*** (4.71)
$lnTech_{it}$	-.0102*** (7.36)	-.0879*** (4.40)	.04936*** (1.95)	.5901 (0.85)	-.05520*** (-8.97)	1.766*** (16.27)
$lnGDP_{it}$	.2495*** (3.53)	.2443*** (3.63)	.3196*** (6.01)	.3024*** (5.44)	.2351*** (5.31)	.1331** (2.26)
$lnECONS_{it}$	.9112*** (28.44)	.8954*** (25.38)	1.409*** (18.25)	1.833*** (16.45)	1.657*** (19.78)	.8145*** (16.27)
$lnPOP_{it}$	.2761*** (5.56)	.4054*** (7.31)	.2149*** (3.49)	.1971*** (3.42)	.1586** (2.51)	.4135*** (10.11)
$lnEXP_{it}$	.0226 (0.95)	.0197* (1.91)	-.0396 (-1.31)	-.0379 (-1.36)	.0199 (0.82)	-.0327 (-1.05)
Constant	-9.509*** (-22.92)	-9.872*** (-20.36)	-11.65*** (-21.05)	-20.95*** (-16.60)	-13.87*** (-22.52)	-6.930*** (-13.05)
F-test	944.06 (0.000)	1528.60 (0.000)	1590.02 (0.000)	1065.08 (0.000)	527.13 (0.000)	1476.45 (0.000)
Observations	1800	1800	1800	1800	1800	1800
Groups	60	60	60	60	60	60

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

The results indicate that carbon emissions decrease despite the rebound effect for all joint interactions between energy consumption and technological progress proxies. This is an indication that there is an inverted U shape relationship between energy consumption and carbon emissions across technological progress. It suggests that as technology increases, the impact of energy consumption on carbon emission is turning from positive to negative[17]. It is important to note that this mechanism is not only due to energy efficiency gains induced by technological progress but also to the rise of green technologies such as renewable energies, which fundamentally change the structure of energy consumption. In conclusion, the results of this study indicate there is a positive relationship between energy consumption and carbon emissions. That is, in general, energy consumption increases carbon emissions. However, model 3 reveals that technological progress can play a role as a regulatory mechanism in that process by mitigating the positive effect of energy consumption through energy efficiency and energy mix structure changes.

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

5.3.4 Subsample analysis

Table 8 presents the results of the impact of technology advancement on carbon emissions across different income levels, using a Fixed Effect methodology with Driscoll and Kraay standard errors. The full sample is divided into four subsamples: High-income countries (subgroup 1), Upper-middle income countries (subgroup 2), Lower-middle income countries (subgroup 3), and lower-income countries (subgroup 4). In general, the signs of ICT's proxies are negative and significant across all income levels. In high income and upper-middle-income countries, 1% increase in mobile cellular subscriptions decreases carbon emissions by 0.011% and 0.010%, respectively; and a 1% increase in internet use decreases CO2 emissions by 0.007% and 0.006%, respectively. The results are similar in lower-middle-income and lower-income countries. 1% increase in mobile cellular subscriptions decreases CO2 emissions by 0.013% in lower-middle-income countries and 0.05% in lower-income countries. Carbon emissions decline by 0.036% and 0.033% when internet connection increases by 1% in lower-middle-income and lower-income, respectively. Globally, ICT appears to be a good tool to reduce CO2 emissions.

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

Energy consumption is positive and statistically significant in all regressions. This is consistent with the literature since we expect a positive relationship between energy consumption and carbon emissions (Dinda and Coondoo, 2006; Akinlo, 2008). Regarding GDP per capita, this variable is statistically significant and positively related to carbon emissions in most 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 (Seldan and Song, 1994; Borghesi, 1999). High population density means more demand for fossil fuels to provide more energy and fuel to an increasingly mechanized life.

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

Table 8. Subsample regressions results

Dependent variable: CO2 emissions								
	Technology – Mobile				*Technology – Internet*			
	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4
$\ln TECH_{it}$	**-.01144*** (-3.87)**	-.01074*** (-4.90)	-.01309** (-2.06)	-.05697*** (-5.12)	-.00748*** (-3.35)	-.00622* (-1.88)	-.00368* (-1.92)	-.03378** (-2.67)
$\ln GDP_{it}$	.15863** (2.13)	.05808* (1.93)	.04536 (0.37)	1.0664*** (8.31)	.15497** (2.16)	.024814 (0.51)	.10644 (0.85)	.78996*** (6.18)
$\ln ECONS_{it}$	.98442*** (24.52)	1.0167*** (27.76)	1.0747*** (20.25)	1.4445*** (6.35)	1.0037*** (23.98)	1.0320*** (23.07)	1.0700*** (23.28)	1.1955*** (5.27)
$\ln POP_{it}$	.0938974 (0.73)	.0276064 (1.05)	.32013** (2.17)	.56710* (1.83)	.048451 (0.41)	-.00014 (-0.05)	.17147 (1.15)	.55098** (2.11)
$\ln EXP_{it}$	-.09221*** (-3.71)	.02159 (1.45)	.12829** (2.62)	.07072 (1.24)	-.09389*** (-3.54)	.00382 (0.28)	.05449 (1.49)	.05399 (0.73)
Constant	-5.5115*** (-11.17)	-7.1692*** (-18.05)	-11.689*** (-10.13)	-20.845*** (-14.06)	-5.4119*** (-12.40)	-6.4642*** (-22.73)	-9.6474*** (-15.03)	-17.265*** (-8.97)
F-test	466.80 (0.000)	1782.00 (0.000)	139.62 (0.000)	139.62 (0.000)	1011.85 (0.000)	2052.96 (0.000)	892.18 (0.000)	32.71 (0.000)
Observations	450	450	450	450	450	450	450	450
Groups	15	15	15	15	15	15	15	15
	Technology – Patent				*Technology – R&D*			
	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4
$\ln TECH_{it}$	**.03200* (1.91)**	-.00183 (-0.24)	.04766** (2.07)	.06031** (2.09)	.0176199 (0.37)	.00259 (0.09)	.05523* (1.77)	.00990 (0.27)
$\ln GDP_{it}$	.19035** (2.59)	.01961 (1.30)	-.02650 (-0.24)	.79436*** (6.50)	.148569* (1.87)	.08021*** (3.03)	.12814 (0.92)	.78957*** (6.37)
$\ln ECONS_{it}$	.95866*** (22.47)	1.0561*** (28.82)	.95445*** (11.46)	1.0624*** (3.92)	.97276*** (27.86)	.97069*** (27.17)	1.0206*** (17.07)	1.6470*** (8.33)
$\ln POP_{it}$	-.00118 (-0.05)	-.05520 (-1.53)	.12896** (1.99)	.17980 (0.88)	-.007788 (-0.07)	-.03803 (-0.84)	-.14929 (-0.93)	-.26542* (-1.92)
$\ln EXP_{it}$	-.14761*** (-7.25)	-.01930** (-2.17)	.12222*** (3.21)	-.04810 (-0.62)	-.13368*** (-7.61)	-.04402** (-2.67)	.05821 (1.50)	.08102 (0.99)
Constant	-4.0776*** (-13.85)	-5.7985*** (-17.98)	-9.686*** (-36.03)	-13.024*** (-6.24)	-4.2226*** (-12.70)	-5.2001*** (-19.92)	-9.1747*** (-31.63)	-17.585*** (-9.04)
F-test	321 (0.000)	779.98 (0.000)	2186.24 (0.000)	32.71 (0.000)	409 (0.000)	1176.74 (0.000)	4383.35 (0.000)	47.03 (0.000)

Observations	450	450	450	450	450	450	450	450
Groups	15	15	15	15	15	15	15	15

	Technology – Articles				***Technology – TFP***			
	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4	Sub-group 1	Sub-group 2	Sub-group 3	Sub-group 4
$\mathrm{lnTECH}_{\mathrm{it}}$	**-.19050*** (-5.01)**	-.01291* (-1.90)	.01789 (0.60)	.14772 (1.22)	.06825 (1.31)	.04891** (-2.69)	.22824*** (4.22)	.02029 (0.18)
$\mathrm{lnGDP}_{\mathrm{it}}$	.43937*** (4.01)	.16310*** (5.74)	-.06271 (-0.79)	.59554*** (4.15)	.13375* (1.79)	.02723 (1.23)	.20652* (-2.10)	.74166*** (6.98)
$\mathrm{lnECONS}_{\mathrm{it}}$	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)
$\mathrm{lnPOP}_{\mathrm{it}}$	.42653* (2.05)	.05574* (1.72)	.04524 (0.26)	-.75502** (-2.68)	.085676 (0.79)	.06385* (1.74)	.22742** (2.20)	.96544*** (5.60)
$\mathrm{lnEXP}_{\mathrm{it}}$	-.06086** (-2.46)	-.08416*** (-7.25)	.10041*** (3.17)	.19568*** (3.12)	-.12700*** (-6.31)	-.01920* (-1.74)	.12104*** (3.49)	.23041*** (3.05)
Constant	-8.9548*** (-9.89)	-4.8398*** (-17.46)	-8.9752*** (-13.59)	-17.917*** (-10.33)	-4.1999*** (-12.18)	-5.8452*** (-18.34)	-9.5029*** (-28.35)	-16.212*** (-8.11)
F-test	1045 (0.000)	3136.36 (0.000)	2622.34 (0.000)	130.62 (0.000)	274.72 (0.000)	1220.88 (0.000)	492.04 (0.000)	90.73 (0.000)
Observations	450	450	450	450	450	450	450	450
Groups	15	15	15	15	15	15	15	15

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

In all four groups of countries, mobile cellular subscriptions and internet connections reduce carbon emissions. This result aligns with 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[18] channels: increasing energy efficiency and decreasing the cost of renewable energy adoption. This negative impact seems to outweigh the positive impact ICT has on carbon emissions as a result of also contributing to the increase in GDP. Even though the magnitude of mobile cellular subscriptions and internet connection coefficients in the estimation results are not very high, they remain negative and statistically significant in all income groups. Thus, investment in the ICT sector can be recommended as a good policy to combat climate change. Science and technology publications are associated with decreased carbon emissions in high-income and upper-middle-income countries. Science and technology publications fail to significantly impact carbon emissions in lower-middle and low-income countries. This is not surprising given the considerable gap in scientific publications between high-income countries and low-income countries.

6 Conclusion

The relationship between technological change and carbon emissions is complex. Numerous studies show that technological progress has a dual effect on global CO2 emissions. On the one hand, technology reduces overall CO2 emissions by reducing energy intensity, adjusting the energy structure, and fostering the diffusion of green technology in industries and countries. On the other hand, technology increases CO2 emissions by increasing energy consumption and economic growth. The purpose of this 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 **CO2** emissions when using various technology measurements. Notably: Information and telecommunication technology (mobile cellular subscription and percentage of internet users); the number of patents applications; public R&D expenditure; total factor of productivity (TFP); and the number of science and technology publications.

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 complementing the latter with the Bruno (2005) LSDVC methodology

[18] 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.

as a robustness check, the following mixed results have been found: ICT variables appear to be good instruments for carbon reduction. The net effect of ICT variables on 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 science and technology publications are 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 technological progress with energy consumption and assessing their common impact on carbon emissions. Results reveal that carbon emissions decrease despite the rebound effect for all joint interactions. There is an inverted U shape relationship between energy consumption and carbon emissions across technological progress. It suggests that as technology increases, the impact of energy consumption on carbon emission is turning from positive to negative because of the energy efficiency induced by technology and the increasing share of green technology in the energy mix.

The second question was to determine whether the impact of our measurement of technological progress depends on a country's economic development level. The full sample is divided into four sub-samples according to their income level to answer this question. 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 significantly impact carbon emissions in high-income countries. Science and technology publications are negatively associated with carbon emissions only in high-income and upper-middle-income countries.

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

Regarding upper-middle-income countries, the results are not very clear. 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 be that upper-middle countries are reaching a point where the gains from energy savings due to technological improvement equal the increase of energy consumption due to technological improvement, resulting in an insignificant impact on carbon emissions. Another explanation is the lack of stringent environmental regulations that can convince industries to adopt green-friendly products. Green patents and green R&D expenditure can very well be present in the market. But if there are no solid regulations to "force" industries to adopt and use them, they may not have the expected negative effect on carbon emissions.

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

Climate change requires a collective effort from governments, businesses, and households 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 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 to decrease carbon emissions through encouraging behaviors such as reducing the movement of people using cars[19], 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[20]. (2) Governments worldwide should have a common agreement to encourage green patent applications and intensify policies that will encourage firms and industries to produce less damaging products to the environment. (3) Public R&D expenditure should be more directed towards projects that will produce environmentally friendly products and technologies. (4) Science and technology publication should be promoted as it fosters the debate on reaching green and sustainable development solutions. (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, 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 assess further the effect of green R&D expenditure and green patents on carbon emissions in different countries income groups.

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

[20] There has been a sharp decline of CO_2 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.

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Appendix

Table AA1

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	Gambia
Netherland	Kazakhstan	Uzbekistan	Madagascar
Poland	Malaysia	Venezuela	Mali
Chile	Romania	Vietnam	Uganda

Table AA2

Descriptive statistic: full sample

variables	Observations	Mean	Stand dev	Min	Max
CO2 emissions	1753	4.333644	4.751069	.0335559	20.17875
GDP per capita	1798	10849.17	15133.8	164.3366	56842.3
Energy cons	1517	1.917049	1.911527	0.1188983	8.455547
Population	1729	124.0924	167.6538	2.18872	1239.579
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 AA3 **Descriptive statistic: Sub-sample**

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

R&D expenditure					
High-income	423	1.997422	.9313076	.477058	5.108209
Upper-middle income	369	1.095182	.8507465	.0008862	4.872204
Lower-middle income	334	.561821	.3235109	.0328966	1.258751
Lower-income	345	.2460996	.0928364	.01465	.72657
Patents					
High-income	450	42260.74	98495.01	70	606956
Upper-middle income	450	11071.12	21211.33	72	148187
Lower-middle income	432	2742.065	7236.495	10	50055
Lower-income	435	26.85517	24.2772	1	193
Mobile cell					
High-income	449	65.90508	51.41677	0.9	191.0315
Upper-middle income	435	54.49689	54.49927	.0002027	180.4934
Lower-middle income	414	39.7524	44.62241	.0002315	164.4406
Lower-income	366	29.02564	35.82879	.0006089	139.529
Internet					
High-income	426	44.21311	34.01286	0.8	96.02286
Upper-middle income	406	22.78703	24.16181	0.5	81.20105
Lower-middle income	370	13.70277	17.96182	.0001113	74
Lower-income	390	4.689112	7.177908	.0000175	38
TFP					
High-income	450	.8612446	.1484321	.508876	1.22886
Upper-middle income	440	.6324319	.1964714	.2530827	1.143904
Lower-middle income	434	.5423953	.2005938	.1254694	1.10942
Lower-income	235	.3365696	.0890791	.1556337	.5653373
Science Article					
High-income	285	70037.76	91813.01	1557.36	433192.3
Upper-middle income	285	29719.91	74960.12	190.17	528263.3
Lower-middle income	285	6238.554	18231.27	5.89	135787.8
Lower-income	285	165.4247	234.6959	3.14	1994.44

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

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

Exports					.037715 (1.42)
Constant	.543195*** (33.66)	-4.5273*** (-18.87)	-7.8918*** (-50.65)	-10.284*** (-35.18)	-11.688*** (-78.85)
Hausman test					
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 level of significance at a 10 (5) [1] %

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

Dependent variable: CO2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
Technology – Internet	.042476*** (6.61)	.010519 (4.22)	.001194 (0.66)	-.01817*** (-5.46)	-.01896*** (-5.80)
GDP		.55238*** (11.20)	.25492*** (5.05)	.26636*** (5.53)	.16373*** (2.85)
Energy Consumption			.88767*** (22.71)	.84047*** (24.14)	.91670*** (27.46)
Population density				.61974*** (10.66)	.63268*** (10.14)
Exports					.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 level of significance at a 10 (5) [1] %

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

Dependent variable: CO2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
Technology – Patent	.23240*** (7.96)	.10479*** (4.92)	.03328** (2.39)	.00697 (0.63)	.009291 (0.78)
GDP		.59308*** (15.08)	.29664*** (9.35)	.25080*** (7.29)	.19216*** (17.66)

Energy Consumption			.84149*** (19.86)	.83445*** (16.81)	.86201*** (17.66)
Population density				.25193*** (5.50)	.30051*** (4.85)
Exports					-.003307 (-0.11)
Constant	-1.0462*** (-5.70)	-5.0638*** (-22.90)	-8.0452*** (-41.15)	-8.4744*** (-33.21)	-8.2919*** (-25.34)
	63.40 (0.000)	568.15 (0.000)	1269.24 (0.000)	1304.06 (0.000)	1507.26 (0.000)
Observations	1800	1800	1800	1800	1800
Groups	60	60	60	60	60

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

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

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

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

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

Dependent variable: CO2 emissions					
	regression 1	regression 2	regression 3	regression 4	regression 5
Technology – TFP	.300593*** (3.63)	.06347 (1.23)	.10896** (2.11)	.12426** (2.67)	.14493** (2.60)

GDP		.65009*** (29.14)	.24276*** (11.24)	.15027*** (7.19)	.118187* (1.70)
Energy Consumption			.86363*** (33.15)	.80085*** (27.40)	.90441*** (25.28)
Population density				.36650*** (8.44)	.41710*** (10.72)
Exports					-.01068 (-0.35)
Constant	.944870*** (15.71)	-4.6712*** (-22.19)	-7.3215*** (-35.58)	-7.592*** (-38.46)	-7.7284*** (-19.73)
	13.21 (0.001)	751.84 (0.000)	1113.00 (0.000)	996.27 (0.000)	1571.14 (0.000)
Observations	1800	1800	1800	1800	1800
Groups	60	60	60	60	60

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

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

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

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