The role of green technology on carbon emissions: Does it differ across countries' income levels?

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ABSTRACT

This study examines the impact of green technology on CO_2 emissions in a sample of 45 countries, divided into three income categories between the periods of 1989-2018. Renewable energy consumption and environmental-related patents are used as indicators of green technology. We consider the production of renewable energy and the development of climate-related technologies as "two sides of the same coin". One needs to be complemented by the other for countries to be successful in the fight against climate change. After applying the fixed-effect method with Driscoll and Kraay standard errors, results reveal that renewable energy consumption significantly reduces CO_2 emissions in the full sample and all three subsamples (High-income, Upper-middle-income, and Lower-middle income countries). However, environmental-related patents significantly lower CO_2 emissions only in very high-income countries. This paper also examines how CO_2 emissions influence the development of green technology and carbon-intensive technology. A negative association is found between renewable energy and CO_2 emissions in the high-income and upper-middle-income groups. Because higher carbon emissions encourage high-income and upper-middle-income countries to invest in renewable energy, and this translates into lower carbon emissions over time. Environmental-related patents respond positively to carbon emissions only in high-income countries. The results obtained in this study allow us to draw important conclusions for energy policies. Among the necessary measures to be adopted, developing countries should not neglect the promotion of green innovation, which is a critical condition for carbon neutrality achievement.

Keywords: Green technology; Income groups; renewable energy consumption; environmentally-related patents; Driscoll and Kraay standard errors.

JEL codes: O30, O32, C23, Q56

1. Introduction

Global warming is increasingly becoming a major concern for human societies. According to the IPCC 2018 report (2018), human activities are estimated to have caused more or less 1.0° C of global warming above pre-industrial levels, with a probable of 0.8° C to 1.2° C. If human activities continue to increase at the current rate, global warming is likely to reach 1.5° between 2030 and 2052. The greenhouse gases emitted by humans from the pre-industrial period to the current period will persist for centuries and will continue to cause long-term changes in the environment and the climate system, such as ecosystem disruption, ocean level rise, and scarcity of resources (IPCC, 2018). Many solutions are considered by scientists and policymakers to face environmental degradation. Among the solutions, technological progress is considered an important way to achieve the critical transition from fossil fuel energy to renewable energy production. Numerous studies show that the effect of aggregate technology on carbon emissions is either positive or inconclusive (Dinda and Coondoo, 2006; Akinlo, 2008; Bosetti et al., 2011, Milindi and Inglesi-Lotz, 2021). This can partially be explained by the fact that most technologies developed since the industrial revolution are not environmentally friendly, and many of them have been developed to accommodate or improve fossil-fuel consumption-based machines or products. There is a consensus that technological progress should be redirected toward the development of green products than carbon-intensive ones (Asongu, Le Roux and Biekpe, 2017; Cheng et al., 2019; Churchil et al., 2019). Although it is theoretically predicted that the higher the number of climate-related technologies and eco-innovations the better for combating climate change, there is limited empirical evidence to support this (Barbieri et al., 2016; Su and Moniba, 2017).

Green technologies are technologies that reduce the harmful effects of human activity on the environment (Keniel and Gleen, 2012). Green technologies include waste recycling, wastewater treatment, electric vehicle, vertical farming, and renewable energy. Green technologies and eco-innovations are crucial in improving energy efficiency (Lee and Yook, 2015, Zhang et al., 2017; Shahbaz and Sinha, 2018). Advanced green technologies allow the economy to produce a level of output consuming a lower level of energy. Moreover, green technological innovation could lead to quicker adoption of renewable energy to meet energy demands and change the energy consumption structure (Garrone and Grilli, 2010; Hashmi and Alam, 2012). According to IEA (2018), renewable energies account for 16.4 per cent of final energy consumption in the world in 2018. This is about 1 per cent more than in 1990 (15.5 per cent). However, during the same period, carbon emissions increased from 22.5 billion metric tons to 34.2 billion, a rise of 64 per cent (World Bank, 2019). Thus, even if the production of renewable energy has tremendously increased in the last 28 years (more than 200 times for wind and 500 times for solar), fossil fuel energy consumption has also dramatically increased due mainly to its relatively low costs and ease of operation during the same period (BP, 2018). The share of renewable energy in the world energy consumption is still far lower than the share of fossil fuels energy because of the relatively high cost and technological barriers of renewable energy production in many countries (Chen and Lei, 2018; Khan and al., 2020).

Understanding the relationship between green technology production and carbon emissions deserves further investigation for the following reasons. Firstly, some studies suggest that green technology can either increase or decrease carbon emissions, under certain conditions (Jaffe et al., 2002; Acemoglu et al., 2009), these conditions are linked to different factors such as income and time. Secondly, the effect of environmental-related technology becomes uncertain in the long run due to the existence of the rebound effect[1]. Thirdly, the impact of green technology on carbon emissions, especially in developing countries, is uncertain due to the lack of environmental regulations and a real cooperation policy of technological transfer with developed countries. The lack of environmental regulations can reduce the diffusion of green technology, resulting in a weak impact of green technology on carbon emissions (Cheng et al., 2019). Fourthly, some studies suggest that many countries have not reached a threshold that represents the level of green technology innovations necessary to start reducing CO_2 emissions (Su and Moniba, 2017; Du, Li and Yan, 2019; Cheng et al., 2019). For instance, despite the increased level of renewable energy consumption, the mitigating effect on CO_2 emissions is limited due to the smaller proportion of renewable energy use in the energy mix (Su and Moniba, 2017). Fifthly, investigations of reverse causality from carbon emissions to green technologies are rare in the literature. This is important to investigate if carbon emissions expansions have triggered different responses in terms of technological progress in groups of countries at different development stages.

Therefore, this study's purpose is to examine the nature of the relationship between green technology and CO_2 emissions and thus contribute to the overall academic debate on the topic. To do so, the following research objectives will be answered:

1) What is the impact of green technologies, demonstrated via two different proxies (environmental-related patents and renewable energy consumption), on carbon emissions?

[1] The rebound effect is a situation in which the additional energy saved due to the improvement in energy efficiency (more efficient heating system, insulation, fuel-efficient vehicle, etc.) will be offset by an increase in energy demand (Gu et al, 2019; Milindi and Inglesi-Lotz, 2021). This ultimately shows that the impact of green technology on carbon emissions is difficult to predict when considering human behavior to new technology.

2) Does this impact depend on the level of economic development? Or in other words, does the impact differ in different country income groups?
3) The reverse causality: How do carbon emissions and economic growth affect the adoption of green technology and carbon-intensive technology in different country income groups?

To answer these three questions, this paper will use two methodologies: The fixed effect with Driscoll and Kraay standard errors (1998) and Bruno's (2005) biased-corrected LSDV methodology. This study will be carried out on a panel of 45 countries divided into 3 groups according to their level of income[2]. Thus, we will have 15 high-income countries, 15 upper-middle-income countries, and 15 lower-middle-income countries. The study period runs from 1989 to 2018. We believe that the relationship between green technology and carbon emissions may differ across different country income groups. This is due to differences in terms of financial capacity (Grossman and Krueger, 1995; Dinda and Coondoo, 2006), level of CO2 emissions specific to each group of countries (Hashmi and Alam, 2019), and the presence of stable political institutions and environmental regulations that are stronger and more enforced in some groups of countries than in others (Cheng et al, 2019). Therefore, a comparison of how green technology interacts with climate change in lower-middle, upper-middle, and high-income countries will be conducted.

This study contributes to the literature in the following three ways. Firstly, this study will be one of the scarce research that has analyzed the impact of green technologies on carbon emissions in different countries' income groups. Most research focuses only on two groups: developing and developed countries while this study will explore the nexus between environmentally friendly technologies and CO_2 emissions in three income groups. This will allow us to make comparisons of this relationship in groups of countries that are at different stages of development.

Secondly, this paper uses two indicators of green technology and examines their different impact on carbon emissions in each country's income group. We regard green technology innovation (green patents) and renewable energy production as "two sides of the same coin" and the latter needs to be complemented by the former for countries to be successful in fighting against climate change. The production of renewable energies can be regarded as a specific objective to be achieved in the sense that when we talk about renewable energies, governments and private investors know that they have to invest

[2] Countries are allocated to their respective income group according to the World Bank classification of income per capita (Lower-middle, \$1026 to \$3995; Upper-middle income, \$3996 to \$12375; High income, \$12376 or more). To constitute our dataset, we have followed the sampling methodology used by Milindi and Inglesi-Lotz (2021). We have selected in each income category, the 15 countries that have produced the most carbon emissions during the years 2000-2018.

in energy sources such as solar, wind, and hydro to obtain clean energy. But this is only a "first step". The "second step", which is more diffuse, would be to design or modify machines, devices, or processes that have been predominantly created to be powered by fossil fuel energy to allow them to be powered by renewable energies. This second step aims to promote the transition from an industry model based on fossil fuel energies to a model based on renewable energies. This step also consists of manufacturing machines and devices that are more efficient, more ecological, and less energy-consuming. The second step encompasses technological innovation and this can be reflected by the number of environmentally-friendly patents declared by each country each year (Gu et al, 2019). To successfully achieve carbon neutrality, we believe that these two stages are linked, and constitute "two sides of the same coin"[3]. The group of countries which both invest massively in renewable energies and technological innovation are more able to reverse the carbon emissions curve. Therefore, this study will investigate which group of countries performs better in terms of renewable energy development and eco-friendly innovations.

Thirdly, this paper will examine the reverse causality: carbon emission to technology. The paper will determine how CO_2 emissions influence the development of green technology and carbon-intensive technology. Particularly, we will examine countries' reactions in terms of technology used when carbon emissions and GDP increase. How do countries react when carbon emissions and GDP increase? Do they invest in green technology or carbon-intensive technology? This will be interesting to assess especially for poor countries. When carbon emissions and GDP increase it is expected that countries increase their investment in green technology to fight environmental degradation. This is often relatively easy for high-income countries since they possess the means and capacity to do so. But this is not always the case for lower-income countries, as these countries are often tempted to invest in carbon-intensive technology despite having growing GDPs and carbon emissions. Carbon-intensive technology is relatively cheaper and very widespread compare to green technology. The examination of this issue would enable us to draw some important lessons for planning and adopting green energy policy, particularly in developing countries that will face increased energy demands during their development process.

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

[3] A typical example is the transport industry. An "optimal" impact on carbon emissions can be obtain only if electrical vehicles, which are an example of green technology innovation, are charged with electricity from renewable energy, and not from fossil fuel energy.

2. Literature review

A growing number of existing studies in the broader literature have examined the relationship between green technology and CO_2 emissions. These studies can be divided into two categories. The first category analyses the impact of eco-innovation, represented by green patents, on CO_2 emissions; while the second investigates the effect of renewable energy consumption on carbon emissions.

The paper by Zhang et al. (2017) falls in the first category. The authors use panel data technics (SGMM) to analyze the impact of environmental innovations on reducing carbon emissions of 30 provinces in China. They describe environmental innovations as measures taken by relevant entities (private households, unions, firms) that apply new technology, introduce new efficiency processes of energy, and new ideas aiming at contributing to a sustainable and proper environment. These environmental measures comprise innovation performance (economic development level and energy performance), innovation resource (R&D investment), knowledge innovation (number of patents produced, expansion of ICT), and innovation environment (pollution and environment regulation). They show that most environmental innovations help in reducing carbon emissions. In particular, R&D expenditure, patent, and energy efficiency. They also found that initial measures taken by CHINA for green gas emission reduction are effective. This study uses comprehensive measures of environmental innovation. Du, Li, and Yan (2019) investigated the impact of green technology innovation on green gas emissions. The analysis is done on 71 countries from 1996 to 2012. The researchers use green technology innovation instead of general technology advancement as a proxy for technology. They also look at how the interaction between technology innovation and income affects carbon emissions. The authors pose two questions. First, can green technology innovations effectively reduce CO_2 emissions? Second, are there some regime transitions for the effect of green technology innovations on CO_2 emissions under different income levels? The study found there exists a per capita income threshold which is around 35000$. Green technology does not appear to reduce green gas emissions in countries where income is below that threshold. But it significantly mitigates green gas emissions in countries above that income threshold. Cheng et al. (2019) investigate the impact of various variables on carbon dioxide emission: renewable energy, foreign direct investment, GDP per capita, environmental patent, and exports. The analysis is done for the BRICS countries and the period runs from 2000 to 2013. The authors emphasize two strategies that are at the center of the BRICS's action against global warming: (1) the development of renewable energy sources and (2) the development of energy efficiency technology. The results indicate that environmental patents, exports, and GDP per capita increase carbon emissions while renewable energy and foreign direct investment decrease them. The authors explain the positive impact of patents on carbon emissions by the lack of environmental regulations that can allow the diffusion of sophisticated technology in the BRICS countries.

Hashmi and Alam (2019) estimate the effect of innovation and environmental regulations on carbon emission in OECD countries from 1999 to 2014. The authors highlighted that eco-friendly technology adoption and deployment and stringent environmental regulations are the key factors to fight against global warming. Environmental tax revenue is used as a proxy for environmental regulations. The authors employ panel fixed and random effect, GMM methodology to estimate the results. The findings show that a 1% increase in technology innovation patent lowers carbon emissions by 0.017% and when environmental tax revenue per capita increases by 1%, carbon emissions decrease by 0.03% in OECD countries. The particularity of this study is that it separates two concepts: aggregate technology and green technology and compare the different effect aggregate technology and green technology on carbon emissions. Tobelmann and Wendler (2019) employed the GMM methodology to assess the impact of green technology innovations on carbon emissions in 27 European Union countries for the period of 1992 to 2014. Environmental-related patents have been used to represent green technology innovations. The results showed that green technology has contributed to reducing carbon emissions. However, its effect is not sufficient to offset the positive impact of economic growth on carbon emissions. The authors also found that the impact of innovative activities on carbon emissions varies across countries depending on their level of development.

While many papers in the literature have been focusing on how innovation impacts greenhouse gas emissions, Su and Moaniba (2017) propose to examine the reverse effect, how innovations respond to climate change. The authors examine how climate change affects technological innovation in a panel dataset of 70 countries, using environmental patents as a proxy for technological innovation. To examine how the trend in the development of environmentally friendly technology has shifted in response to the number of carbon emissions, the authors use various econometrics techniques such as the generalized method of moment, fixed-effect logistic regression, and random effect. The empirical findings suggest that green gas emissions influence the development of eco-friendly innovations. Furthermore, countries, where carbon emission is very high, tend to respond more to developing environmentally friendly technology. Hakimi and Inglezi-Lotz (2019) have also examined the reverse causality, CO_2 emissions to the green innovation process in 60 countries split into 36 developed and 24 developing economies, between the periods of 2008-2014. The paper employed environmentally-related patents as an indicator of the green innovation process. Findings indicate that, regarding developed economies, the innovation process responds positively to total CO_2 emissions and CO_2 emissions from natural gas. Regarding developing economies, results show that there is not a significant impact from climate change on the green innovation process. Paramati, Mo, and Huang (2020) examined the effect of financial development, foreign direct investment, green technology, trade openness, and per capita income on green gas emissions in a group of 25 OECD countries from 1991-2016. Green technology is represented by environmentally friendly innovation. The paper includes financial development in the model and assesses its impact on carbon emissions. The authors argue that financial development facilitates the obtention of capital to invest in green technology projects. The results from Group mean estimators reveal that green technology, trade openness and FDI reduces green gas emissions while per capita income and financial development increase them.

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

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

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

Hussain et al, (2020) have investigated the role of environmental-related technology in abating consumption-based carbon emissions in a panel of 7 emerging countries (China, Brazil, Russia, India, Turkey, Mexico, and Indonesia) from 1990 to 2016. Results showed that environmental-related technology must include renewable energy to mitigate carbon emissions. The authors also found that imports and GDP growth deteriorate the environment. Mongo, Belaid, and Ramdani, (2021) have employed an autoregressive distributed lag model (ARDL) to analyze the effect of environmental innovations, renewable energy consumption, trade openness, and GDP per capita on CO2 emissions for 15 countries in Europe, from 1991 to 2014. Findings indicate that environmental technologies lower carbon emissions in the long term, however, they increase carbon emissions in the short term. The authors explain this opposite effect by the existence of the rebound effect in the European energy sector.

Razzaq et al. (2021) have examined the asymmetric inter-linkages between green technology innovation and carbon emissions in the BRICS countries from 1990 to 2017. The authors have employed a quantile to quantile framework to estimate the results, arguing that the nexus between green technology and carbon emissions is non-linear due to technological advancement, structural changes, social and economic reforms in the BRICS countries. Results show that green innovations reduce carbon emissions only at higher emissions quantile in BRICS countries. However, at lower quantile, green innovation is positively related to carbon emissions. Results also suggest that higher carbon emissions create pressure on the government who increases its investment in green technologies leading to a reduction of carbon emissions. Lyguan et al. (2021), have found similar results for highly decentralized economies.

This study follows the paper by Du, Li, and Yan (2019), and Nguyen and Kakinaka (2019). However, in addition to examining the impact of green technology on CO_2 emissions in countries at different development stages, this article is contributing to solving the problem of climate change by demonstrating technological innovations response of countries to climate change. Specifically, we will analyze the reaction of countries in terms of the type of technology used, when carbon emissions and GDP increase. This kind of relationship has not yet been extensively examined in the literature, such as those identified above.

3. Theoretical model

Global warming is the consequence of several factors. Mainly, it is the production of energy (electricity, heating, etc.) and fuel for transport (mainly cars, but also aviation and maritime transport) that cause global warming. Deforestation, large-scale agriculture, and the expansion of livestock are also amongst the causes of global warming (IPCC, 2014). The climate change issue is mainly linked to the acceleration of economic growth, energy consumption, population growth, and technology advancement since the industrial revolution.

In this paper, we follow Du, Li, and Yan (2019); Milindi and Inglesi-Lotz (2021); by using four factors that are among the main drivers of carbon emissions: economic growth; population, technology, and trade. Therefore, this study is based on the following theoretical model:

$$CO_2\ emission_{it} = f(GDP_{it}, POP_{it}, OPN_{it}, TECH_{it}) \quad (1)$$

3.1. Variable selection

3.1.1. CO_2 emissions

Following the work by Cheng et al. (2019) and Hashmi and Alam (2019), we use CO_2 emissions per metric tons as a proxy of CO_2 emissions performance in a country. CO_2 emissions are our dependent variable and the data of CO_2 emissions are collected from the World Bank (2019).

3.1.2. Renewable energy

Renewable energies refer to a set of means of producing energy from theoretically unlimited sources or resources, available without a time limit or which can be reconstituted more quickly than they are consumed (Nguyen and Kakinaka, 2019). The exploitation of renewable energies theoretically generates few pollutants: in particular, electricity from renewable sources emits very little CO_2, especially when compared to fossil fuels such as coal and oil. For this reason, renewable energies are in particular a privileged vector in the fight against global warming. In this paper, we follow Nguyen and Kakinaka (2019), and Nathaniel and Iheonu (2019) to utilize the percentage of renewable energy consumption in total energy consumption as an indicator of green technology in a country. The data on renewable energy is collected from the World Bank (2019).

3.1.3. Green patents

The patenting of green technologies makes it possible to measure the efforts made and the pace of innovation in a country. Green innovations are an effective tool against carbon emissions as they are processes whereby green products are created, leading to a reduction of energy intensity, consequently to fewer carbon emissions. It is expected that green patents will reduce carbon emissions but under certain circumstances. Some scholars argue that green patents need to increase sufficiently to mitigate carbon emissions (Cheng et al., 2019; Hashmi and Alam 2019). Moreover, green patents need to be coupled with stringent environmental regulations to lead to carbon abatement. Following the paper by Su and Moniba, (2017); Du and Li, (2019), in this paper we use green patents as an indicator of green technology innovations. The data on green patents are collected from the OECD statistics database (OECD, 2018).

3.1.4. GDP per capita

For a country to develop it needs a lot of energy. Unfortunately, energies that have been exploited and used for decades come mostly from fossil fuels. This has inexorably led to an increase in carbon dioxide emitted into the atmosphere. It is therefore expected that, at least at an early stage of development of a country, economic growth may lead to environmental degradation. The data of per capita GDP are collected from the World Bank (2019).

3.1.5. Population

Population growth is considered one of the main drivers of carbon emissions. Again, since the energy used to feed economies comes from fossil fuels, more people means more demand for oil, gas, coal, and other fuels mined or drilled from below the Earth's surface, leading to higher greenhouse emissions. According to the Maddison Project Database (2018), the world population has increased from 1.6 billion to 6 billion in the twentieth century (Maddison Project Database, version 2018). During the same period, CO_2 emissions grew 12-fold (IEA, 2018). With a population expected to exceed 9 billion in the next 50 years, environmentalists are more and more concerned about the earth's ability to cope with the increasing destruction of the ecosystem caused by human activities. In this paper, we use population density as a measure of population. The data of population density comes from the World Bank (2019).

3.1.6. Terms of trade

The globalization that shapes the world today is essentially based on flows, which reflect the explosion of world trade. Facilitated by multiple factors, this boom certainly concerns commodities, but also increasingly flows of information or capital (Shahbaz et al., 2017). Several factors such as the establishment of free trade zones, the development of maritime and land transport, the existence of multinational companies scattered around the world, explain the explosion of global trade. According to the IEA (2018), pollution from global trade constitutes a substantial share of world CO_2 emissions. During the last decade, a significant amount of research has been conducted to determine the relationship between carbon emissions and trade (Antweiler, Copeland and Taylor, 2001; Sebri and Ben-Salha, 2014; Shahbaz et al., 2017) However, the results of this research are variable (the relationships are either positive or negative), and a specific consensus has not yet been found. Studies that have found a positive relationship assume that trade promotes economic growth, which in turn negatively affects the environment by increasing the amount of carbon emissions into the atmosphere. Studies that have found a negative relationship argue that it mainly depends on whether the merchandise exported by a country is environmentally friendly or not (Ertugrul et al., 2016). As an illustration, it can be expected that countries that export oil and coal will experience higher carbon emissions since these merchandises are carbon-intensive. Whereas, on the other hand, countries that export cleaner energy or more eco-friendly products will experience fewer carbon emissions problems. In this paper, we use trade openness as a measure of trade. The data is collected from the World Bank (2019).

Figure 1

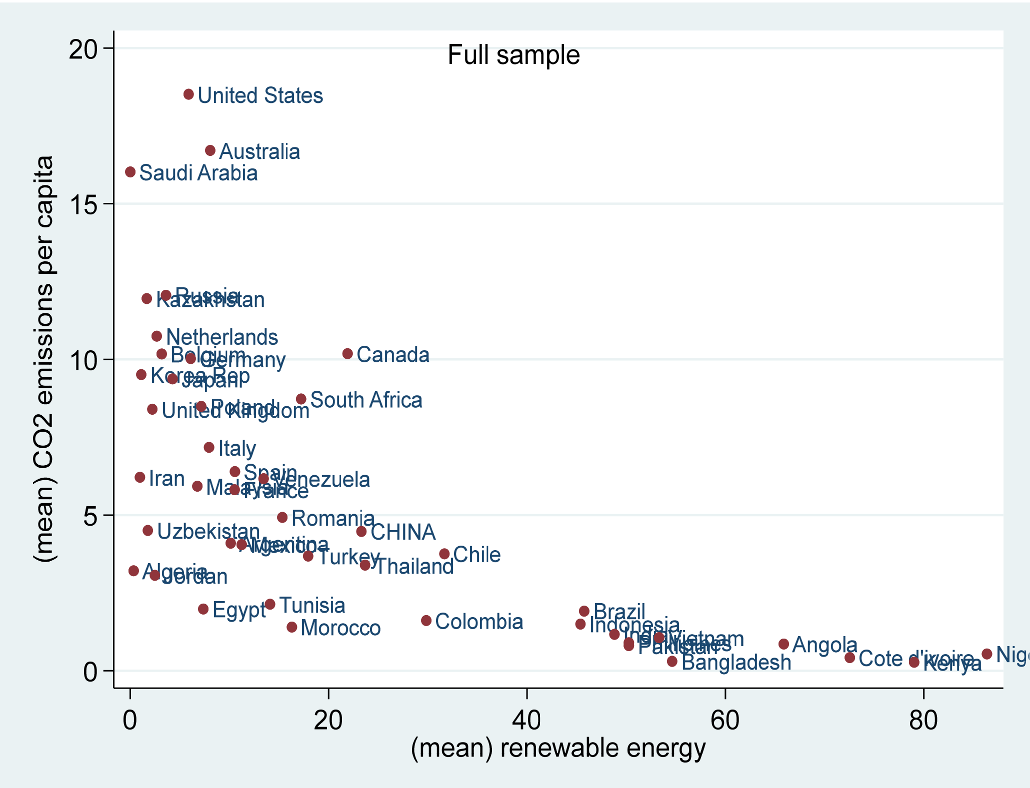


Figure 2

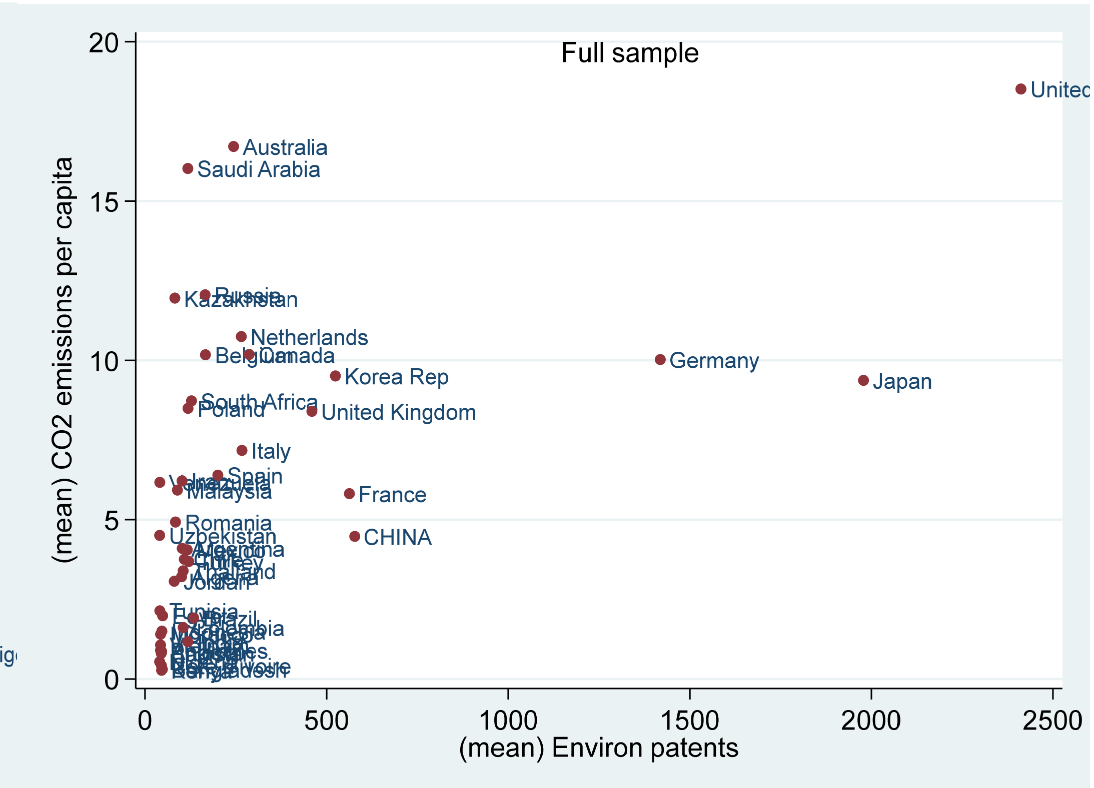


Figure 1: two way scatter plot of renewable energy consumption (in percentage) and CO_2 emissions (in metric tons per capita).

Figure 2: two way scatter plot of the number of environmental-related patents and CO_2 emissions.

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

4. Empirical model and econometric methodology

4.1. Empirical model

To analyze the interaction between carbon emissions and green technology, three-panel models are established. In the first panel model, we investigate the impact of green technology on CO_2 emissions in the full sample of 45 countries. We also examine the same relationship in three different income groups. Given that the long-run relationship between CO_2 emissions and its explanatory variables may significantly depend on the development stage, we divide the full sample into three income groups: high, upper-middle, and lower-income groups. This study assigns countries into an income group according to the World Bank classification of income. The second model specification is a dynamic panel model, and it is used as a robustness check to verify the results found in the first-panel model. The third-panel model examines the reverse causality, in particular, we analyze how variations in carbon emissions and GDP per capita affect technology adoptions in different country income groups.

The first-panel model is as follows:

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

Where the subscripts i and t refers to countries and time. Y_i is the unobservable country-specific characteristics and $u_{i,t}$ is the i.i.d. disturbance terms. CE_{it} refers to carbon emissions in metric tons per capita. X'_{it} represents a vector of control variables including GDP per capita, population and trade openness. $GTECH_{it}$ is our variable of interest, it represents green technology which will be replaced by two different indicators of green technology. More specifically, model (1) will be divided into two different sub-models and each sub-model has its indicator of green technology:

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

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

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

When analyzing the impact of green technology in different country income groups, the following submodel will be added in the results table to examine the effect of green technology innovation on CO_2 emissions in very high-income countries:

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

$VEPAT_{it}$ represent green patents in very high-income countries. Model (1b) and Model (1c) have the same composition in terms of dependent and explanatory variables. However, the sample dataset is different. In the subsample analysis, we will examine the impact of renewable energy (model 1(a) and green innovation technology model 1(b) on CO_2 emissions in different countries' income groups (high income, upper-middle income, and lower-middle-income countries). The purpose of sub-model (1c) will be to investigate the impact of green innovation technology on carbon emissions specifically in very high-income countries[4]. These are countries that have on average, during our study period, a GDP per capita greater than 36000$. This distinction is purposely done because green innovation may have a different effect on carbon emissions in a specific income range. Following the World Bank classification of economies, each country is allocated to a specific income category according to its level of income. Countries that have a GDP per capita greater than 12500$ fall into the high-income category. It is logical to expect that green technology innovation may not have the same influence on CO_2 emissions in a country that has a GDP per capita of 15000$ compare to a country that has a GDP per capita of 40000$, even if they both belong to the high-income category. Thus, we believe a simple distinction between high-income countries and very high-income countries will bring some new insight to the analysis.

Many studies have shown that most environmental indicators, CO_2 emissions included, are considered to have a certain time lag effect and that environmental impacts present some dynamic sustainability (Kais and Sami, 2016; Zhang et al. 2017). Based on these issues, our second empirical specification is a dynamic panel model with a first-order lag term for carbon emissions. We decided to adopt a one lag model specification to preserve the maximum possible number of freedom available for the estimates. The dynamic panel model is as follows:

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

$$\ln CE_{it} = \beta_0 + \ln CE_{it-1} + \ln(REN)_{it}\beta_1 + X'_{it}\rho + Y_i + u_{i,t} \qquad 2(a)$$

$$\ln CE_{it} = \beta_0 + \ln CE_{it-1} + \ln(EPAT)_{it}\beta_1 + X'_{it}\rho + Y_i + u_{i,t} \qquad 2(b)$$

$$\ln CE_{it} = \beta_0 + \ln CE_{it-1} + \ln(EPAT)_{it}\beta_1 + X'_{it}\rho + Y_i + u_{i,t} \qquad 2(c)$$

Similar to model 1(c), here model 2(c) will examine the relationship between green technology innovation and carbon emissions only in very high-income countries.

The third-panel model examines the reverse causality from CO_2 emissions to technology. The empirical framework of model (3a) and (3b) follows the approach of Sadorsky (2009)**,** and Nguyen and Kakinaka (2019) in which the demand for renewable (3a) and nonrenewable energy (b) depends on real output per capita, oil price, and carbon emissions. In our model, trade openness and population density are added as additional explanatory variables. In model (3b), we use non-renewable energy consumption as an indicator of carbon-intensive technology[5], and similar to previous models (1 and 2), renewable energy consumption is employed as an indicator of green technology development.

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

[5] The evolution of carbon intensive technology (such as number combustion engines vehicles, electricity generation from fossil fuel sources, etc.) has followed similar evolution of non-renewable energy consumption, which in our point of view, makes it a good proxy for carbon intensive technology. More non-renewable energy consumption is also an indication that an economy as a whole invest more in technologies that are fossil-fuel friendly than green energy friendly.

Model (3) is established to answer the following question: Does carbon emissions influence the development of green technology and/or carbon-intensive technology? And how the trend to develop green technology and carbon-intensive technology is influenced by the level of carbon emissions in our three groups of countries. When carbon emissions and GDP increase it is expected that countries increase their investment in green technology to fight environmental degradation. This is often relatively easy for high-income countries since they possess the means and capacity to do so. But this is not always the case with poor countries, as these countries are often tempted to invest in technology that accommodates non-renewable energy despite having growing GDPs and carbon emissions. Model (3a) and (3b) will investigate these hypotheses.

$$\ln REN_{it} = \beta_0 + \ln(CE)_{it}\beta_1 + \ln(GDP)_{it}\beta_2 + \ln(Oilp)_{it}\beta_3 + X'_{it}\rho + Y_i + u_{i,t} \quad (3a)$$

$$\ln NOREN_{it} = \beta_0 + \ln(CE)_{it}\beta_1 + \ln(GDP)_{it}\beta_2 + \ln(Oilp)_{it}\beta_3 + X'_{it}\rho + Y_i + u_{i,t} \quad (3b)$$

$$\ln EPAT_{it} = \beta_0 + \ln(CE)_{it}\beta_1 + \ln(GDP)_{it}\beta_2 + \ln(Oilp)_{it}\beta_3 + X'_{it}\rho + Y_i + u_{i,t} \quad (3c)$$

In the above models, $NOREN_{it}$ represents non-renewable energy consumption, which can also be seen as an indicator of carbon-intensive technology. GDP_{it} refers to GDP per capita. $Oilp_{it}$ refers to oil price and it represents the price of renewable and non-renewable energy. Conversely to the work of Sadorsky (2009), and Nguyen and Kakinaka (2019), we use average fuel-pump prices (GIZ data, 2021) instead of a general crude oil price applied to all countries as a proxy for energy price. Fuel-pump price is an end-user price, and it is more specific and realistic in the sense that it reflects the final oil price that consumers face in each country. We use oil price as a relative price of renewable energy because renewable energy contains various sources of energy such as hydro, solar, wind, geothermal, waves, so it is generally difficult to identify the exact price. Although we recognize this issue, we consider oil price as a direct determinant of fossil fuel energy consumption and an indirect determinant of variation in renewable energy consumption. In this regard, it can be expected that an increase in Oil price will reduce fossil fuel energy consumption, resulting in higher demand for renewable energy. X_{it} represent some additional regressors that can further explain variation in the three dependents variables.

4.2. Econometric methodology

This paper employs the fixed-effect method with Driscoll and Kraay's standards errors to estimate the results of empirical models (1) and (3). Countries are different from each other, and each country's carbon emissions are not affected by the same factors in the same way. By incorporating country-specific effects in the models, all the effects that may influence each country's carbon emissions (beyond those variables already included in the model) will be incorporated. Another reason for using a fixed effect is the correction of potential endogeneity problems since the within estimator wipes out the individual effects through demeaning and thus making the OLS coefficients unbiased and consistent (Baltagi, 2008). Potential limitations of the fixed effect method include the presence of serial correlation, heteroskedasticity, and cross-sectional dependence in the model. In this case, estimated coefficients are still consistent, but they will no longer be efficient. The standard errors of the estimates will be biased. To solve this problem, this paper uses Driscoll and Kraay's standard errors. Besides being heteroscedasticity consistent, these standard error estimates are robust to very general forms of cross-sectional and temporal dependence (Hoechle, 2007).

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

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \qquad (4)$$

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

$$u_{it} = u_i + v_{it} \qquad (5)$$

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

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

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

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

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

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

Following the consolidated literature on dynamic panel data models (Kiviet, 1995, 1999; Blundell and Bond, 1998; Bun and Kiviet; 2003, Bruno 2005), we used Bruno's (2005) biased-corrected LSDV methodology to estimate model specification (2). When a lagged dependent variable is included among the regressors, the Nickell (1981) biased will arise as a possible violation of the classical assumptions. We will have an endogeneity problem since CE_{it-1} is correlated with the unobserved heterogeneity Y_i. The LSDVC method corrects the alleged endogeneity bias of the lagged dependent variable without using any instrumental variable (Piva and Viveralli, 2007; Justesen, 2008; Abrate et al., 2009; Garrone and Grilli, 2010). In our case, the LSDVC estimator is initialized by a consistent dynamic panel estimator (Arellano and Bond) and then rely on a recursive correction of the bias of the fixed effects estimator.

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

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

4.3. Data

In this study, we compile an unbalanced panel data covering 45 economies. The panel data comprises 15 high-income, 15 upper-middle-income, and 15 lower-middle-income countries. The dataset provides a period of 30 years, from 1989 to 2018. To constitute our dataset, this study follows the sampling methodology employed by Milindi and Inglesi-Lotz (2021). Similarly to their work, we have followed the World Bank country classification by income (World Bank, 2020) and have selected 15 countries in each 3 income groups (high-income, upper-middle-income, and lower-middle-income). The 15 countries selected per income group are the largest CO2 emitters in their respective income groups. To clarify further, the sample was chosen based on 3 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 group of income throughout the study period (1989 – 2018)[6]. The second criterion is the national level of carbon emissions. We have selected, in each income group, the countries which emitted the most CO2 during the period 2000-2018. The third criterion is the availability of data, in particular, the availability of environmental-related patent data to represent green technology. The combination of these 3 criteria led to the selection of 15 countries per income group. In 2016, the 45 economies selected in this study represented 90 per cent of global GDP, and 88 per cent of global CO2 emissions (World Bank, 2019).

The variables used in this study were collected from different sources. Table 1 shows the descriptions and sources of the data collected. Tables with descriptive statistics for the full sample and subsamples are presented in the Appendix. Data on CO_2 emissions (metric tons per capita); GDP per capita (in constant 2010 US$); trade openness; renewable and non-renewable energy consumption (percentage of total final energy consumption) and population density were drawn from the World Bank's Development Indicators (WDI, 2019). Data on green technology patents were collected from the Organization for Economic Cooperation and Development (OECD, 2020).

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

Table 1. Variables description

Variables	Description	Sources
$\ln CE_{it}$	Carbon dioxide emissions in metric tons per capita. CO_2 emissions include the combustion of fossil fuels for electricity generation and heat production (in industries, households, etc.), transportation, and the industrial process including the manufacturer of cement.	WDI (World Bank, 2019)
$\ln REN_{it}$	Renewable energy consumption represents the share of renewable energy in total final energy consumption.	WDI (World Bank, 2019)
$\ln EPAT_{it}$	Environmentally related patents.	OECD (2020)
$\ln NOREN_{it}$	Non Renewable energy consumption represents the share of fossil fuels energy in total final energy consumption. Fossil fuel comprises coal, oil, petroleum, and natural gas products.	WDI (World Bank, 2019)
$\ln Oilp_{it}$	End-user fuel price in Constant \$. Price of Gasoline 95 octane at petrol stations	GIZ (2018)
$\ln GDP_{it}$	Per capita real gross domestic product in 2010 constant US\$ term.	WDI (World Bank, 2019)
$\ln TOPN_{it}$	(Exports/Imports) in 2010 constant US\$ term	WDI (World Bank, 2019)
$\ln POP_{it}$	Population density per square kilometers	WDI (World Bank, 2019)

Note: all variables are in natural log.

5. Results estimations

5.1. Estimation procedure

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

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

Step 2. The Maddala and Wu (1999), and the Im, Pesaran, and Shin (2003) (IPS) tests are performed to investigate the univariate characteristic of each variable.

Step 3. Cointegration among variables is verified using the Kao (1999), Pedroni (2004), and Westerlund (2005) cointegration test. Also, a Granger causality test is employed to verify the causal relationship among panel variables in the model (1) and (3).

Note that due to space limitation, we present tables for diagnostic and cointegration tests only for the full sample and high-income countries. Diagnostic and cointegration test results for upper-middle and lower-middle countries are available in the Appendix.

Step 4. A fixed-effect method is used to estimate panel models (1) and (3). Bruno's (2005) biased-corrected LSDV methodology is employed to estimate panel model (2).

5.1.1. Diagnostic testing

Before carrying out estimations, several statistical tests are conducted to ensure the dataset meets the required assumptions and conditions for each model selected. When using panel data, problems such as serial correlation, heteroskedasticity, and cross-sectional correlation may arise. Table 2 summarizes the results of the diagnostic test for the full sample and high-income countries sample. Breusch-Pagan's (1980) LM-test and Wald tests confirm the presence of panel effect in the models. The significant p-values from the Wooldridge test and the Pesaran cross-sectional dependence (CD) test indicate the presence of serial correlation and cross-sectional dependence, respectively. The p-value from the Wald test for GroupWise heteroskedasticity is significant, indicating that error term variances vary with explanatory variables in all models specification. In summary, the dataset suffers from heteroskedasticity, serial correlation, and cross-sectional dependence. Therefore, the fixed effect methodology with Driscoll and Kraay standards errors, which is the method proposed in this study, turns out to be appropriate for estimating the results.

Table 2. Diagnostic test: serial correlation, heteroskedasticity, cross-sectional dependence, time fixed effect, and panel effect.

Full sample					
	Model (1a)	Model (1b)	Model (3a)	Model (3b)	Model (3c)
	Statistic	Statistic	Statistic	Statistic	Statistic
Serial correlation	22.19 0.000***	134.9 0.000***	83.19 0.000***	92.01 0.000***	10.734 0.002***
Heteroskedasticity	9348 0.000***	8153 0.000***	27535 0.000***	91548 0.000***	2353.11 0.000***
Pesaran CD	12.71 0.000***	7.251 0.000***	0.011 0.971	-0.423 0.7863	0.1578 0.456
Time fixed effect	0.264 1.000	0.894 0.626	0.472 0.803	0.406 1.000	1.012 0.331
Panel effect	334.3 0.000***	264.1 0.000***	545.1 0.000***	630.35 0.000***	69.5 0.000***
High-income sample					
	Model (1a)	Model (1b)	Model (3a)	Model (3b)	Model (3c)
	Statistic	Statistic	Statistic	Statistic	Statistic
Serial correlation	8.224 0.012**	93.484 0.000***	47.18 0.000***	17.15 0.000***	10.916 0.005***
Heteroskedasticity	558.29 0.000***	1488.5 0.000***	466.2 0.000***	3101 0.000***	386.07 0.000***
Pesaran CD	10.703 0.000***	5.989 0.000***	33.05 0.000***	-1.897 0.0632*	8.882 0.000***
Time fixed effect	0.280 1.000	0.843 0.698	1.799 0.043**	0.834 0.585	2.337 0.000***
Panel effect	228.60 0.000***	226.45 0.000***	502.4 0.000***	376.1 0.000***	92.91 0.000*

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

5.1.2. Panel unit root test and cointegration

The Im, Pesaran, and Shin (2003) (IPS) and the Maddala-Wu (1999) tests are performed to determine which variables in the data are stationary and which are non-stationary. We use these two tests because they assumed individual unit root processes for each variable in the empirical models, thus better suited for detecting cross-section heterogeneity in the dataset (Baltagi, 2008). Besides, unlike other unit root tests (such as the Levin-Lin-Chu, and the Harris-Tzavalis), the IPS and Maddala-Wu tests do not require a strongly balanced panel. We subtract cross-sectional means by demeaning the series to assist with cross-sectional correlation and cross-sectional dependence. We use the AIC information criteria and set the number of lags at 2. Table 3 displays unit root test results. It can be observed that in the full sample, per capita GDP, renewable energy, and population density are not stationary, while all other variables are stationary. In the high-income sample, CO_2 emissions and environmental-related patents are stationary while all other variables are nonstationary. Unit root test results are more or less similar for other subsamples (upper-middle-income and lower-middle-income countries). Consequently, cointegration tests are necessary to avoid spurious relationships when estimating regressions with non-stationary variables.

Table 3. IPS and Maddala-Wu unit root tests.

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

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

The cointegration test is performed by using the Westerlund (2005), Pedroni (1999, 2004), and Kao (1999) tests. When there is cointegration in the models tested, it means that the results of the regressions are not spurious and there is a long-run relationship amongst variables. The Kao and Pedroni test verify the alternative hypothesis that the variables are cointegrated in all panels, while the Westerlund test verifies the hypothesis that the variables are cointegrated in some or all panels. Cointegration results are presented in Table 4. In the full sample, except for the Dickey-Fuller statistic in panel model 1(b), and 3(a), and the variance ratio in model 1(a), all other statistics are statistically significant at least at a 10% level. In the high-income sample, the modified Phillips-Perron statistic is not significant in models 1(a) and 3(a), but all other statistics are significant at conventional levels of significance. Other samples cointegration tests (upper-middle and lower-middle-income samples), which can be found in the appendix, also exhibit similar results. Thus, our study concludes that cointegration exists in all sample models.

Table 4. Cointegration tests

Full sample					
Cointegration test	Model 1(a)	Model 1(b)	Model 3(a)	Model 3(b)	Model 3 (c)
	Statistic	Statistic	Statistic	Statistic	Statistic
Kao test					
Modified Dickey-Fuller t	-1.7473***	1.1883*	-1.3903*	-6.5345***	-1.9914*
Dickey-Fuller t	-1.9149**	0.5027	-1.1461	-5.4770***	-3.6198***
Augmented Dickey-Fuller t	-1.0909*	1.7327**	1.4312*	-5.0021***	1.8431**
Unadjusted modified Dickey-Fuller t	-1.9360**	-1.4778*	-4.6603***	-8.0231***	-7.1113***
Unadjusted Dickey-Fuller t	-2.0236**	-1.5376*	-3.1333***	-6.0135***	-6.2538***
Westerlund test for cointegration					
	Statistic	Statistic	Statistic	Statistic	
Variance ratio	-1.1725	-1.6589**	-3.4502***	-2.6398***	-2.5987***
Pedroni test for cointegration					
	Statistic	Statistic	Statistic	Statistic	
Modified Phillips-Perron	1.9420**	1.6592**	1.9706**	2.3693*	2.3225*
Phillips-Perron t	-6.7723***	-5.1598***	-4.6190***	-3.3583***	-2.6342*
Augmented Dickey-Fuller t	-4.3395***	-3.8971***	-4.2255***	-3.1507***	-3.2659***
High-income sample					
Cointegration test	Model 1(a)	Model 1(b)	Model 3(a)	Model 3(b)	Model 3(c)
	Statistic	Statistic	Statistic	Statistic	Statistic
Kao test					
Modified Dickey-Fuller t	-1.6772***	1.1654*	-1.2084*	-5.2358***	-0.8924
Dickey-Fuller t	-1.8952**	0.4521	-1.1056	-5.8796***	-0.9151
Augmented Dickey-Fuller t	-1.1257*	1.1986*	1.4584*	-5.0653***	1.6485**
Unadjusted modified Dickey-Fuller t	-1.7986**	-1.4546*	-4.5089***	-6.1154***	-2.3502***
Unadjusted Dickey-Fuller t	-2.0236**	-1.5376*	-3.1333***	-6.0135***	-1.7354***
Westerlund test for cointegration					
	Statistic	Statistic	Statistic	Statistic	
Variance ratio	-2.2520**	1.3396*	-1.4577*	-2.6727***	1.6154*
Pedroni test for cointegration					
	Statistic	Statistic	Statistic	Statistic	
Modified Phillips-Perron	0.5853	1.4634*	1.1552	1.7878**	1.6291*
Phillips-Perron t	-4.3750***	-1.6015**	-3.0137***	-1.8351***	-2.0231**
Augmented Dickey-Fuller t	-4.0094***	-1.2839*	-3.8387***	-1.3705*	-0.1538

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

5.1.3. Dumitrescu Hurlin causality test

The Dumitrescu and Hurlin (2012) Granger causality test is employed to verify the causal relationship among panel variables in models (1) and (3). Table 4 reports the Dumitrescu Hurlin causality test results for the full sample. Due to the unbalancedness of our dataset, we restrict our sample from 1999 to 2018. Results show that all explanatory variables included in the model (1) and (3) granger cause their respective dependent variables.

Table 4. Dumitrescue Hurlin causality test

Full sample			
Sample: 1999-2018	W-bar	Z-bar	Prob
H0: Variable does not Granger-cause $\ln \mathrm{CE}_{\mathrm{it}}$ (Model 1a and 1b)			
$\ln\mathrm{REN}_{\mathrm{it}}$	2.7736	8.4131	0.0000***
$\ln\mathrm{EPAT}_{\mathrm{it}}$	1.5133	2.4350	0.0149**
$\ln\mathrm{GDP}_{\mathrm{it}}$	5.1718	19.788	0.0000***
$\ln\mathrm{POP}_{\mathrm{it}}$	4.6346	17.240	0.0000***
$\ln\mathrm{OPN}_{\mathrm{it}}$	2.2802	6.0726	0.0034***
H0: Variable does not Granger-cause $\ln\mathrm{REN}_{\mathrm{it}}$ (Model 3a)			
$\ln \mathrm{CE}_{\mathrm{it}}$	3.7165	12.885	0.0000***
$\ln\mathrm{GDP}_{\mathrm{it}}$	2.5852	7.5193	0.0000***
$\ln\mathrm{POP}_{\mathrm{it}}$	3.4481	11.612	0.0000***
$\ln\mathrm{Oilp}_{\mathrm{it}}$	2.8963	8.1254	0.0000***
$\ln\mathrm{OPN}_{\mathrm{it}}$	1.6183	2.9331	0.0034***
H0: Variable does not Granger-cause $\ln\mathrm{NOREN}_{\mathrm{it}}$. (Model 3b)			
$\ln \mathrm{CE}_{\mathrm{it}}$	3.3566	11.178	0.0000***
$\ln\mathrm{GDP}_{\mathrm{it}}$	2.7892	8.4867	0.0000***
$\ln\mathrm{POP}_{\mathrm{it}}$	4.0651	14.538	0.0000***
$\ln\mathrm{Oilp}_{\mathrm{it}}$	3.8523	11.589	0.0000***
$\ln\mathrm{OPN}_{\mathrm{it}}$	1.6327	3.0013	0.0027***
H0: Variable does not Granger-cause $\ln\mathrm{EPAT}_{\mathrm{it}}$. (Model 3c)			
$\ln \mathrm{CE}_{\mathrm{it}}$	2.0015	4.7503	0.0000***
$\ln\mathrm{GDP}_{\mathrm{it}}$	2.4172	6.7224	0.0000***
$\ln\mathrm{POP}_{\mathrm{it}}$	3.5485	12.0887	0.0000***
$\ln\mathrm{Oilp}_{\mathrm{it}}$	4.2549	4.6155	0.0012***
$\ln\mathrm{OPN}_{\mathrm{it}}$	3.4861	5.9534	0.0000***

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

5.2. Results estimation

In this section, we discuss the results of the impact of green technology on carbon dioxide emissions. We apply two methods for estimating the regression results: the fixed-effect method with Driscoll and Kraay standard errors and the Bruno LSDVC corrector for robustness check. Our preferred model will be the fixed effect with Driscoll and Kraay standard errors because these standard errors are unbiased and robust in the presence of serial correlation, cross-sectional dependence, and heteroskedasticity in the dataset (Hoechle, 2007).

The section is divided into three subsections. In the first subsection, we examine the relationship between green technology and carbon emissions in the full sample using the fixed-effect method with Driscoll and Kraay's standard errors and the Bruno LSDVC corrector. We evaluate if the trend in CO_2 emissions is responsive to two indicators of green technology: renewable energy and environmental-related patents. The same relationship is analyzed in the second subsection where we examine the influence of green technology on $C0_2$ emissions in the different country income groups. Finally, in the third subsection, we investigate the reverse causality, which is the causality from CO_2 emissions to technology.

5.2.1. Full sample analysis

Table 5 presents the full sample results. Overall, results show that renewable energy consumption reduces carbon emissions in both fixed effect and Bruno LSDVC results. The estimated coefficient on $\ln(\mathrm{REN})_{\mathrm{it}}$ is -0.08 in fixed effect, which indicates that a 1 per cent increase in renewable energy consumption decreases carbon emissions by 0.08 per cent, ceteris paribus. The full sample results also show that green technology innovations, represented by green patent applications, do not have a clear impact on carbon emissions. The result in Model (1b) shows that the coefficient of $\ln(\mathrm{EPAT})_{\mathrm{it}}$ is estimated as 0.009 in fixed effect and 0.004 in Bruno LSDVC. They are both insignificant at the 10% level. This suggests that, overall, we do not find evidence supporting that green technology innovations can effectively curb CO_2 emissions in the full sample.

Table 5. Full sample results

Dependent variable: CO_2 emissions				
	Fixed effect		LSDVC	
	model (1a)	model (1b)	model (1a)	model (1b)
$\ln(\mathrm{CE})_{it-1}$			.407745*** (3.84)	.60248*** (6.31)
$\ln(\mathrm{REN})_{it}$	-.08030*** (-9.61)		-.03429* (-1.97)	
$\ln(\mathrm{EPAT})_{it}$		.009118 (1.56)		.004835 (1.57)
$\ln\mathrm{GDP}_{it}$	.55323*** (19.35)	.51069*** (13.27)	.047171 (0.42)	.18784* (1.79)
$\ln\mathrm{POP}_{it}$	.36595*** (4.25)	.18543*** (1.77)	.38560** (2.57)	.216233 (0.93)
$\ln\mathrm{TOPN}_{it}$	.06727** (2.35)	.04218 (0.74)	-.00026 (-0.61)	-.05166 (-1.12)
Constant	-4.9993*** (-11.61)	-4.1089*** (-9.90)		
F-test	218.14 (0.000)	89.35 (0.000)	50.87 (0.000)	32.16 (0.000)
Observations	1350	1350	1350	1350
Groups	45	45	45	45

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

Regarding other core drivers of carbon emissions, the results show that GDP per capita, population density, and trade openness have a positive and statistically significant impact on carbon emissions in both fixed effect and Bruno LSDVC results. These results are consistent with most of the literature that has found a positive relationship between these variables and carbon emissions (see Hu et al., 2005; Wang, 2007; Clarke et al., 2008; Allen, 2012; Bhattacharya et al., 2015).

5.2.2. Subsample analysis

Tables 6 and 7 present the results of the impact of green technology on carbon emissions across different income levels using the fixed effect methodology with Driscoll and Kraay standard errors and the Bruno LSDVC, respectively. The full sample is divided into three subsamples: High-income countries, Upper-middle income countries, and Lower-middle income countries. Estimated results reveal that renewable energy consumption is negatively associated with carbon emissions in all three groups of countries.

Table 6. Subsample analysis

Dependent variable: Ln CO_2 emissions							
Fixed effect with Driscoll and Kraay							
	High income			Upper-middle income		Lower-middle income	
	Model (1a)	Model (1b)	Model (1c)	Model (1a)	Model (1b)	Model (1a)	Model (1b)
$\ln(\mathrm{CE})_{\mathrm{it}-1}$							
$\ln(\mathrm{REN})_{\mathrm{it}}$	-.2122*** (-16.98)			-.2636** (-6.62)		-.3661*** (-14.68)	
$\ln(\mathrm{EPAT})_{\mathrm{it}}$		.0092 (1.08)			-.0196 (-0.82)		.0124 (1.12)
$\ln(\mathrm{VEPAT})_{\mathrm{it}}$			-.0217* (-1.96)				
$\ln\mathrm{GDP}_{\mathrm{it}}$	.5263*** (6.35)	.2436** (2.79)	-.0231 (-0.73)	.4918*** (12.13)	.5915*** (7.46)	.6293*** (12.13)	.7990*** (6.41)
$\ln\mathrm{POP}_{\mathrm{it}}$	-.1312 (-0.61)	-.4471* (-1.76)	-.2688 (-0.62)	.1498*** (4.67)	.5912** (2.85)	.0296 (0.26)	-.1042 (-0.36)
$\ln\mathrm{TOPN}_{\mathrm{it}}$	0.044 (0.79)	-.1651* (-1.71)	-.2271*** (-3.32)	.0988* (1.92)	.0933* (1.89)	0.0492* (1.96)	.0336 (0.54)
Constant	-2.350*** (-4.06)	2.407* (2.10)	4.913*** (7.18)	-3.294*** (-5.60)	-6.244*** (-4.74)	-1.307** (-2.26)	-5.42*** (-4.97)
F-test	123.48 (0.000)	16.76 (0.000)	14.49 (0.000)	217.32 (0.000)	80.74 (0.000)	338.23 (0.000)	59.58 (0.000)
Observations	450	450	450	450	450	450	450
Groups	15	15	8	15	15	15	15

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

A 1 per cent increase in renewable energy consumption decreases carbon emissions by 0.21 per cent in high-income countries, 0.26 per cent in upper-middle-income countries, and 0.36 per cent in lower-middle-income countries. Similarly to the full sample results, coefficients on environmental-related patents are positive but statistically insignificant in all three groups of countries. Model (1c) is introduced to further investigate the environmental patent coefficient sign. The purpose of model (1c) is to verify if environmental-related patents will have a different impact on CO_2 emissions in very high-income countries compared to high-income countries. Very high-income economies consist of 10 countries that have an average per capita income of 36000$ during our study period. Results show that the coefficient on green patents turns out to be negative and statistically significant at a 5 per cent level. These results are similar to those found by Du, Li, and Yan (2019).

In general, results suggest that green technology innovations, represented in this study by environmentally-friendly patents, significantly contribute to carbon abatement only in very high-income countries. In the introduction, we described the production of renewable energies and the development of green innovation technologies as a "two side of the same coin" arguing that their complementarity will allow a country or a group of countries to achieve carbon neutrality more quickly (IRENA, 2019). The results of this study show that during our study period, only countries with a very high income seem to be on the right track to achieve the complementarity so necessary to reduce CO_2 emissions. However, given the low magnitude of the green patents coefficient, we can assume that there is still a lot of effort to be made in terms of green investment and policy incentives in this area even for these very high-income countries.

Regarding other countries, the level of innovation in green technology seems to have not yet reached a point that allows a significant reduction of carbon emissions. This does not mean that green technology innovations are not present or valuable. It means that they are simply not produced in sufficient quantity to slow down the curve of CO_2 emissions. The level of green innovation needed to combat global warming is very subjective and depends on one country or group of countries to another. For example, the amount of eco-friendly innovation produced in very high-income countries may not be sufficient for upper-middle-income economies. It is therefore important to take into account the characteristics of each country or group of countries in order to understand the underlying reasons that do not allow better promotion of green technology innovations[7].

Five main reasons can explain the differences in results between the very high-income group and the upper-middle and lower-middle-income group. Firstly, environmental issues do not have the same priority in high and low-income countries. In low-income countries, governments and economic actors face more challenges that they consider as more pressing and more vital for their people (Akinlo, 2008; Antonakakis, Loannis, Filis, 2017; Adom, 2019). These include issues of poverty, unemployment, infrastructure, and lack of energy. The problems related to the development of green technologies which will allow the

[7] As it can be observed from the patents graph (figure 2), the 10 countries which are classified in this study as "very high income countries" have the highest number of patents. The estimations results show that this increasing quantity of green patents coincides with a mitigation of carbon emissions. The quantity of green patents is also indicative of the efforts put in terms of investment in R&D in green technology innovation (Gu et al., 2019). Another aspect which certainly plays an important role in reducing carbon emissions, but which can hardly be proven, is the quality of green technology inventions represented by these patents. It is not enough to have a large amount of patents but it is also necessary that these patents are sufficiently valuable to bring a good contribution in reducing the level CO_2 emissions (Hall, Jaffe and Trajtenberg, 2005). In view of the results, it seems that high quality inventions are developed in these 10 countries.

attainment of sustainable development are rather seen as distant problems which will be solved once an acceptable level of per capita income is reached (Antonakakis, Loannis, Filis, 2017). Secondly, green technology state subsidies are far greater in high-income countries than in lower-income countries. In high-income countries, small and medium enterprises, and even individuals, are supported by the government and the financial system in a common effort to develop and expand the utilization of green technologies and renewable energies (Boutabba, 2014; Kim and Park, 2016). This is very critical for industries and companies involved in the development of these technologies since the production of environmentally friendly technologies is a relatively new field, and therefore requires significant financial resources compared to carbon-intensive technologies. According to the International Renewable Energy Agency (IRENA, 2019), the estimated subsidy for renewable energy worldwide was around USD 166 billion in 2017. Subsidies for the generation of renewable energies amounted to 128 billion, and subsidies for transport to 38 billion. The European Union constitutes 54 percent of the total share of renewable energy subsidies in 2017, followed by China, with 14 % (23 billion), Japan with 11% (19 billion), the United States with 9 % (16 billion), India with 2 % (4 billion) and the rest of the world with slightly less than 9% (15 billion). These figures show that there is still a long way to go for developing countries in terms of green technology subsidies.

Thirdly, a large difference in terms of transfer of technology and human resources between high-income countries and the other groups of countries (Fu, Kok, Dankbaar, Ligthart, and Van, 2018). The creation of green technologies requires a well-qualified workforce capable not only of producing eco-friendly products but also of absorbing cutting-edge technological knowledge from the rest of the world. In low-income countries, there is often a deficit of high-skilled workers compared to developed countries. In addition, low-income countries are often victims of brain drain which may hinder the development of local green industries (Docquier, Lohest, and Marfouk 2007; Varma and Kapur2013). According to a joint paper released by the OECD, World Bank, and ILO (2015), the number of highly skilled migrants coming to work in Europe has been continuously growing in recent years. In 2010-2011, nearly a fifth of highly skilled migrants came from developing countries such as China, India, and the Philippines (Bailey and Clara H. Mulder, 2017).

Table 7. Subsample analysis

Bruno LSDVC							
	High income			Upper-middle income		Lower-middle income	
	Model (1a)	Model (1b)	Model (1c)	Model (1a)	Model (1b)	Model (1a)	Model (1b)
$\ln(\mathrm{CE})_{\mathrm{it}-1}$	.7635*** (24.45)	.9231*** (325.1)		.8030*** (24.16)	.8797*** (35.29)	.7905*** (20.16)	.7861*** (17.39)
$\ln(\mathrm{REN})_{\mathrm{it}}$	-.0576*** (-20.40)			-.0326*** (-4.27)		-.1933*** (-3.62)	
$\ln(\mathrm{EPAT})_{\mathrm{it}}$		-.0139 (1.45)			.0070 (0.42)		.0073 (1.15)
$\ln(\mathrm{VEPAT})_{\mathrm{it}} \times \mathrm{D}_1$			-.0147** (-2.25)				
$\ln\mathrm{GDP}_{\mathrm{it}}$	.1536*** (23.68)	.1012*** (32.24)	-.0845 (-1.44)	.1234*** (8.05)	.0331*** (5.13)	.1230*** (5.30)	.1968*** (3.27)
$\ln\mathrm{POP}_{\mathrm{it}}$	-.1575*** (-13.42)	-.1073*** (-3.71)	.0088 (0.23)	.0345*** (11.02)	.0225 (0.12)	-.0412 (-1.30)	-.1360 (-1.23)
$\ln\mathrm{TOPN}_{\mathrm{it}}$	-.0172*** (-5.38)	-.0115* (-1.66)	-.0225** (-2.26)	-.0095 (-0.44)	-.0357 (1.06)	.0176* (1.69)	.0134 (0.45)
Groups	15	15	8	15	15	15	15

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

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

From lighting products (fluorescent lamps) to electrical, household, and thermal appliances; the production processes of the various devices must integrate environmental characteristics.

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

5.2.3. Reverse causality analysis

This subsection presents the results of the "reverse causality" which is how the increase in CO_2 emissions and other factors influence the adoption of green technology represented by renewable energy and environmental patent, and the adoption of carbon-intensive technology represented non-renewable energy consumption. Table 8 shows the estimated long-run elasticities of renewable energy (model 3a), non-renewable energy (model 3b), and environmental patent (model 3c) with regard to carbon emissions, real income per capita, oil price, population density, and trade openness for each of the three income groups.

Regarding the high-income group, renewable energy is negatively associated with carbon emissions, but positively associated with GDP per capita, oil price, and trade openness; while non-renewable energy is positively associated with carbon emissions and negatively related to GDP per capita, oil price, trade openness, and population density. Similar to Nguyen and Kakinaka (2019) findings, the large coefficients of carbon emissions in model 3(a) compare to model 3(b), suggest that renewable energy is more sensitive to carbon emissions than non-renewable energy. The coefficient on carbon emissions in model (3c) is positive and statistically significant at a 1 per cent level. This means that an increase in carbon emissions Triggers a positive and significant response of climate-related patents in high-income countries.

Concerning the upper-middle-income group, renewable energy has a negative relationship with CO_2 emissions, but a positive relationship with GDP per capita, oil price, and trade openness; while non-renewable energy has a positive relationship with carbon emissions and population density. The relationship between non-renewable energy and GDP is negative and significant at 5 per cent level. Here again, the magnitude of the coefficient on carbon emissions shows that renewable energy is more sensitive to variations in carbon emissions than non-renewable energy. Findings in model (3c) suggest that carbon emissions do not have a significant effect on climate-related patents in upper-middle-income countries.

Figure 3

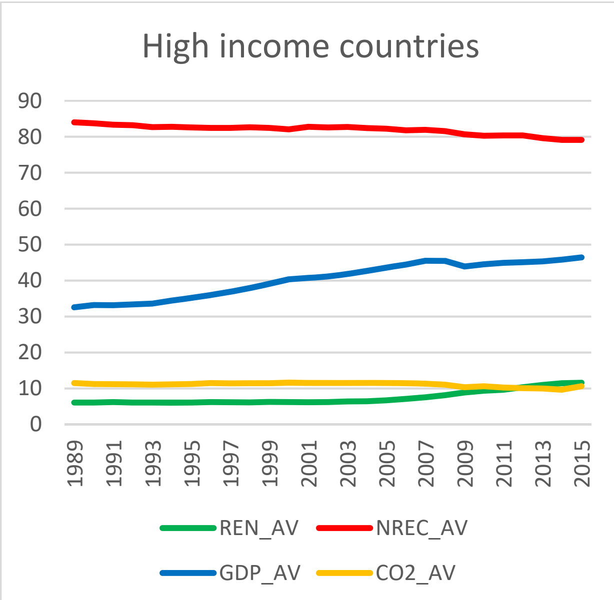


Figure 4

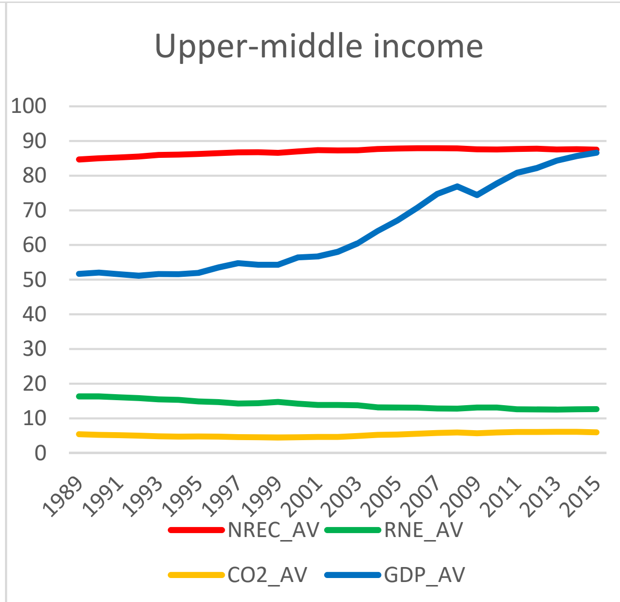
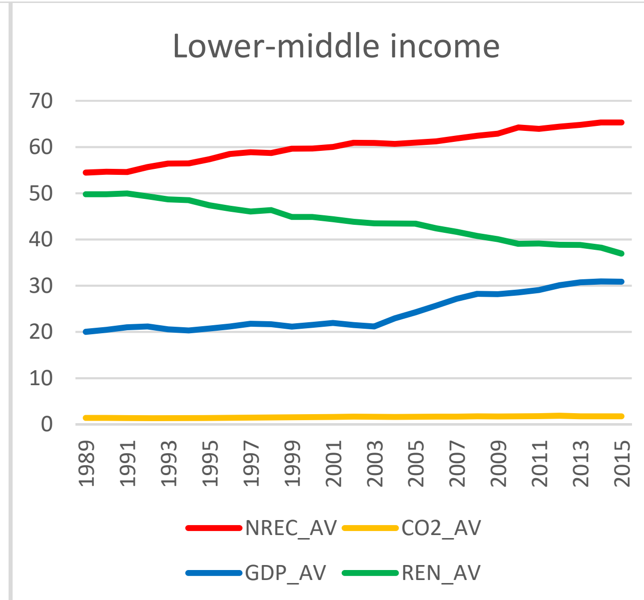


Figure 5



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

We use graphs to better understand coefficient signs of CO_2 emissions and GDP per capita in table 8. We plot average values of four variables[8]: Average renewable energy consumption (REN_AV), average nonrenewable energy consumption (NREC_AV), average GDP per capita (GDP_AV), and average carbon emissions per capita (CO2_AV). Note that, in order to have a standard scale, the average value of GDP per capita has been divided by 100 in the upper-middle and lower-middle-income figures; and by 1000 in the high-income figure.

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

Concerning the lower-middle-income group, results show that renewable energy consumption is negatively related to GDP per capita, while non-renewable energy consumption is positively related to GDP per capita and carbon emissions. The relationship between renewable energy and CO_2 emissions is negative but not statistically significant at the conventional level of significance. The carbon emissions variable has a positive but no statistically significant coefficient in model (3c), indicating that climate-related technology does not vary with changes in carbon emissions in lower-middle-income countries.

Table 8. Reverse causality analysis

Fixed effect with Driscoll and Kraay									
Dependent variable: (3a) renewable energy; 3(b) nonrenewable energy									
	High income			Upper-middle income			Lower-middle income		
	Model (3a)	Model (3b)	Model (3c)	Model (3a)	Model (3b)	Model (3c)	Model (3a)	Model (3b)	Model (3c)
$\ln(\mathrm{CE})_{\mathrm{it}}$	-1.667*** (-14.81)	.1542*** (9.87)	.8732*** (2.45)	-.854*** (-6.72)	.1435*** (8.53)	.5656 (0.95)	-.1030 (-0.10)	.0954*** (4.86)	.3114 (1.21)
$\mathrm{lnGDP}_{\mathrm{it}}$	.7209*** (5.02)	-.0308* (-1.81)	2.465*** (7.52)	.1300* (1.74)	-.0520** (-2.92)	2.355*** (6.67)	-.401*** (-8.62)	.3553*** (5.63)	1.953** (2.31)
$\mathrm{lnOilp}_{\mathrm{it}}$	.4461*** (10.83)	-.0161* (-1.96)	1.067*** (3.72)	.1918*** (3.27)	-.0032 (-0.49)	.3720*** (3.01)	.2198*** (3.34)	-.101** (-2.93)	-.7812 (-0.86)
$\mathrm{lnPOP}_{\mathrm{it}}$	.6770** (2.17)	-.1072** (-2.27)	3.099*** (6.30)	-.695*** (-5.25)	.0703*** (6.72)	5.633*** (5.31)	-.364*** (-4.70)	.0413 (0.55)	5.915*** (3.33)
$\mathrm{lnTOPN}_{\mathrm{it}}$	.4461*** (10.83)	-.0312* (-1.94)	1.067*** (3.72)	.2350* (1.77)	.0191* (1.93)	1.383*** (11.26)	-.068*** (-3.10)	.0015 (0.09)	.2155 (0.41)
Constant	-8.652*** (-4.26)	5.016*** (22.84)	-54.9*** (11.01)	3.358** (2.74)	4.353*** (23.23)	-46.9*** (-7.83)	8.295*** (16.54)	1.302*** (4.41)	-43.71*** (-3.28)
F-test	279.80	90.25	101.77	170.51	209.8	202.47	94	78.82	49.4
Observations	450	450	450	450	450	450	450	450	450
Groups	15	15	15	15	15	15	15	15	15

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

The comparisons of the results between lower-middle, upper-middle, and high-income countries, and the figures (figure 3-5) displayed above, should help us in understanding the differences in terms of estimated elasticities between these three income groups. First, we start by analyzing the relationship between renewable energy and carbon emissions. A common result in all income groups is that renewable energy has a negative relationship with carbon emissions. Our results showing a negative relationship in high-income countries coincide with the work of Nguyen and Kakinaka (2019). However, this finding contrasts with those of Nguyen and Sadorski (2009), who have found a positive relationship between renewable energy and carbon emissions in lower-income countries. Demonstrating the relationship between renewable energy consumption and carbon emissions is debatable. Because this relation can hardly be explained without referring to both income and the share of non-renewable energy consumption in final energy consumption. In our point of view, a negative relationship between renewable energy and carbon emissions should be expected. This is because the development and expansion of renewable energy mitigate environmental problems of carbon emissions, which implies the negative relationship between carbon emissions and renewable energy. However, as depicted in Figures 3 and 5, this relationship has different directions depending on whether we are in a high-income or lower-income group. In the high-income group as carbon emissions decrease, renewable energy increases. One main reason behind this is the growing share of renewable energy compared to non-renewable energy[9] in the energy mix, this translates into a reduction of carbon emissions per capita, implying a negative relationship between renewable energy and carbon emissions. In lower-income economies, the opposite happens. As carbon emissions increase, renewable energy consumption decreases. This can be explained by the fact that, in the energy mix, the share of non-renewable energy is continuously growing compare to the share of renewable energy[10]. The consequence is higher carbon emissions per capita, implying a negative association between carbon emissions and renewable energy.

Second, we examine the association between renewable energy and GDP per capita. Renewable energy is positively related to GDP per capita in high income (see figure 3), but it is negatively related to GDP per capita in lower-middle-income countries (see Figure 5). These results are consistent with the findings of Nguyen and Kakinaka (2019). Explanations of these results are similar to those given in the previous section. The development and expansion of renewable energy are not always among the priorities of the government agenda in lower-income countries. Governments often put less priority on environmental

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

issues and focus on other important development goals, such as economic growth, reduction of poverty, infrastructure development, better education, and health system. In addition, there are fewer subsidies for renewable energy production in lower-income economies compare to higher-income economies. Production of renewable energy tends to require advanced technology with relatively high costs. Thus, making it difficult for industries involved in the green energy sector to afford high-cost production, and hence being competitive compare to fossil fuels industries. Moreover, environmental laws and policies are better implemented in high-income countries than lower-income countries (Hashmi and Alam, 2019).

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

Given that the coefficients on carbon emissions and GDP per capita have similar signs in high-income and upper-middle-income countries for model (3a) and (3b), the comparison of their magnitudes will allow us to identify certain aspects of the results that must be underlined. In high-income countries, the coefficients on carbon emissions and GDP per capita are higher in model (3a) than in model (3b), in absolute value[11]. This is an indication that high-income countries tend to invest more in renewable energy and less in non-renewable energy as their carbon emissions and income increase. This result is consistent with the EKC hypothesis, according to which the demand for a cleaner environment grows stronger with higher and higher incomes. In high-income countries, there is gradually an awareness of environmental issues by political and economic actors; but above all, an awareness of the general public on environmental and climatic issues. People who have already reached a high standard of living are becoming more and more environmentalist, and find it difficult to endure daily air pollution, sea pollution, large-scale deforestation, and the destruction of biodiversity. Since the political actors depend on their public to be elected or re-elected, they align themselves progressively behind the environmentalist positions of their voters.

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

In upper-middle-income countries, carbon emissions and GDP per capita coefficients are higher in model (3a) than in model (3b), in absolute value[12]. This indicates that upper-middle-income countries invest more in renewable energy than in fossil fuels energy as their GDP per capita and carbon emissions rise. The developing countries have this opportunity to continue their development with a cleaner energy

[11] Model (3a) |-1.667| |0.7209| > Model (3b) |0.1542| |-0.308|
[12] Model (3a) |-0.854| |0.1300| > Model (3b) |0.1435| |-0.0520|

structure and more respectful of the environment. Renewable energy capacities installed in emerging countries (such as China, Brazil, Russia, and South Africa) have increased by roughly 160 per cent over the past decade. This share constitutes 43 per cent of global capacity according to the International Renewable Energy Agency (IRENA, 2019). China is considered to be the largest green energy market in the world. China is replacing fossil fuels with green energies at an accelerating rate. According to a United Nations report published in 2018, this country invested more than $ 127 billion in 2017, this constitutes 45 per cent of the global investment in green energy (UN, 2018).

In low-income countries, the coefficient on carbon emissions is positive and statistically significant in model (3b), but statistically insignificant in model (3a). The coefficient on GDP is negative and statistically significant in model (3a), while is positive and statistically significant in model (3b). This is an indication that in lower-income countries, higher carbon emissions and income, lead to higher consumption of non-renewable, and lower consumption of renewable energy. Lower middle countries are facing major energy challenges. The demand for energy, which continues to increase, is stimulated by constant economic and demographic growth (IRENA, 2019). Therefore low-income countries need a constant increase in energy supply. But unfortunately, fossils fuel energy is preferred to the detriment of renewable energy. Our sample shows that in 1989, the average share of renewable energy in total energy consumption was 49 per cent (see figure 3). This share drops to 36 per cent in 2015. During the same period, the share of non-renewable energy increases from 54 per cent to 65 per cent. Unlike the developed economies, low-income economies have the opportunity to pursue sustainable energy development as a basis for long-term prosperity, by devoting from the start of their development a large part of their energy mix to renewable energies. However, as revealed by the results of this study, this did not seem to be the case during our study period.

6. Conclusion and policy implications

Recent studies have found contradictory results when examining the relationship between aggregate technology and CO_2 emissions. Some studies have found that aggregate technology increases CO_2 emissions (Cheng et al, 2019), while others found that aggregate technology can mitigate CO_2 emissions but only under certain conditions[13] (Garrone and Grilli, 2010; Li and Wang, 2017; Churchill et al., 2019). The impact of aggregate technology on CO_2 emissions often depends on the counterbalancing effect of

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

carbon-intensive technology and green technology in aggregate technology (Milindi and Inglesi-Lotz, 2021). Therefore, this paper proposes to disaggregate aggregate technology and examine the impact of green technology on CO_2 emissions in a sample of 45 countries, divided into three income categories between the periods of 1989-2018. This paper sought to answer three questions:

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

We use two indicators of green technology development: renewable energy consumption and environmental-related patents. We regard green technology innovation (environmental-related patents) and renewable energy production as "two sides of the same coin" and the latter needs to be complemented by the former for countries to be successful in the transition towards low-carbon economies. After applying the fixed-effect method with Driscoll and Kraay standard errors and complement the latter with the Bruno (2005) LSDVC methodology as a robustness check, results for a sample of 45 countries show that renewable energy consumption reduces carbon emissions in both fixed effect and Bruno LSDVC results. However, green technology innovations do not significantly impact carbon emissions. We also found that key determinants of carbon emissions such as GDP per capita, population density, and trade openness are positively related to carbon emissions in the full sample.

2) To analyze whether the impact of renewable energy and environmental-related patents on CO_2 emissions depends on the level of economic development of a country.

To answer this question, the full sample is divided into three sub-samples according to their level of income (15 high-income countries, 15 upper-middle-income countries, and 15 lower-middle-income countries). After running estimations models using the fixed effect methodology with Driscoll and Kraay standard errors for the three subsamples, the results reveal that renewable energy consumption significantly reduces CO_2 emissions in all three subsamples. However, environmental-related patents significantly lower CO_2 emissions only in very high-income countries. This is a group of 10 countries in our high-income sample that has high CO_2 emissions per capita, and a GDP per capita above 36000$.

3) To examine how an increase in carbon emissions and economic growth affect the adoption of green technology and carbon-intensive technology in different country income groups.

Renewable energy consumption and environmental patents are used as indicators of green technology development, while non-renewable energy consumption is employed as an indicator of carbon-intensive technology. The analysis shows the clear differences between the groups of low- and high-income countries. A negative association is found between renewable energy and CO_2 emissions in the high-income and upper-middle-income groups. Because higher carbon emissions encourage high-income and upper-middle-income countries to invest massively in renewable energy, and this translates into lower carbon emissions over time. GDP per capita increase renewable consumption in high-income and upper-middle-income countries but decrease renewable energy consumption in lower-income countries. In lower-income countries, an increase in carbon emissions and income are associated with higher consumption of non-renewable, and lower consumption of renewable energy. Green patents respond positively and significantly to the increase in carbon emissions only in high-income countries. Results also show that higher oil price promotes the adoption of renewable energy in all group of countries. Population density positively affects renewable energy adoption in high-income economies. However, it negatively affects renewable energy adoption in upper and lower middle income countries. Trade openness is positively associated with renewable energy in high-income and upper-middle-income countries but negatively associated with renewable energy in lower middle income.

Climate change requires a collective effort from governments, businesses, and households if we are to succeed in limiting the increase of a global temperature below 1.5 degrees by 2100 as stated in the Paris agreement (2015). The policy implications that can be drawn from this study are as follows: (1) government and industries should continue to promote the development and expansion of renewable energy around the world to fight climate change. (2) Environmental issues must be fully integrated among the top priorities of governments, especially in developing countries which must understand that it will cost less to deal with these issues now than in the future. The good management of the environment and natural resources must be considered, no longer as an obstacle to development, but as its precondition, and constitutes a key element of any program intended to improve the living conditions of the populations. (3) Governments, especially those in low- and upper-middle-income countries, should continue and increase their subsidies to projects that save energy and use renewable energy. (4) Besides intensifying investments in renewable energies, countries should not neglect investments in green innovations (such as electric cars, carbon capture technology, efficient machines, and lightning, etc.). The two go together and will allow achieving carbon neutrality more quickly. Broader and deeper global efforts on technology collaboration are critical to facilitate low-carbon technology development and deployment. (5) Since low- and upper-middle-income countries seem to be lagging behind in producing green innovations, they should at least continue to invest heavily in education to acquire a high-skill labor force that can absorb and exploit external knowledge in terms of innovation in green technologies.

A more important involvement of the financial sector will also be helpful. States should continue to encourage the financial sector to participate in the development of a green economy. It is about reorienting funding now directed towards fossil fuels in order to increase funding for renewable energies and projects in favor of energy efficiency[14]. Banks can support renewable energy and green technology projects and prevent the construction of new high-emitting units. This will also allow the reduction of high installation costs of renewable energies. Finally, the policy recommendations listed above 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.

Due to the unavailability of some data, this study was unable to use several other green technology indicators to assess their impact on carbon emissions. Future research can use other proxies such as green public and private R&D expenditure per country, or the level of credit allocated by the financial sector to the development of green projects in each country. Other more specific indicators may also be employed, such as the production and use of electric vehicles or the development and adoption of carbon storage technology. Future research could also assess the effect of green technology on sectoral carbon emissions (emissions from the power sector, manufacturing sector, transport sector, etc.). This assessment may allow determining in which sector green technology has more impact on carbon abatement and the reasons that can explain such impact.

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

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Appendix A

A.1. Sampled countries (1989-2018)

High-income	Upper-middle income	Lower-middle income
	45 countries	
Germany	China	Angola
France	Argentina	Bangladesh
United Kingdom	Brazil	Cote d'Ivoire
United States	Mexico	Egypt
Italy	Iran	Indonesia
Canada	Russia	India
Spain	Turkey	Kenya
Japan	South Africa	Morocco
Saudi Arabia	Thailand	Nigeria
South Korea	Algeria	Pakistan
Australia	Colombia	Philippines
Belgium	Venezuela	Tunisia
Netherland	Kazakhstan	Uzbekistan
Poland	Malaysia	Jordan
Chile	Romania	Vietnam

A.2. Descriptive statistic: full sample

Variables	Observations	Mean	Stand dev	Min	Max
CO_2 emissions	1,327	5.647408	4.763908	.133613	20.17875
GDP per capita	1,348	14275.46	16080.63	398.8521	56842.3
Population	1,339	140.9964	184.8893	2.18872	1239.579
Ren. Energy	1,215	22.06828	23.81995	.0059765	88.83185
Env. Patent	1,305	191.6641	624.5274	0	6080.3
Non renew	1,215	76.80319	21.85675	12.99901	99.99678
Terms of trade	1,283	120.5126	88.73144	39.6998	391.8637

A.3. Descriptive statistic: subsample

	Observations	Mean value	Standard deviation	Minimum value	Maximum value
CO_2 emissions					
HI	450	10.08686	4.192539	2.321076	20.17875
UPMI	427	5.231199	3.316332	1.308847	17.42437
LMI	450	1.602891	1.642865	.133613	7.701744
GDP capita					
HI	449	33700.83	13617.77	5510.662	56842.3
UPMI	449	6682.485	2793.98	712.1154	15068.98
LMI	450	2469.366	2871.945	398.8521	14920.45

Population density					
HI	439	179.0955	165.0725	2.18872	529.6521
UPMI	450	54.81616	41.2086	5.503698	148.3488
LMI	450	190.0089	249.634	9.188078	1239.579
Renewable energy					
HI	405	8.22135	8.437722	.0059765	38.61766
UPMI	405	14.0214	12.86628	.0589587	49.86467
LMI	450	43.96209	27.02946	1.17316	88.83185

Nonrenewable energy					
HI	405	83.30612	11.64692	46.22592	99.99678
UPMI	405	86.91605	11.93449	49.83301	99.97792
LMI	405	60.18739	27.12474	12.99901	99.15938
Environmental patents					
HI	435	526.0195	983.9253	0	6080.3
UPMI	435	42.38092	185.2354	0	1958.5
LMI	435	6.591954	27.58999	0	218

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

Appendix B

B.1. Unit root tests

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

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

B.2. Diagnostic tests

Upper-middle income				
	Model (1a)	Model (1b)	Model (3a)	Model (3b)
	Statistic	Statistic	Statistic	Statistic
Serial correlation	29.656 0.000***	15.952 0.000***	4.386 0.054*	43.109 0.000***
Heteroskedasticity	7616.12 0.000***	1187.12 0.000***	99618.5 0.000***	2502.75 0.000***
Pesaran CD	0.386 0.699	-0.743 0.000***	1.909 0.0563*	-1.877 0.0947*
Time fixed effect	0.796 0.754	-0.743 0.4575	0.946 0.544	0.253 1.000
Panel effect	417.25 0.000***	512.22 0.000***	111.67 0.000***	165.87 0.000***

Lower-middle income				
	Model (1a)	Model (1b)	Model (3a)	Model (3b)
	Statistic	Statistic	Statistic	Statistic
Serial correlation	9.091	39.388	11.961	12.398

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