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Technological innovation and the environment

An analysis based on patent counts

by

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Abstract

The increasing concern on the present and future impact of climate change has raised the attention on the relationship between technology and the environment. The aim of this paper is to investigate the impact of green innovation on carbon emissions. Carbon dioxide (CO_2) and Greenhouse Gas (GHG) emissions per capita are used as a proxy for environmental quality. Technological innovation is measured by the number of climate change mitigation patents granted for each country disaggregated by areas of innovation. The estimation strategy entails the use of an OLS with two-way fixed effects for a panel of 47 countries over the period 1976-2012. Overall, we find evidence of a positive relationship between carbon emissions and technological innovation, i.e. pollution can be reduced by adopting new energy efficient technologies. However, the results differ depending on the type of patent variable used. Furthermore, the results vary when the sample is divided into developed and developing countries. Interestingly, the additional regressions show a significant impact of innovations only for the high-income economies sample. These findings can be used to draw policy implications. Given the recent forecast of future increase in carbon emissions, it is paramount to further improve technologies to decouple economic growth from environmental pollution. Moreover, technology transfer between developed and developing countries must be fostered to increase the global effort in pollution reduction.

Keywords: Emissions, Technology, Patents, Environmental Kuznets Curve, OLS fixed effects

Contents

1 Introduction

The global concern on the negative effects of climate change has increased in the recent decades. There is a wide consensus on the need to limit the amount of carbon emissions in the future (Rogelj et al., 2018). Given the strong interconnection between increasing emissions and the rise in temperatures, the reduction is necessary to limit the warming of the planet (Ganda, 2019). The rise in temperature will have large negative consequences on the economic well-being of the society. For example, as highlighted by the "Stern Review: the economics of climate change", climate change will have large negative effects for the world economy and the ecosystem[1]. Furthermore, there is a wide consensus on the role of human economic activities on the increase in carbon emissions (see, for example, Rosa and Dietz, 2012). A large contributing factor in the levels of carbon emissions is given by the interaction between population, consumption and technology. As argued by Rosa and Dietz (2012), the anthropogenic impact on the environment depends on the direction of technological innovation and consumption patterns[2]. At the same time, the environmental impact of consumption is shaped by the technology used to produce and transport goods. The linkage between consumption and technological innovation is highlighted by Arto and Dietzenbacher (2014). The authors argue that population growth and the surge in global consumption levels are the major culprits for the rise in emissions. These, in turn, are partly offset by changes in technological innovation[3]. However, technological innovation alone does not completely offset the rise in emissions stemming from consumption and population growth.

According to the Intergovernmental Panel on Climate Change report (2018), technological innovation and environmental policies are some of the measures that can be adopted to reduce the amount of anthropogenic emissions in the atmosphere. Technological innovation can have a large impact in reducing the impact of climate change (Z. Yan et al., 2017). As illustrated by Li and Wang (2017, p.61), technologies lead to a reduction in emission in two ways: decrease the amount of emissions in the production process and "end-of-pipe" controls. The latter include Carbon Capture and Storage (CCS) of CO_2. However, given the early stages of these innovations, their feasibility and adoption are very limited. In fact, as argued by Sgouridis et al. (2019) in a recent study, CCS technologies have low climate change

[1]The Stern review estimates that, in case of no action against climate change, climate change will lead to an economic loss equal to the 5 percent of global GDP each year. For a short analysis of the Stern review, see Nordhaus (2007).

[2]The relationship between these factors is usually expressed using the IPAT equation. In detail: Impact = Population x Affluence (GDP) x Technology

[3]For example, Arto and Dietzenbacher (2014) claim that, for the period 1995-2008, population growth and consumption led to an increase in GHG emissions by 60%. Changes in technology, i.e. cleaner sources of energy, more efficient production and changes in inputs, led to a reduction of almost 30% for the same period.

reduction potential given their limited installed capacity. Conversely, greater reductions can be achieved by using renewable energy sources. Hence, the development of low-carbon technologies is paramount to reduce the amount of carbon emissions (Nordhaus, 2007). Furthermore, emissions intensity reduction should be a priority also in developing economies, as they are expected to experience large growth in consumption and population levels (Arto and Dietzenbacher, 2014).

The aim of this paper is to investigate the impact of technological innovation on carbon emissions. We collect data for 47 countries over the period 1976-2012. Carbon dioxide (CO_2) and Greenhouse Gases (GHGs) emissions per capita are used as a proxy for environmental degradation. We collect data on the number of climate change mitigation patents granted for each country to measure green innovation. In addition, we disaggregate the indicator according to the type of technological area addressed, i.e. we obtain four different indicators that measure innovation in the transportation, energy, buildings and production of goods sectors. The estimation method entails the use of OLS with two-way fixed effects. As a robustness check, we divide our panel into developed and developing countries subsamples. Our results show heterogeneous effects of emissions reduction due to technological innovation, i.e. results vary according to the area and countries examined.

The contributions of this paper are manifold. First, we present a detailed analysis on the impact of green innovation on emissions by disaggregating our main regressor, i.e. the granted patent variable, into four different areas of innovations. This allows us to capture the heterogeneity of the positive effect of technological innovation on the environment. In contrast with previous studies, we use data on granted patents instead of patents applications, since we argue they provide a more precise indicator of (successful) technological innovation. Second, we divide the sample into high and low-income economies to investigate whether the impact of green innovation on emissions differs according to the level of economic development of a country. This provides a further analysis on the relationship between economic growth, technological advancement and environmental quality. Finally, we take advantage of the larger time series of patent data to examine the technology-environment nexus over a larger time frame.

The paper is organised as follows. Chapter 2 illustrates the theoretical underpinning of the technology, environment and economic growth nexus. In addition, we provide a general overview on the use of patents in economics and discuss the previous literature findings. The empirical strategy used to disentangle the relationship between environment and green innovation is presented in Chapter 3. Data and econometric issues are discussed in Chapter 4. Then, in Chapter 5 we present our results and robustness checks. The discussion and comparison to previous literature findings are provided in Chapter 6. Finally, Chapter 7 concludes.

2 Environment, economic growth and technology

2.1 Environmental Kuznets Curve

The relationship between economic growth and pollution is frequently depicted as inverted-U curve. As countries foster their economic development, the growth in income exerts an increasing pressure on the environment. However, once a threshold is reached, i.e. a specific level of income, the environmental pressure exerted by economic growth diminishes (Grossman and Krueger, 1991). The reduction in the pollution level can be explained by the development and adoption of more environment-friendly technologies, which are only possible if large amount of resources are allocated to R&D. Hence, economic growth, technological innovation and environmental quality are deeply interconnected.

The standard Environmental Kuznets Curve (EKC) regression model is illustrated by the following equation:

$$Emissions_{it} = \alpha_i + \beta_1 GDP_{it} + \beta_2 GDP_{it}^2 + \varepsilon_{it} \tag{1}$$

The addition of income squared is necessary to capture the nonlinear relationship between economic growth and pollution. If the EKC hypothesis holds, β_1 is positive, while β_2 enters with a negative sign (Dinda, 2004). We will use this basic equation as the starting point for our empirical analysis.

Several authors have tested the empirical validity of the EKC. For example, Selden and Song (1994) find evidence of an inverted-U relationship between economic growth and four different types of air pollutants: carbon monoxide, suspended particulate matter, sulfur dioxide and oxides of nitrogen. Similar results are obtained by Dinda and Coondoo (2006) using a panel data of 88 countries over the period 1960-1990. Moreover, the authors find evidence of a bi-directional causal relationship between emissions and economic growth. This entails that there is a feedback mechanism that affects both variables. Such dynamics has important policy implications, since the decrease in pollution in developed countries might not be enough to offset the rising levels of pollution in emerging economies. Apergis and Ozturk (2015) confirm the validity of the EKC hypothesis on a panel of 14 Asian economies over the period 1990-2011. Furthermore, contrary to Dinda and Coondoo (2006), they do not find any evidence of a bi-directional relationship between income and emissions, but only a one-directional effect of income on emissions.

An important determinant of the inverted-U curve is technology (Andreoni and Levinson, 2001). In fact, the mechanism behind the improvement in environmental quality, once a turning-point income level is reached, cannot be solely explained by economic growth. As argued by Andreoni and Levinson (2001), the shape of the curve is determined by the relationship between technological development in the production of goods and in emissions abatement. According to Popp et al. (2010, p.875) the impact of innovation depends on the direction of technological change, i.e. the effect of innovation is dichotomous. First, new technologies can lead to economic growth and to an increase in the use of resources. Consequently, the rise in economic output leads to an increase in emissions and to a negative impact on the environment. This is the scale effect (for a more detailed analysis, see Tsurumi and Managi, 2010). Second, technological innovation can decrease the rate of carbon emissions and thus mitigate the impact that economic growth exerts on the environment (Jaffe, Newell, and Stavins, 2000).

The presence of an inverted-U relationship between economic growth and environmental quality relies on the existence of increasing returns to scale in the abatement technologies (Andreoni and Levinson, 2001). In addition, a developed economy has a lower marginal cost for abating pollution, while the opposite is true for an emerging economy[4]. Stokey (1998) claims that countries with low income levels have only access to dirty technologies, while high-income economies have access to cleaner technologies which contributes to a reduction in the environmental pressure of economic growth. In short, the validity of the EKC hypothesis relies on the degree of improvements in abatement technologies.

The different share of technological innovation efforts between countries is also highlighted by Popp (2012). For example, in 2007 research expenditures from US and Japan was 46% of the total, while OECD countries combined accounted for the 80%. Innovation in climate change related technologies follows a similar path[5]. As previously discussed, the level of economic development of a country is an important determinant of the degree of innovation conducted. For example, Lanjouw and Mody (1996) find that technologies aimed at mitigating air pollution are mainly patented by high income economies, such as the US, Germany and Japan. On the other side, less complex technologies are patented also by developing countries. Similar results are presented by Dechezleprêtre et al. (2011): high income countries account for the majority of the cutting-edge environmental-friendly innovations. On the other hand, developing economies do carry out some research, but it is mostly focused on the internal market with low global adoption potential. This can be partly explained by the different need of technological innovation: emerging economies develop and implement technologies that are not needed or obsolete in high income countries

[4] A large determinant of increasing returns in the presence of large fixed costs. A low-income country might not have enough economic resources to overcome the large fixed cost necessary in developing and adopting cleaner technologies. Hence, it is unlikely to generate increasing returns to scale in abatement technologies (Andreoni and Levinson, 2001).

[5] A detailed analysis of the country-share of total innovation for our panel will be presented in the data section, in Chapter 4.

(Popp, 2012). Hence, developed countries have a predominant role in technological innovation.

2.2 Technological innovation and the environment

The analysis of the relationship between green innovation and pollution is conducted using different types of technology indicators. According to Popp (2012), technological innovation can be measured in two ways: input and output. Input measures are R&D expenditure (as % of GDP) and number of researchers per country. Output measures are patent data. As argued by Haščič and Migotto (2015), input measures present several drawbacks. First, they report aggregated data, which does not allow to filter the green R&D (Popp, 2005). Second, data availability is an issue since only high-income countries have detailed information on the investments on research. Third, data on the private sector share of expenditures is usually missing or incomplete. Lastly, there could be a gap between the amount of resources spent and the innovation generated. In fact, according to Johnstone et al. (2010), R&D expenditures and number of research personnel reflect the innovative capacity of a country, i.e. the resources available to develop new technologies, rather than the effective amount of innovation generated. Hence, given these major limitations, we have opted for the number of patents as the proxy for innovation.

Despite these limitations, several authors have investigated the relationship between technological innovation and environmental quality using R&D expenditures data. Studies at country level or firm level yield similar results, i.e. R&D expenditures lead to a reduction in emissions. For example, Garrone and Grilli (2010) investigate the link between public R&D in energy and CO_2 per GDP for 13 developed economies between 1980 and 2004. The authors find a positive link between energy efficiency and public R&D, but no significant relationship between emissions and R&D.The focus on public investments is useful given the features of the R&D markets. In fact, since technological innovation is characterised by high risks and various degrees of success, public investment is necessary to remedy for market failures and foster knowledge spillovers. As argued by Popp (2010), government support in R&D is needed to overcome market failures. On the others side, it can be argued that these public funded technologies might be of little help if they are not easily available or difficult to implement in the private market (Garrone and Grilli, 2010).

Li and Wang (2017), examine the impact of technological change on CO_2 emissions for a panel of 95 countries over the period 1996-2007. They find a positive impact of technology on emissions, i.e. technology contributes to a decrease in CO_2 emissions. Furthermore, the results hold also when the scale effect of technology on economic output is accounted for. However, a limitation of the abovementioned studies is the short time span of the analysis, which does not allow to examine the long-run relationship of the phenomenon. On the other side, Churchill et al. (2019) investigate the relationship between R&D and carbon emissions for G7 countries in the period 1870-2014. They find a heterogeneous impact of technological innovation on the level of emissions depending on the period examined. In detail, R&D contributes to a reduction in emissions for the majority of the years investigated; yet, the technology variable coefficient enters with a positive sign for the 1955-1990 period. This can be explained by the scale effect as these countries experienced large growth rates and an increasing opening to trade (Churchill et al., 2019). These, in turn led to an increase in R&D and in carbon emissions. Hence, the positive sign is a result of the increase in the economies' scale.

The heterogeneity in the development of clean technologies at the firm level is illustrated by Lee and Min (2015). The authors examine the relationship between R&D and carbon emissions on a sample of Japanese firms over the period 2001-2010. They differentiate between green R&D and non-green R&D (Lee and Min, 2015). In this way, they capture the effect of an increase in R&D in energy-intensive industries. The authors find evidence of a significant reduction in carbon emissions due to green R&D. At the same time, non-green R&D does not effectively reduce CO_2 emissions, but it works in the opposite direction, thus attenuating the positive effect of clean technologies (Lee and Min, 2015).

Contrary to R&D expenditures, patent data is a measure of output (Albino et al., 2014). A patent is the right granted by a government to an inventor and it prevents a third party from using the invention for a certain period[6]. The patent application procedure involves several steps and large monetary costs. Furthermore, the filing of a patent usually occurs after the development of the technology has begun[7]. Given these barriers, we can argue that inventors are willing to embark in the patenting procedure only if they deem their invention valuable and if it meets the patenting requirements (Harhoff, 2016). In other words, the procedure itself acts as a guarantee for high-quality inventions (Hascic and Migotto, 2015). Hence, patent data reports the success of the innovative process, rather than the innovative capacity. The objective of the innovation can be easily categorised given the level of detail contained in a patent application. In addition, the high level of international standardisation and the availability of long time series on patent data, allow for

[6] In the case of a patent issued by the United States Patent and Trademark Office (USPTO), protection lasts 20 years from the date of application (Popp, Juhl, and D. K. Johnson, 2003).

[7] According to Haupt et al. (2007), the timeline of technological patenting follows an S-shaped curve. In short, at the initial phase in the development of a new technology, few patent applications are made. Once the uncertainty around the potential application of the technology diminishes, there is a surge in patent applications. Finally, as the rate of innovation decreases due to the maturity of the technology, the number of patent filings decreases. For a more detailed analysis, see Haupt et al. (2007).

detailed cross-country comparisons (Albino et al., 2014).

The use of patent data is not new in economics. Economists have used it to examine technological innovation, market competition between firms or countries and their role as a source of economic growth (Griliches, 1990, Kortum, 1993 and Thomas, 2001). Several authors have investigated the relationship between R&D activity and patents. One of the first investigation was conducted by Comanor and Scherer in 1969. The authors found a large correlation between innovation inputs, i.e. R&D and number of researchers, and number of patents for a sample of manufacturing firms (Comanor and Scherer, 1969). Similar results are found by Scherer (1983) for a panel of US industrial corporations. Firms that invest more in R&D are also the ones that are more likely to have their technologies patented.

Patent data is not exempt from limitations. For example, it does not report the entire "universe" of technological innovations, since some technologies cannot be patented[8]. In addition, some patents might be granted, but the technology is not adopted in the real world. Yet, as highlighted by Haščič and Migotto (2015), since individuals and firms face heavy costs to patent an invention, one could argue that there is a higher probability that the technology will be adopted. Furthermore, as reported in the OECD Patent Manual (OECD-EUROSTAT, 2009), the criteria of "significant invention" is a necessary condition for the granting of a patent. In conclusion, we can claim that patent data mainly includes innovations that generate an improvement on the current level of technological innovation.

Technological innovation is a multifaceted phenomenon. Patent counts are useful to obtain an output measure of the process, but they reveal scarce information regarding the quality of the innovation. In fact, the heterogeneity in the quality of technological innovation is a widely discussed issue in economics[9]. In the recent past, there has been a push for increasing the quality of patents (Squicciarini, Dernis, and Criscuolo, 2013). The presence of low-quality patents generates some drawbacks. For example, it can slowdown innovation and diminish the incentives to foster technological advancements (Hall, Graham, et al., 2004). The heterogeneous quality entails that the contribution of a new technology widely varies according to the improvement generated compared to the previous technological level. However, patent data remains a reliable measure of the impact of technological innovation. For example, according to Svensson (2015), there is a positive correlation between a patent successful grant and its commercialisation. Hence, patented technologies

[8]In fact, according to Hall et al. (2001, p.5), inventions can be patented only if they meet the criteria set by the patent office. For example, the USPTO grants the patent right only if "the invention is non-trivial, novel and has a commercial application".

[9]To examine the quality of innovation several different approaches are used. For example, Nagaoka et al. (2010) use number of patent citations, while number of countries where the invention is patented is used by Lanjouw et al. (1998) and Harhoff et al. (2003).

are likely to be implemented and represent a reliable link to economically relevant innovations (Albino et al., 2014). In short, given the lengthy process of patenting we argue that patent data yield a robust measure of significant technological innovation. Furthermore, the grant of a patent is an implicit proof of a meaningful improvement in the old technology or of the creation of a new one.

The use of patent data in examining the impact of green innovations on carbon emissions is quite novel. For example, a recent study by Wurlod and Noailly (2018) investigates the impact of green innovation, proxied by number of patents, on energy intensity for 14 sectors in OECD countries between 1975 and 2005. They find evidence of an overall reduction in energy intensity due to technological innovation. Furthermore, the reduction is larger for recent years and energy-intensive industries. Hence, technological innovation has a heterogeneous impact, which depends on the period and sectors examined. Voigt et al. (2014) analyse the impact of patents on energy intensity reduction for a panel of 40 major economies over the period 1995-2007. They find evidence of a large effect of energy use reduction due to technological innovation[10]. A recent paper by Cheng et al. (2019) examines the impact of technological innovation on carbon emissions for the BRIICS countries over the period 2000-2013. The authors use environmental related patents as an indicator of technology development[11]. Furthermore, they include control variables such as exports, GDP per capita, renewable energy supply and FDI inflows. The estimation is carried out by using a pooled OLS and a panel quantile regression. Contrary to the previously discussed literature, the authors do not find evidence of a reduction in emissions due to technological innovation. In fact, the patent variable enters with a positive coefficient (even though not all the estimated coefficients are significant). The authors argue that a possible explanation can be found in the lack of environmental regulation, which is important in the reduction of carbon emissions and to foster technological innovation[12].

Chen and Lei (2018) examine the relationship between environmental quality and technological innovation using a panel quantile regression. They collect data on CO_2 emissions, total patents applications[13] and control variables for a panel of 30

[10]Their study differs from the main literature since they applied a Logarithmic mean Divisia Index to analyse the trends in energy consumption. This method allows for the decomposition between changes in energy use due to technological advancements or structural changes in the economy. Furthermore, these effects are investigated both at the country and sectoral level.

[11]In detail, the patent variable includes climate change mitigation, water adaptation and environmental management technologies.

[12]For example, environmental regulation impact on carbon emissions has been examined by Ren et al. (2018) and Zhao et al. (2015). Both papers find evidence of a positive, yet heterogeneous impact of environmental regulation on pollution. In other words, environmental-related laws can reduce carbon emissions and improve eco-efficiency. Environmental regulation is also a driver of technological innovation. As highlighted by Guo et al. (2017), regulation fosters the development of green technologies, which in turn has a positive impact on economic growth.

[13]A limitation of this study is the use of total patent applications rather than environmental-

countries over the period 1980-2014. They find evidence of mixed impact of technological innovation. In detail, the reduction in emissions is larger and significant for high-emissions countries, while the opposite is true for low-emissions countries. The findings can be explained by the existence of a positive relationship between economic growth and technological innovation (Chen and Lei, 2018). In other words, higher economic growth leads to larger investments in the development of cleaner and more advanced technologies. At the same time, economic growth is also the main culprit for the rise in emissions.

Yan et al. (2017) investigate the impact of low-carbon technologies on carbon emissions for a panel of 15 large economies over the period 1992-2012. The analysis is three-fold. First, the authors examine the overall impact of green innovations. Then, the environmental-related technology is further divided into two sub-categories: clean and "grey" technology. The former includes the patents for low-carbon emissions, i.e. carbon neutral technologies. The latter includes the remaining patents, which have a relatively higher negative impact on the environment. In fact, the grey category also includes technologies that improve the energy efficiency but do not necessarily reduce carbon emissions (Z. Yan et al., 2017). Not surprisingly, the results vary depending on the indicator used. The aggregate measure of technological innovation does not reduce carbon emissions[14]. However, the more detailed analysis yields different results. First, clean technologies significantly decrease CO_2 emissions. This can be easily explained given the carbon-neutrality of these innovations, even though their full potential depends on the economic profitability and on the replacement of old carbon-intensive technologies (Z. Yan et al., 2017). On the other side, grey patents do not significantly reduce carbon emissions, since they can still contribute to CO_2 emissions (Z. Yan et al., 2017). In fact, the improvement in energy efficiency does not necessarily entail a substantial reduction in emissions.

In short, most of the studies summarised find evidence of a reduction in carbon emissions due to technological innovation. Moreover, similar results are obtained irrespective of the technological innovation indicator used. As we have illustrated, the impact of green innovation on environmental degradation is quite heterogeneous. Low-carbon technologies have a greater impact in emissions reduction. On the other hand, mixed results are found when using less carbon neutral technologies.

related patents.

[14]This finding can be partly explained by the heterogeneity of the indicator. In fact, clean patents are described as "high-quality" innovations, while the grey patents also include "low-quality" technologies.

3 Empirical strategy

To investigate the relationship between technological innovation and carbon emissions, a plethora of different estimation strategies have been used in the previous literature. Several authors have opted for panel quantile regressions (see, among others Cheng et al., 2019 and Chen and Lei, 2018). Another widely used approach is the Ordinary Least Squared Fixed Effects (for example, Yan et al. 2017). The use of Fixed Effects captures unobserved heterogeneous factors, that otherwise would be included in the error terms. In studies with a small time period, several authors have opted for the use of the General Method of Moments (for example, Wang et al. 2012).

Our baseline model includes the Environmental Kuznets Curve which is then augmented with additional regressors. We include the number of green patents related to climate change mitigation technologies as our main variable of interest[15]. We further disaggregate our patent variable to account for the different areas of technological innovation addressed[16]. In detail, the patent variable is divided in transport (*cc_transport*), energy (*cc_energy*), goods production (*cc_goods*) and buildings (*cc_building*) patents[17]. We can assume that the first three are the most relevant, since energy transformation, goods production and transportation account for a large share of global emissions[18]. We have created a new variable *cc_tot* in order to capture the full impact of the climate change mitigation technologies on emissions. This new indicator is obtained by summing all the 4 subcategories. One advantage of the variable is that it accounts for the overall effect of the climate change mitigation technological area. On the other hand, it presents a large degree of heterogeneity, since it includes technologies with a very different spectrum of action. Nonetheless, we believe that its inclusion in our estimation strategy can yield some useful insights on the overall impact of climate change mitigation technologies on emissions. In addition, we include trade openness, total population, FDI inflows, fossil fuel energy consumption and an index of democracy as control variables.

The patent variable includes the number of granted patents. Since it takes some years for a patent to be granted, the variable can be described as a lagged measure of green innovation. The multidirectional relationship between technology, GDP and emissions can lead to endogeneity issues. For example, there can be a contem-

[15] Y02 code according to the International Patent Classification (IPC) system.

[16] Our choice of patents indicator is similar to the one adopted by Cheng et al. (2019). However, in contrast to their methodology, we only use climate change mitigation patents, while the authors include also water adaptation and environmental management technologies.

[17] A detailed description of the technologies included in each patent variable is presented in Chapter 4.

[18] According to the IPCC Mitigation of Climate Change Report (2015), in 2010 the transport sector accounted for 14%, energy production for 25%, industrial production for 21%, while buildings for 6% of global emission.

poraneous effect stemming from technological innovation and GDP on emissions. Furthermore, as examined by Su and Moaniba (2017), carbon emissions can lead to an increase in the development of climate change adaptation technologies. However, we argue that endogeneity is not an issue for our estimation strategy. Our argument rests on the presence of a lag between technology invention and granting of a patent. As previously discussed, it takes on average 3 years for a patent to be granted. Hence, the contemporaneous levels of emissions are affected by technological innovation, but not vice versa.

Our baseline nonlinear model with first differenced variables is illustrated by the following equation:

$$\Delta Emissions_{it} = \beta_0 + \beta_1 \Delta Pat_{it} + \beta_2 \Delta GDP_{it} + \beta_3 \Delta GDP_{it}{}^2 + \beta_4 \Delta Controls_{it} + \mu_t + \delta_i + \epsilon_{it} \quad (2)$$

where $Emissions_{it}$ may be either CO_2 per capita or GHGs per capita. Pat is patent counts and is the main variable of interest. GDP_{it} and GDP_{it}^2 are included to account for the impact of economic growth on pollution (as illustrated by the EKC hypothesis). Controls include all our control variables, i.e. trade openness, population, fossil fuel energy consumption, FDI inflows, democracy index, μ_t is year fixed effects, δ_i is country fixed effects[19] and ε_{it} is the error term (which is assumed to be $i.i.d$).

This study uses a nonlinear model which is estimated by OLS with country and year fixed effects[20]. When using panels with large N and small T, the Nickell bias leads to inconsistent estimates if fixed effects are included in a dynamic model (Nickell, 1981). However, the bias disappears when the panel contains a large T (Ganda, 2019). Since our panel includes T=37, we can safely assume that the Nickell bias is not a concern in our estimation strategy. Two-way fixed effects are used to account for country and year specific shocks that otherwise would be included in the error terms[21] (Álvarez-Herránz et al., 2017).

In the economics literature, GDP and carbon emissions are often described as nonstationary time series[22]. As we will show in the next chapter, the presence of nonstationary variables and the lack of cointegration do not allow for the use of a long-run estimation strategy, such as an error correction model. Hence, since non-

[19]We use clustered standard errors at the country level in order to obtain consistent estimates in the presence of heteroscedasticity and within-group correlation, i.e. errors correlated within clusters, but not between clusters.

[20]Given the presence of several zeros in our patent variable, we have opted for using raw data instead of taking logs to avoid reducing the number of observations. This entails that we cannot interpret our findings as elasticities. Furthermore, there is no general consensus on the log-transformation of the data in the previous literature.

[21]In detail, country fixed effects account for time invariant factors that vary between country. On the other side, year fixed effects account for time varying factors, e.g. shocks, that affect all the countries.

[22]For example, Wang et al. (2012), Ganda (2019), Dinda (2018) find that GDP and emissions are nonstationary in levels, but stationary in first differences.

stationarity can yield spurious results, we estimate the model with first differenced variables (Kaufmann, Kauppi, and Stock, 2006). The use of first differences allows us to remove the unit root process and it makes possible to use the estimation techniques developed for stationary panels[23]. Furthermore, as suggested by Woolridge (2010), we have opted for first differencing all the variables included in our regression to have a more homogeneous interpretation of the results. Table 1 reports the description of the variables used in our estimation.

Table 1: Variables description

Variable	**Description**
co2_capita	Per capita CO_2 emissions (expressed in Kton)
ghg_capita	Per capita GHG emissions (expressed in CO_2 equivalent Kton)
cc_transport	Number of climate change mitigation patents for the transport sector
cc_energy	Number of climate change mitigation patents for the energy sector
cc_building	Number of climate change mitigation patents for the improvement of buildings energy efficiency
cc_goods	Number of climate change mitigation patents for goods production
cc_tot	Sum of the climate change mitigation patents category
wdi_gdpcap	GDP per capita in constant 2010 US$
wdi_sq_gdp	GDP per capita in constant 2010 US$ squared
wdi_trade	Sum of exports and imports of goods and services as a share of GDP
wdi_pop	Total population (expressed in millions)
wdi_fdiin	Foreign Direct Investments, net inflows in current US$
wdi_fossil	Fossil fuel energy consumption as a share of total energy
polity	Index of democracy

When examining the relationship between green innovations and carbon emissions, there is no general concordance on the inclusion of the lagged dependent variable as an additional regressor. For example, Álvarez-Herránz et al. (2017) and Carrión-Flores and Innes (2010) include one lag of the dependent variable in their model. On the other side, Fernández Fernández et al. (2018), Cheng et al. (2019) and Yan et al. (2017) do not include the lag of emissions. The inclusion of the lagged dependent variable can be useful to capture some of the dynamics, as the level of emissions last year can partly explain emissions this year (Keele and Kelly, 2006). However, our case is different, since first differencing the emissions variable removes a large degree of the potential dynamics. Hence, we have opted for not including the dependent variable lag as an additional regressor for our baseline specification. As a matter of fact, the exclusion rests on two main factors: the small dynamics included in a first-differenced variable and the lack of a predominant strategy in the previous patent-emissions literature. However, we will include the regression results with the lagged dependent variable in the appendix, as a robustness check.

The use of time fixed effects allows to account for year-specific shocks, e.g. finan-

[23]According to Woolridge (2010), the OLS estimator is consistent in first-differences.

cial crises, that otherwise would be included in our error terms and lead to biased estimates. As highlighted by Gow et al. (2010), the use of time fixed effects reduces the impact of these common shocks. For these reasons, we argue that the inclusion of time fixed effects captures the potential cross-sectional dependence in our data.

4 Data

The data used in our paper has been collected from various sources. The sample includes 47 countries for the 1976-2012 period (N=47 and T=37). The choice of countries and time is dictated by data availability. The countries included are mainly large economies (OECD members) and other developing countries that significantly contribute to global emissions. For example, developed economies are the ones with the most significant levels of investments in research (Churchill et al., 2019). The exclusion of less relevant economies is due to the small contribution to the global share of innovation and emissions. Thus, their exclusion allows for a more direct analysis of the phenomenon. In short, our selection of countries yields a direct investigation on the extent to which the largest emitters and innovator can contribute to global emissions.

4.1 CO_2 and GHG emissions

The data on CO_2 and Greenhouse Gases (GHG) emissions has been retrieved from the EDGAR v.4.3.2 dataset. It reports country-level emissions of fossil fuels and industrial processes, for all anthropogenic activities. The GHG data includes CO_2 (carbon dioxide), CH_4 (methane) and N_2O (nitrous oxide) emissions[24]. These are calculated by using national data on fossil fuel production, population, energy consumption, industrial and agricultural statistics (Janssens-Maenhout et al., 2017) and IPCC values for the emission factors. In our analysis, both emissions variables are expressed in per capita levels[25].

The choice of two distinct dependent variables rests on the heterogeneous impact of these gases on the atmosphere. According to Brander and Davis (2012), the main GHGs are carbon dioxide, nitrous oxide, methane and ozone. These have different atmospheric lifetimes, i.e. the time necessary for a pollutant to return to its natural level (either by being absorbed or converted into another gas). A frequently used

[24]The GHG variable includes the values expressed in carbon dioxide equivalent, which allows to count different gases in a common unit. In detail, the measure is obtained by multiplying the gas by its global warming potential. In this case, the CO_2-equivalent methane measure is obtained by multipliying it by 25, while nitrous oxide by 298. A more detailed discussion is provided in the next paragraph.

[25]The use of per capita emissions is in line with Cheng et al. (2019) and Álvarez-Herránz (2017) studies.

measure of a gas contribution to climate change is the "global warming potential". It describes the amount of warm that a gas produces compared to the carbon dioxide contribution for a specific time range, usually 100 years (Brander and Davis, 2012). For example, CO_2 has an index of 1, since it is used as the benchmark value. Methane (CH_4) has an index of 25, which entails that 1kg of methane has the same impact of 25kg of CO_2. Nitrous oxide (N_2O) has an index of 298, which is significantly larger compared to the other GHGs. In short, methane and nitrous oxide retain more heat compared to carbon emissions. Hence, their inclusion in our dependent variable is relevant given their greater contribution to the warming of the atmosphere.

On the other side, nitrous oxide and methane have a shorter atmospheric lifetime compared to CO_2, which can persist in the atmosphere for several centuries. In detail, methane lasts for about a decade in the atmosphere, while nitrous oxide for more than one hundred years (Ehhalt et al., 2001). Furthermore, CO_2 is the largest contributor to climate change, followed by methane and nitrous oxide (Stocker et al., 2013).

As we have examined, these gases have different impacts on the atmosphere. Furthermore, they also differ for atmospheric lifetime. Thus, to capture the heterogeneous effects of these gases, we have opted for the use of two dependent variables. The first dependent variable includes only carbon dioxide emissions. This allows us to examine the impact of technological innovation on the major contributor to climate change. Furthermore, isolating CO_2 emissions is important given their large share in the GHGs total[26]. The second dependent variable includes carbon dioxide, methane and nitrous oxide. This indicator yields the overall relationship between GHGs and technological innovation.

At the global level, CO_2 emissions per capita have been stable for the last three years, up to 2016. Yet, the situation at the country level is quite heterogeneous. For example, the developed economies, such as US, Japan, the Russian Federation and the EU28 group have all witnessed a decrease in emissions[27] . Likewise, China has experienced a stable decrease in emissions per capita since 2015, which is mainly due to the change in their energy sector composition, i.e. coal consumption has decreased (Janssens-Maenhout et al. 2017). The opposite is true for India and Indonesia which have all increased their emissions. For example, the upward trend in India's emissions levels is mostly due to its high rate of economic growth and the increase in the demand of energy, which is largely supplied by oil and coal

[26]For example, in 2017 CO_2 accounted for 73% of total GHGs (Olivier and Peters, 2018).

[27]According to Arto and Dietzenbacher (2014), developed countries have stabilised their national emissions in production, but increased the consumption embodied emissions at the global level. On the other side, developing economies have experienced an increase in both the consumption and production embodied emissions.

consumption (BP, 2017).

Greenhouse Gas emissions per capita have been rising in the 1976-2012 period, mainly due to the rise in CO_2 emissions. In detail, CH_4 share of GHGs emissions declined from 27% in 1970 to 19% in 2012. Similarly, the N_2O share oscillated between 7% in 1970 and 6% in 2012. The overall decrease is mainly attributed to the shift from agricultural to industrialised economies for developing countries (Janssens-Maenhout et al., 2017). The global trend has experienced a downturn in the 1980s and 1990s, which was then followed by an increase until 2012. At the country level, the EU28 group, the Russian federation and Japan experienced a decrease in GHG emissions. On the other side, emerging economies, such as China and India, increased their emissions.

4.2 Patent data

Technological innovation is measured by the number of environmental related patents granted by the United States Patent and Trademark Office (USPTO). The data is retrieved from the OECD database. As already discussed, the choice of patents granted, rather than patent applications, aims at capturing the impact of effective and significant innovation[28]. However, the total patents granted could not be fully representative of the technology used if the technology is adopted before the patents are granted or if the technology is not patented at all. It can be argued that this bias is relatively smaller compared to the upward bias that could stem by including patents that might not be granted[29]. In fact, the use of granted patents might lead to a downward bias in our estimations, if a large share of technologies is implemented but not granted. As we can see from the summary statistics presented in Table 3, the OECD dataset reports also fractional count patents. This is necessary to account for patents that have multiple (and foreign) inventors[30]. Furthermore, the method avoids the inclusion of the same patent for multiple countries. Patents are attributed to a country by the inventor's residence, which allows to have a detailed picture of the efforts in innovation for each country (OECD-EUROSTAT, 2009).

The first subcategory, i.e. transport, covers technologies related to road, rail, air and maritime transport. Furthermore, different types of engines are covered, from the conventional internal combustion engine, to hybrid and electric engines. It also includes fuel efficiency-improving technologies aimed at reducing GHGs emissions.

[28] Carrión-Flores and Innes (2010) argue that data on patent application better captures the timing of discovery. However, since we are interested in examining the aggregate impact of technological advancement, granted data represents a more suitable indicator of green innovation.

[29] The previous literature mainly uses patent application data as a proxy for technological innovation (see, among others Wurlod and Noailly, 2018, Cheng et al., 2019 and Yan et al., 2017. On the other side, Dinda (2018) uses granted patents.

[30] For example, if a patent has been co-invented by one German and one American, then it will be counted as $\frac{1}{2}$ of a patent for Germany and $\frac{1}{2}$ for the US.

Finally, energy-storing and recharging technologies are included (e.g. electric charging stations for road vehicles). The breadth of this category entails the inclusion of technologies with a heterogeneous potential in climate change mitigation. For example, carbon emissions are significantly reduced by the implementation of an electric engine, rather than an improvement in a vehicle fuel-efficiency[31].

The second subcategory, i.e. energy, includes technologies with the objective of producing and transmitting energy. The energy-production category covers renewable energy, which can be divided into several sources. For example, renewable energy can be obtained from wind, solar thermal and photovoltaic, geothermal and hydro sources. This category includes also non-fossil fuels, such as biofuels and waste-generated fuels, and nuclear energy. Furthermore, it covers technologies that mitigate every type of fuel generated emission (fossil and non-fossil), i.e. technologies that improve output efficiency. Finally, energy storage technologies (e.g. batteries) and transmission technologies are included. Hence, as we can see, this subcategory is composed of low-carbon emissions technologies, such as renewable ones, but also from less carbon efficient technologies.

The building subcategory covers energy-efficient technologies and the integration of renewable energy in constructions. The former includes energy-efficient lightning and heating, but also the adoption of smart grids. The latter covers all the renewable technologies that can be installed on a building, from photovoltaic panels to biomasses for heating. We can argue that the contribution on the reduction in emissions stemming from these technologies is smaller compared to the other subcategories.

The goods processing subcategory is quite heterogeneous. First, it includes all the technological improvements aimed at the reduction in emissions generated from the production of goods in various sectors[32]. Second, it also includes technologies that are used in the final production of goods, from storing goods to assemblage.

[31]See, for a more detailed discussion, Helmers and Marx (2012) and Cerovsky and Mindl (2008).

[32]Among others, technologies that reduce the production of GHGs in the industrial sector. Furthermore, technologies related to the agriculture sector are also included. These are particularly important given the relatively large production of GHGs, in particular methane and nitrous oxide from agriculture (J. M.-F. Johnson et al., 2007).

Figure 1: Total patents by area of innovation

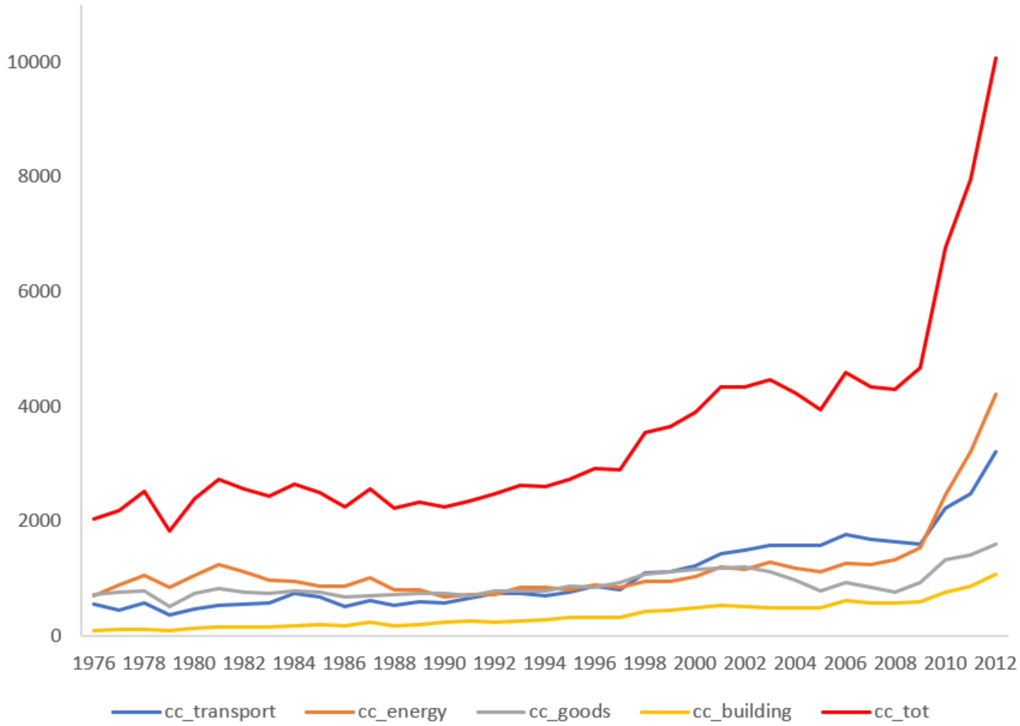

Figure 1 plots the time series of our green innovation variables for the entire panel. In general, we can see an upward trend in the number of granted patents. Specifically, an increase is experienced in the last few years, which is highlighted by the sharp rise in the *cc_tot* line. There seems to be a convergence between the patents in the energy and transport areas. Furthermore, these two variables represent the largest contribution to innovation in our sample since they almost double *cc_goods* and *cc_buildings* patent counts.

Table 2 shows the country share of global technological innovation in our dataset. For each patent variable, the share is calculated by dividing the total number of patents granted per country over the total global number of patents for the 1976-2012 period. The same procedure is used to calculate the share of CO_2 and GHG emissions per capita. The table illustrates some general patterns. First, the developed countries group accounts for a disproportionally large share of technological innovation. This, as previously discussed, is to be expected given the larger amount of R&D produced by these countries[33]. Similarly, these countries largely contribute to global (per capita) pollution, with the 78% and 71% of CO_2 and GHG emissions, respectively[34]. Emerging economies produce relatively more green patents in the

[33] Raiser et al. (2017) argue that these differences stem from different amount of R&D and investments, institutional capabilities and lack of commercialisation of innovations. Furthermore, patent regimes can act as a barrier to the creation of knowledge, particularly in low-income countries.

[34] However, given that these measures are expressed at per capita level, they do not yield a clear-cut interpretation on the total share of emissions, since they depend on the demographic trend of a country.

Table 2: Country share of patents and per capita emissions

Country	Transport	Energy	Building	Goods	Total	CO_2cap	GHGcap
Developed Countries							
Australia	0.52%	0.75%	0.38%	1.01%	0.71%	4.00%	4.37%
Austria	0.56%	0.32%	0.33%	0.82%	0.52%	1.93%	1.76%
Belgium	0.09%	0.32%	0.15%	1.01%	0.41%	2.71%	2.40%
Canada	1.40%	2.30%	2.25%	3.31%	2.28%	5.01%	3.69%
Czech Republic	0.02%	0.05%	0.08%	0.07%	0.05%	3.47%	2.86%
Denmark	0.10%	1.02%	0.42%	0.48%	0.54%	2.57%	2.37%
Estonia	0.00%	0.00%	0.01%	0.01%	0.00%	4.62%	3.79%
Finland	0.13%	0.28%	0.37%	0.71%	0.35%	2.71%	2.59%
France	2.18%	3.36%	2.18%	4.13%	3.08%	1.64%	1.57%
Germany	11.89%	7.84%	5.88%	8.55%	9.05%	2.79%	2.39%
Greece	0.04%	0.04%	0.02%	0.02%	0.03%	1.73%	1.66%
Hungary	0.04%	0.07%	0.26%	0.19%	0.11%	1.57%	1.46%
Iceland	0.00%	0.00%	0.00%	0.00%	0.00%	2.37%	2.25%
Ireland	0.02%	0.04%	0.13%	0.03%	0.04%	2.18%	2.61%
Israel	0.12%	0.76%	0.56%	0.32%	0.43%	1.89%	1.55%
Italy	0.96%	0.76%	1.21%	1.80%	1.13%	1.71%	1.46%
Japan	38.12%	17.46%	20.65%	14.74%	23.36%	2.16%	1.67%
Korea	1.11%	1.81%	4.64%	1.10%	1.71%	1.78%	1.45%
Luxembourg	0.03%	0.01%	0.01%	0.08%	0.03%	6.35%	4.87%
Netherlands	0.25%	0.79%	1.83%	1.26%	0.85%	2.48%	2.33%
New Zealand	0.08%	0.10%	0.14%	0.06%	0.09%	1.72%	3.30%
Norway	0.02%	0.20%	0.10%	0.28%	0.16%	2.12%	2.34%
Poland	0.00%	0.02%	0.01%	0.09%	0.03%	2.27%	2.19%
Portugal	0.01%	0.02%	0.01%	0.02%	0.02%	1.04%	1.01%
Romania	0.01%	0.02%	0.04%	0.02%	0.02%	1.53%	1.41%
Singapore	0.01%	0.08%	0.26%	0.06%	0.07%	2.10%	1.65%
Spain	0.10%	0.34%	0.12%	0.25%	0.22%	1.46%	1.30%
Sweden	1.01%	1.16%	0.88%	0.92%	1.02%	1.67%	1.61%
Switzerland	0.48%	1.23%	0.78%	1.58%	1.04%	1.52%	1.30%
United Kingdom	1.87%	2.14%	1.57%	3.49%	2.35%	2.25%	2.07%
United States	38.28%	55.33%	52.55%	51.35%	48.85%	4.61%	3.96%
Total Developed	99.43%	98.61%	97.80%	97.75%	98.56%	77.97%	71.25%
Developing countries							
Argentina	0.02%	0.07%	0.00%	0.03%	0.04%	0.88%	1.48%
Brazil	0.04%	0.06%	0.04%	0.16%	0.08%	0.40%	0.80%
Chile	0.01%	0.01%	0.01%	0.09%	0.03%	0.70%	0.84%
China	0.19%	0.39%	1.48%	0.38%	0.44%	0.71%	0.74%
India	0.08%	0.22%	0.12%	0.38%	0.21%	0.21%	0.29%
Indonesia	0.00%	0.00%	0.00%	0.00%	0.00%	0.26%	0.43%
Iran	0.00%	0.01%	0.00%	0.02%	0.01%	1.13%	1.33%
Mexico	0.05%	0.04%	0.06%	0.28%	0.11%	0.83%	0.94%
Peru	0.00%	0.00%	0.00%	0.01%	0.00%	0.27%	0.38%
Philippines	0.01%	0.02%	0.11%	0.01%	0.03%	0.19%	0.30%
Russia	0.11%	0.38%	0.10%	0.47%	0.29%	3.05%	2.75%
Saudi Arabia	0.00%	0.04%	0.01%	0.10%	0.04%	3.00%	3.86%
South Africa	0.03%	0.10%	0.23%	0.31%	0.15%	1.73%	1.57%
Thailand	0.01%	0.03%	0.02%	0.00%	0.01%	0.50%	0.69%
Turkey	0.00%	0.01%	0.00%	0.01%	0.00%	0.70%	0.77%
United Arab Emirates	0.00%	0.01%	0.02%	0.00%	0.01%	7.46%	11.57%
Total Developing	0.57%	1.39%	2.20%	2.25%	1.44%	22.03%	28.75%

buildings and goods production areas of innovation compared to the transport and energy areas. The uneven distribution of green patents entails that our results will be mostly driven by the technological innovation process in the developed countries. However, we argue that, as developing countries still account for around a fourth of per capita emissions, their inclusion in our sample yields a more comprehensive analysis of the innovation-emissions relationship[35].

[35]Furthermore, developing countries are expected to experience an increase in their emissions level in the next decades due to economic growth (Capuano, 2018). Hence, the inclusion of these nations in our analysis is useful to draw policy implications.

4.3 Control Variables

The control variables are collected from the Quality of Government Standard dataset (2019 edition) and the World Development Indicators database. In detail, GDP per capita (constant 2010$) is used to account for the impact of economic growth on the environment. Furthermore, we have included the square of GDP per capita to capture the nonlinear relationship between economic growth and environmental quality, as highlighted by the EKC hypothesis. Trade openness, measured as the sum of exports and imports of goods and services as percentage of GDP, is included given its impact on environmental degradation (for a more detailed discussion, see Grossman and Krueger, 1991 and Managi, Hibiki, and Tsurumi, 2009). Total population data is used to account for the human footprint on the environment[36]. FDI inflows are included to control for the presence of the Pollution Haven hypothesis. Foreign capitals can foster economic growth, which in turn leads to an increase in carbon emissions. Fossil fuel energy consumption reports the percentage of energy that is produced using non-renewable resources[37]. Furthermore, energy consumption is strictly correlated to economic growth[38]. Finally, we include the level of democracy index *polity*, since democratic governments have higher levels of environmental quality (see, for example, Lægreid and Povitkina, 2018). The index ranges between 0 (least democratic) and 10 (most democratic).

Table 3: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
co_2_capita	9.069	6.938	0.378	63.313	1739
ghg_capita	12.78	14.91	1.363	322.633	1739
cc_transport	22.536	98.434	0	1321.314	1739
cc_energy	25.064	112.902	0	2191.538	1739
cc_buildings	7.649	33.78	0	489.089	1739
cc_goods	18.994	71.075	0	818.871	1739
cc_tot	74.243	302.025	0	4820.812	1739
wdi_gdpcap	25354.843	20791.44	263.231	113682.039	1626
wdi_sq_gdp	1074886192.321	1672560432.842	69290.359	12923606016	1626
wdi_trade	72.217	59.603	8.385	441.604	1615
wdi_pop	87.386	217.763	0.22	1351	1706
wdi_fdiin	3.001	8.790	-58.323	252.308	1570
wdi_fossil	77.908	18.782	10.255	100	1662
polity	7.806	3.026	0	10	1675

[36] For the sake of an easier interpretation of the coefficients, population is expressed in millions.
[37] These include oil, coal, petroleum and natural gas products.
[38] Some authors use the share of renewable energy instead of the fossil fuel share. However, due to data availability, we have opted for the latter one. At the same time, we do not use total energy consumption as a control variable in order to avoid any collinearity issue with the GDP variable.

4.4 Unit root and cointegration tests

Unit root tests are common practice in the time series literature, where a large T is available. Given the large time period examined in this paper, we test for the presence of unit roots by using the Im-Pesaran-Shin (IPS) and the Fisher-type tests. These two have the same null hypothesis, i.e. all panels contain a unit roots, but different alternative hypotheses. The IPS alternative hypothesis tests if some panels are stationary. On the other side, the Fisher-type alternative hypothesis is valid if at least one panel is stationary. We subtract cross-sectional averages in order to account for heterogeneity in the panel. Furthermore, both tests include one lag and no trend.

As we can see from Table 4 the variables present a mixed order of integration. In detail, the IPS test shows that only the FDI inflows variable is stationary in levels. The Fisher-type tests yields some different results. The FDI inflows, democracy index, transport, building and goods patents variables are stationary in levels. The difference in results can be explained by the different alternative hypothesis of the tests. On the other side, all variables are stationary in first differences.

Table 4: Unit root tests

Variable	IPS	Fisher	IPS(1)	Fisher(1)
co2_capita	3.1519	3.0977	-15.5463***	-16.8769***
ghg_capita	1.6576	1.4820	-15.9453***	-17.2096***
cc_transport	na	-10.0836***	na	-29.5156***
cc_energy	7.4947	-0.6904	-23.3895***	-24.6748***
cc_building	na	-5.9727***	na	-33.6337***
cc_goods	na	-5.4205***	na	-31.6006***
cc_tot	8.1420	1.1470	-23.0950***	-24.6808***
wdi_gdpcap	7.6306	6.6318	-14.2417***	-15.5378***
wdi_sq_gdp	10.4257	8.1111	-13.7455***	-15.0567***
wdi_trade	3.4857	3.5242	-22.5302***	-24.2785***
wdi_pop	6.0471	4.4821	-7.3974***	-8.0144***
wdi_fossil	1.8949	1.2107	-18.7087***	-20.1441***
wdi_fdiin	-5.2845***	-5.7792***	-26.9003***	-28.4171***
polity	na	-2.7519***	na	-18.1335***

Na=insufficient number of time periods to compute w-t-bar

Our unit root tests are concordant to the economic literature. Carbon emissions and GDP are usually described as non-stationary processes. Álvarez-Herránz et al. (2017) find evidence of I(1) series for both these variables. Similarly, Hossain (2012) argues in favour of non-stationarity in levels for carbon emissions, GDP and trade openness. On the other side, Ganda (2019) finds weak evidence of stationarity in the patent variable for a panel including OECD countries over the period 2000-2014. At the same time, the author finds that foreign direct investment inflows are stationary in levels, which is concordant to our results.

The presence of unit roots can yield to biased estimates if not properly accounted for. The issue can be solved if the I(1) variables are cointegrated. However, the cointegration tests showed contradicting results: the CO_2 variable presented lack of cointegration, while slightly significant cointegration was found for the GHG dependent variable[39]. For these reasons, we estimate our model using first-differenced variables.

5 Estimation result

The impact of technological innovation on carbon emissions is examined by using the number of patents related to climate change mitigation technology. As previously discussed, we take advantage of the detailed disaggregation of our patent variable to decompose the analysis into specific areas of innovation. The chapter presents the results of the estimation strategy using the four different patent related variables: transport, energy, buildings and goods production technologies. Furthermore, an extra regression including the sum of our four indicators, i.e. *cc_tot* is carried out in order to capture the overall impact of climate change related technologies. For each patent variable, we run two regressions: the first one using CO_2 per capita emissions as the dependent variable and the second one using GHGs per capita emissions. First, we present our findings obtained by the baseline empirical strategy. Then, we divide the sample in developed and developing countries as a robustness check. Finally, we compare the results with the previous literature.

5.1 Baseline estimation

The baseline estimation follows the model specified in Chapter 3. We run a regression with the same order of patent indicators for the two different dependent variables, i.e. CO_2 and GHGs per capita emissions. Tables 5 and 6 are organised as follows. Column 1 reports the impact of transport related technologies for CO_2 and GHGs emissions per capita, respectively. Column 2 illustrates the technological innovation impact in the energy production. Column 3 presents the effect of building related technologies on pollution. Column 4 illustrates the impact of technological innovation in the production of goods on carbon emissions. Finally, column 5 reports the overall impact of the entire range of climate change technologies obtained by the sum of the four variables. Given the different nature of the data, we will only comment on the sign and relative magnitude of the coefficients.

[39]We have decided to not include the results of the cointegration tests due to their inconclusiveness. A possible explanation on the lack of cointegration is the large persistence of unmodeled natural emissions (for a more detailed analysis, see Kaufmann, Kauppi, and Stock, 2006).

As expected, the relationship between green patents and emissions is heterogeneous. The patent variables estimated coefficients are all negative but vary in significance levels and magnitudes. Overall, technological innovation has a more significant and greater impact on GHG per capita emissions. This can be explained by the different types of emissions that are related to, for example, transport, production of goods and energy.

Table 5 reports the estimation results for the impact of green technologies on CO_2 emissions per capita. In column 1 the estimated coefficient for the transport patent variable has the expected negative sign, but it is not significant. On the other side, the estimated coefficient in column 2 is negative and significant at the 5 percent level. This entails that technological innovation in the energy sector effectively reduces CO_2 emissions. The buildings coefficient in column 3 enters with the expected negative sign, but it is not significant. Similarly, in column 4 the coefficient for patents in goods production is negative, but not significant and very small. Finally, column 5 reports the estimation results when using the sum of all the climate change related technology. As it can be seen, the coefficient is negative and significant at the 5 percent level[40].

The control variables enter with the expected signs. First, GDP per capita is significant at the 1 percent level and positive. This is in line with the previous literature findings: economic growth increases carbon emissions (see, for example, Saboori et al., 2014 and Muhammad, 2019). On the other side, the GDP per capita squared coefficient is negative and significant (at the 1 percent level), which confirms the EKC hypothesis. In fact, there is a nonlinear relationship between economic growth and CO_2. These results are concordant with the predominant literature (for a more detailed discussion, see Hu et al., 2018 and Zoundi, 2017). The trade variable enters with a positive, yet nonsignificant coefficient. Interestingly, the population variable (expressed in millions) has a negative and significant (at the 1 percent level) coefficient. This entails that as population grows, carbon emissions decline[41]. The fossil fuel energy consumption coefficient enters with a positive and significant sign. In fact, non-renewable energy consumption is one of the major contributors to carbon emissions. This is in line with the findings of Boontome et al. (2017), Dogan and Seker (2016) and Long et al.(2015). On the other side, the FDI inflows variable has a negative and significant (at the 5 percent level) coefficient, which entails that FDI inflows lead to a reduction in carbon emissions[42]. Finally, the level

[40]The comparison between the two significant coefficients, i.e. the energy and the total technological innovation illustrates how the former has double the impact in reducing carbon emissions. The result can be partly explained by the large degree of heterogeneity in the green patent variable in column 5.

[41]The finding can be partly explained by the fact that, since emissions are expressed in per capita, an increase in the population, i.e. the denominator, will reduce emissions.

[42]According to Cheng et al. (2019), FDI inflows have a two-fold impact on the environment: the

Table 5: OLS fixed effects estimation results for CO_2 emissions per capita

Variables	(1)	(2)	(3)	(4)	(5)
cc_transport	-0.000585				
	(0.000357)				
cc_energy		-0.000332**			
		(0.000127)			
cc_buildings			-0.000986		
			(0.00105)		
cc_goods				-2.00e-05	
				(0.000352)	
cc_tot					-0.000166**
					(6.59e-05)
wdi_gdpcap	0.000253***	0.000252***	0.000253***	0.000253***	0.000252***
	(4.48e-05)	(4.48e-05)	(4.49e-05)	(4.49e-05)	(4.48e-05)
wdi_sq_gdp	-1.23e-09***	-1.23e-09***	-1.24e-09***	-1.24e-09***	-1.24e-09***
	(3.97e-10)	(3.98e-10)	(3.99e-10)	(4.00e-10)	(3.98e-10)
wdi_trade	0.00599	0.00599	0.00599	0.00599	0.00599
	(0.00445)	(0.00446)	(0.00445)	(0.00446)	(0.00445)
wdi_pop	-0.0426***	-0.0425***	-0.0429***	-0.0424***	-0.0426***
	(0.00659)	(0.00655)	(0.00658)	(0.00644)	(0.00656)
wdi_fossil	0.105***	0.105***	0.105***	0.105***	0.105***
	(0.0268)	(0.0267)	(0.0268)	(0.0267)	(0.0267)
polity	-0.0149	-0.0149	-0.0150	-0.0151	-0.0149
	(0.0102)	(0.0102)	(0.0102)	(0.0102)	(0.0102)
wdi_fdiin	-0.00262**	-0.00262**	-0.00262**	-0.00262**	-0.00262**
	(0.00125)	(0.00125)	(0.00125)	(0.00126)	(0.00125)
Constant	0.0589	0.0623	0.0614	0.0601	0.0613
	(0.0478)	(0.0488)	(0.0489)	(0.0487)	(0.0487)
Observations	1,452	1,452	1,452	1,452	1,452
N	47	47	47	47	47
R-squared	0.296	0.296	0.296	0.295	0.296
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Hausman Test	22.20***	26.85***	23.09***	28.17***	24.48***

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

of democracy variable has a negative, yet nonsignificant coefficient.

Table 6 reports the estimation results for the impact of green patents on GHG emissions per capita. We follow the same empirical strategy used in Table 5. The results are similar to the ones discussed above. However, there is a general increase in the magnitude and in the level of significance of the estimated patent coefficients.

halo effect and the pollution haven hypothesis. The former entails a positive effect of FDI inflows, i.e. they lead to an improvement in the environmental quality of the country of destination. The latter implies the opposite, i.e. FDI inflows lead to an increase in the emissions due to scale effect. In our sample, the estimated coefficient shows the presence of the halo effect.

First, the transport related technology coefficient in column 1 has the same sign as previously, but it is now significant at the 5 percent level. Thus, technological innovation in the transport sector significantly reduces GHG emissions per capita. In column 2, the energy related patent variable has a slightly larger coefficient compared to Table 5. The patent variable coefficients in column 3 and 4 follow the same path as above, i.e. they are negative but not significant[43]. On the other side, the aggregated variable in column 5 is negative and significant (at the one percent level). Furthermore, the coefficient is larger compared to the case with CO_2 as the dependent variable. Finally, the control variables follow the same path as before.

The tables also display the Hausman test in order to evaluate the accuracy of our regression analyses. The Hausman test is performed by comparing the accuracy of the fixed effects model against the random effects model. The Null-hypothesis is that the two models do not significantly differ between each other. Given the significance of the test at the one percent level, we can safely reject the Null-hypothesis. Hence, the fixed effects model outperforms the random effects for all specifications.

As mentioned in Chapter 3, in order to check for the robustness of our empirical strategy we have proceeded to augment our baseline regression with the lagged dependent variable as an additional regressor. The results are showed in Table 2a and Table 3a in the Appendix. In line with our expectations, both the CO_2 and GHG lagged dependent variables enter with a non-significant coefficient[44]. Interestingly, the magnitudes of the green patent estimated coefficients slightly change. For example, both the *cc_energy* and the *cc_tot* coefficients are now larger compared to our baseline regression with CO_2 emissions per capita as the dependent variable. The comparison with GHG emissions per capita as the dependent variable follows the same path. The *cc_energy* coefficient is now larger, whereas the *cc_transport* is smaller.

[43]Interestingly, the *cc_buildings* estimated coefficient is larger compared to all the other patent variables for both the CO_2 and GHG estimations (however not significant). This goes somewhat against our expectations, since we would assume that the impact of improved energy efficiency in buildings has a smaller effect compared to, for example, improvements in the transportation or energy production sector.

[44]This confirms the hypothesis that the use of first differenced variables reduces the dynamics included in these variables. Furthermore, it proves that the use of a static model is appropriate given that the estimated lagged emissions coefficients are not significant.

Table 6: OLS fixed effects estimation results for GHG emissions per capita

Variables	(1)	(2)	(3)	(4)	(5)
cc_transport	-0.000808**				
	(0.000364)				
cc_energy		-0.000353**			
		(0.000154)			
cc_buildings			-0.00224		
			(0.00158)		
cc_goods				-0.000286	
				(0.000516)	
cc_tot					-0.000227***
					(8.23e-05)
wdi_gdpcap	0.000656***	0.000655***	0.000656***	0.000656***	0.000655***
	(0.000218)	(0.000218)	(0.000218)	(0.000218)	(0.000218)
wdi_sq_gdp	-3.44e-09**	-3.44e-09**	-3.44e-09**	-3.44e-09**	-3.44e-09**
	(1.31e-09)	(1.31e-09)	(1.31e-09)	(1.31e-09)	(1.31e-09)
wdi_trade	0.00721	0.00721	0.00722	0.00722	0.00721
	(0.00597)	(0.00598)	(0.00597)	(0.00598)	(0.00597)
wdi_pop	-0.0254*	-0.0253*	-0.0263*	-0.0252*	-0.0254*
	(0.0133)	(0.0132)	(0.0133)	(0.0132)	(0.0133)
wdi_fossil	0.0882***	0.0879***	0.0880***	0.0877***	0.0880***
	(0.0309)	(0.0308)	(0.0309)	(0.0308)	(0.0309)
polity	-0.0250	-0.0251	-0.0251	-0.0251	-0.0249
	(0.0281)	(0.0282)	(0.0282)	(0.0282)	(0.0282)
wdi_fdiin	-0.00554*	-0.00553*	-0.00553*	-0.00554*	-0.00554*
	(0.00314)	(0.00315)	(0.00314)	(0.00315)	(0.00314)
Constant	-0.186	-0.182	-0.182	-0.184	-0.183
	(0.131)	(0.132)	(0.131)	(0.131)	(0.131)
Observations	1,452	1,452	1,452	1,452	1,452
N	47	47	47	47	47
R-squared	0.245	0.245	0.245	0.245	0.245
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Hausman Test	27.96***	34.27***	29.54***	35.23***	31.31***

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5.2 Developed and developing countries

In order to further investigate the heterogeneous impact of green patents on carbon emissions, we divide our panel into two subsamples: developed and developing countries[45]. In fact, as previously discussed, the degree of technological innovation and its impact differs depending on the GDP level of a country. For example, the major innovators are developed nations, while emerging economies usually lack sufficient resources to invest in the development of such technologies. Furthermore, the adoption of new technologies is assumed to be wider in high-income economies, while developing countries usually lag behind. The following four tables illustrate the results of our empirical estimation. First, we report the regression results for CO_2 and GHG per capita emissions for developed countries. Second, the last two tables illustrate the results for the developing economies subsample.

Table 7 reports the estimated coefficients for the panel of developed countries using CO_2 emissions as the dependent variable. As expected, the division into the two subsamples yields some different results. The transport-related patent technology enters with the same (negative) sign, but it is now significant at the 5 percent level. On the other side, the energy and buildings patent variables enter with the expected negative sign, but they are not significant. Surprisingly, the *cc_goods* estimated coefficient is positive but not significant[46]. Finally, *cc_tot* estimated coefficient is negative but not significant.

The control variables follow the same path as our baseline model. The income variable enters with a positive and significant coefficient, while squared income coefficient is negative. Hence, the EKC hypothesis holds for this subsample of countries. Interestingly, now the *polity* coefficient is negative and significant at the 10 and 5 percent level. The negative sign partly confirms the hypothesis that democratic governments (in high-income countries) exert a positive role in reducing carbon emissions (similar results are found by Lægreid and Povitkina, 2018, for a panel of 156 countries).

Table 8 reports the regression results when using GHG emissions per capita as the dependent variable for the panel of developed countries. In line with our previous findings, only the transport related technology is significant (it is now at the 1 percent level). The *cc_goods* estimated coefficient is still nonsignificant, positive, but very small. As in our baseline regression, the magnitudes of the estimated

[45]We use the classification adopted by the UN World Economic Situation and Prospects report (2019) to divide countries according to the level of development. The developed countries subsample includes 31 economies, while the developing one includes 16 economies.

[46]The positive sign of the coefficient can be partly explained by the fact that the variable includes patents that improve energy efficiency in the production of goods. As highlighted by Yan et al. (2017), energy efficiency can also lead to an increase in energy consumption, which in turn increases emissions.

Table 7: Estimation results for CO_2 emissions per capita in developed countries

Variables	(1)	(2)	(3)	(4)	(5)
cc_transport	-0.000667**				
	(0.000280)				
cc_energy		-0.000237			
		(0.000174)			
cc_buildings			-0.00119		
			(0.00114)		
cc_goods				0.000200	
				(0.000395)	
cc_tot					-0.000144
					(8.57e-05)
wdi_gdpcap	0.000208***	0.000207***	0.000207***	0.000207***	0.000207***
	(7.33e-05)	(7.35e-05)	(7.32e-05)	(7.33e-05)	(7.34e-05)
wdi_sq_gdp	-1.00e-09*	-1.00e-09*	-1.00e-09*	-1.00e-09*	-1.00e-09*
	(5.60e-10)	(5.62e-10)	(5.61e-10)	(5.62e-10)	(5.61e-10)
wdi_trade	0.00556	0.00558	0.00559	0.00562	0.00558
	(0.00602)	(0.00604)	(0.00604)	(0.00607)	(0.00603)
wdi_pop	0.0493	0.0531	0.0517	0.0561	0.0529
	(0.0578)	(0.0553)	(0.0560)	(0.0560)	(0.0567)
wdi_fossil	0.145***	0.145***	0.145***	0.145***	0.145***
	(0.0305)	(0.0304)	(0.0305)	(0.0305)	(0.0305)
polity	-0.0586*	-0.0590*	-0.0596**	-0.0598**	-0.0588*
	(0.0289)	(0.0290)	(0.0289)	(0.0289)	(0.0290)
wdi_fdiin	-0.00231*	-0.00229*	-0.00230*	-0.00228*	-0.00229*
	(0.00124)	(0.00125)	(0.00125)	(0.00125)	(0.00124)
Constant	0.0928	0.0972	0.0965	0.0940	0.0962
	(0.0742)	(0.0754)	(0.0758)	(0.0755)	(0.0755)
Observations	925	925	925	925	925
N	31	31	31	31	31
R-squared	0.392	0.391	0.391	0.391	0.391
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

parameters are slightly larger compared to Table 7.

The following tables illustrate the findings for the developing countries subsample. Table 9 reports the regression results with CO_2 as the dependent variable. As expected, the change in sample yields different results compared to the panel with high-income economies. In fact, the transport related variable is not significant anymore. On the other side, the *cc_goods* variable now enters with a negative and significant coefficient at the 5 percent level. Hence, when comparing the two subsamples, our findings show a dichotomous effect of technological innovation in the production of goods. In column 5, the *cc_tot* estimated coefficient is now significant

Table 8: Estimation results for GHG emissions per capita in developed countries

Variables	(1)	(2)	(3)	(4)	(5)
cc_transport	-0.000776***				
	(0.000259)				
cc_energy		-0.000249			
		(0.000195)			
cc_buildings			-0.00200		
			(0.00177)		
cc_goods				3.60e-05	
				(0.000548)	
cc_tot					-0.000178
					(0.000113)
wdi_gdpcap	0.000229***	0.000229***	0.000229***	0.000228***	0.000229***
	(7.50e-05)	(7.52e-05)	(7.49e-05)	(7.50e-05)	(7.51e-05)
wdi_sq_gdp	-1.02e-09*	-1.02e-09*	-1.02e-09*	-1.02e-09*	-1.02e-09*
	(5.50e-10)	(5.53e-10)	(5.50e-10)	(5.53e-10)	(5.52e-10)
wdi_trade	0.00514	0.00517	0.00516	0.00520	0.00516
	(0.00586)	(0.00588)	(0.00587)	(0.00591)	(0.00587)
wdi_pop	0.0515	0.0563	0.0516	0.0604	0.0555
	(0.0723)	(0.0682)	(0.0719)	(0.0682)	(0.0705)
wdi_fossil	0.147***	0.146***	0.147***	0.146***	0.147***
	(0.0308)	(0.0307)	(0.0308)	(0.0308)	(0.0308)
polity	-0.0874*	-0.0879*	-0.0885*	-0.0885*	-0.0876*
	(0.0461)	(0.0461)	(0.0461)	(0.0461)	(0.0461)
wdi_fdiin	-0.00199	-0.00197	-0.00198	-0.00197	-0.00198
	(0.00117)	(0.00118)	(0.00118)	(0.00119)	(0.00118)
Constant	0.0802	0.0850	0.0858	0.0819	0.0843
	(0.0823)	(0.0833)	(0.0838)	(0.0833)	(0.0833)
Observations	925	925	925	925	925
N	31	31	31	31	31
R-squared	0.388	0.387	0.388	0.387	0.387
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

at the 10 percent level.

As illustrated by Table 10, the estimation strategy using GHG emissions as the dependent variable does not yield significant results for most of our variables of interest. In fact, only technological innovation in the production of goods appears to be slightly significant (at the 10 percent level). On the other side, the energy-related patents variable now enters with a positive, yet non-significant, coefficient[47].

[47] A similar finding is illustrated by Cheng et al. (2019). The authors find evidence of an increase in carbon emissions due to the development of green patents for the BRIICS economies. A possible explanation is the large heterogeneity of the patent indicator. In other words, the innovation in the energy sector in developing countries is not primarily directed towards low-carbon technologies.

Table 9: Estimation results for CO_2 emissions per capita in developing countries

Variables	(1)	(2)	(3)	(4)	(5)
cc_transport	-0.00324				
	(0.00508)				
cc_energy		-0.00242			
		(0.00424)			
cc_buildings			-0.000312		
			(0.00998)		
cc_goodsprod				-0.0135**	
				(0.00595)	
cc_tot					-0.00297*
					(0.00150)
wdi_gdpcap	0.000267***	0.000267***	0.000267***	0.000268***	0.000268***
	(6.90e-05)	(6.87e-05)	(6.93e-05)	(6.77e-05)	(6.86e-05)
wdi_sq_gdp	-1.29e-09	-1.29e-09	-1.28e-09	-1.29e-09	-1.31e-09
	(1.12e-09)	(1.11e-09)	(1.13e-09)	(1.11e-09)	(1.11e-09)
wdi_trade	0.00701*	0.00702*	0.00703*	0.00714*	0.00698*
	(0.00355)	(0.00356)	(0.00352)	(0.00371)	(0.00355)
wdi_pop	-0.0266***	-0.0272***	-0.0258***	-0.0282***	-0.0303***
	(0.00540)	(0.00602)	(0.00475)	(0.00559)	(0.00603)
wdi_fossil	0.0303**	0.0302**	0.0303**	0.0304**	0.0301**
	(0.0110)	(0.0110)	(0.0110)	(0.0111)	(0.0110)
polity	0.00130	0.00117	0.00140	0.00242	0.00127
	(0.00970)	(0.00973)	(0.00964)	(0.00986)	(0.00966)
wdi_fdiin	-0.0256	-0.0255	-0.0254	-0.0253	-0.0255
	(0.0184)	(0.0183)	(0.0183)	(0.0184)	(0.0184)
Constant	0.0612	0.0628	0.0584	0.0636	0.0719
	(0.0410)	(0.0417)	(0.0428)	(0.0398)	(0.0428)
Observations	521	521	521	521	521
N	16	16	16	16	16
R-squared	0.247	0.247	0.246	0.250	0.248
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: Estimation results for GHG emissions per capita in developing countries

Variables	(1)	(2)	(3)	(4)	(5)
cc_transport	-0.00514				
	(0.00880)				
cc_energy		0.00125			
		(0.0110)			
cc_buildings			-0.00350		
			(0.0145)		
cc_goodsprod				-0.0160*	
				(0.00878)	
cc_tot					-0.00279
					(0.00337)
wdi_gdpcap	0.000992***	0.000991***	0.000991***	0.000992***	0.000992***
	(0.000134)	(0.000134)	(0.000134)	(0.000133)	(0.000134)
wdi_sq_gdp	-3.33e-09	-3.31e-09	-3.32e-09	-3.32e-09	-3.34e-09
	(3.81e-09)	(3.83e-09)	(3.81e-09)	(3.80e-09)	(3.82e-09)
wdi_trade	0.0107**	0.0108**	0.0107**	0.0109**	0.0107**
	(0.00402)	(0.00400)	(0.00395)	(0.00411)	(0.00399)
wdi_pop	-0.00673	-0.00444	-0.00679	-0.00832	-0.00959
	(0.0164)	(0.0195)	(0.0163)	(0.0157)	(0.0179)
wdi_fossil	0.00313	0.00327	0.00315	0.00323	0.00296
	(0.0239)	(0.0238)	(0.0240)	(0.0240)	(0.0239)
polity	-0.0155	-0.0153	-0.0154	-0.0142	-0.0155
	(0.0316)	(0.0323)	(0.0317)	(0.0316)	(0.0316)
wdi_fdiin	-0.142	-0.142	-0.142	-0.142	-0.142
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
Constant	-0.311	-0.318	-0.311*	-0.309*	-0.303
	(0.180)	(0.189)	(0.174)	(0.175)	(0.183)
Observations	521	521	521	521	521
N	16	16	16	16	16
R-squared	0.344	0.344	0.344	0.344	0.344
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6 Discussion

The hypothesis of a reduction effect in emissions due to technological innovation is confirmed by our findings. The empirical investigation shows heterogeneous effects of green innovation on environmental quality. However, we observe some common trends. First, *cc_tot* enters with a negative and significant (at the 1 percent level) coefficient in both our baseline specifications. Second, green innovation has a greater impact in reducing GHG emissions, compared to CO_2 emissions. This can be explained by the more inclusive measure of emissions represented by the GHGs dependent variable. In fact, as already discussed, these technologies aim at reducing various types of emissions. Third, the transport and energy related technologies have the largest and most significant impact in the reduction of emissions. On the other side, we find low significant effects from innovations in the production of goods or in the improvement in buildings energy efficiency. These findings are to be expected, since transportation and energy production account for a large share in the global emissions (Edenhofer, 2015). Furthermore, as illustrated in Figure 1, the number of granted patents in the energy and transport sector is significantly larger than the other two areas of innovation. However, considerable care should be exercised when investigating the impact of green innovation on environmental quality. In fact, not all technologies have a positive effect in reducing carbon emissions. Improvements in energy efficiency can also lead to an increase in production and thus to an offset in the benefits accrued from mitigating the impact of economic activities (Z. Yan et al., 2017).

This paper provides additional support for the positive relation between green patents and environmental quality. Overall, our findings are in line with the previous literature. For example, the heterogeneous effect of green innovation is also highlighted by Wang et al. (2012). The authors find evidence of a significant reduction in CO_2 emissions stemming from the development of carbon-free energy technologies, but not from less carbon neutral technologies. Similarly, Weina et al. (2016) find evidence of an increase in environmental quality due to green innovation[48]. In detail, technological innovation has a significant impact in the reduction of total CO_2 emissions. Yan et al. (2017) find evidence of a nonhomogeneous relationship between technological innovation and carbon emissions. Specifically, only patents related to low-carbon technologies are found to significantly reduce CO_2 emissions, while other environmental related technologies have a nonsignificant impact[49]. The positive effect of energy related innovation on carbon emissions is also illustrated by Jin et al. (2017) for the case of China. The authors find evidence of a reduction in emissions due to technological development aimed at fostering energy efficiency in the energy sector.

In contrast, the study conducted by Cheng et al. (2019) shows opposite results. Technological innovation leads to an increase in carbon emissions in OECD countries. However, the estimated coefficients are not significant. Heterogeneous findings are also illustrated by Mensah et al. (2018). Technological innovation reduces carbon emissions in some of the developed countries examined, while it increases CO_2 for

[48]In Wang et al. (2012), the analysis is carried out on a panel of Chinese provinces, rather than countries. Furthermore, there is a large degree of heterogeneity between regions. Weina et al. (2016) collect data from Italian provinces and use a STIRPAT in the estimation strategy.

[49]The insignificant impact of these technologies is attributed to their relatively low quality in inducing ground-breaking innovation. At the same time, the authors argue that these technologies might cause a rebound effect, which will increase the level of energy consumption and consequently, emissions.

some others. Fernández et al. (2018) find evidence of a reduction in emissions in developed economies, while the estimated coefficient of the technology variable enters with a positive and significant sign for China. In conclusion, the relationship between green patents and environmental degradation varies depending on the technologies and countries examined.

The lack of significant results in emissions reduction for the sample of developing countries is in line with Chen and Lei (2018). The authors find evidence of a greater impact in emissions reduction for high polluting countries. These findings can be explained by the linkage between economic growth, emissions and technology. As previously discussed, developed countries are the largest emitters, while at the same time they invest large resources in developing new technologies. Hence, green innovation leads to a greater reduction effect in these countries, compared to low emitters. Similar findings are presented by Cheng et al. (2019). The authors claim that the nonsignificant impact of technological innovation on carbon emissions can be explained by the lack of sufficient resources to implement these technologies on a large scale. In addition, restrictions in the technological diffusion between countries can hinder technologies adoption (Cheng, X. Ren, Zhen Wang, and C. Yan, 2019, p.9). For example, Mensah et al. (2018) argue that low degree of technological diffusion, lack of resources to patent technologies and intellectual property rights are some of the causes behind the limited impact of technological innovations in reducing emissions. In our case, the differences in significance levels for the emerging economies subsample can be explained by the relatively small number of patents developed by these countries. In fact, despite the contribution of some emerging economies, e.g. India and China, to the development of low carbon technologies has increased in the recent past, developed countries still account for 90 percent of total innovation (for a more detailed analysis, see Copeland, Žarnic, and Cervantes, 2018, p.9). Another possible explanation is that these innovations have a limited impact in reducing emissions, due to for example, their scarce adoption in the emerging economies. Unfortunately, we are unable to further examine the reason behind the low significance of our results due to the lack of detailed information on the quality of patents granted.

Our paper presents some limitations. As we have discussed in Chapter 2, despite patent data provides a more detailed measure of the technological innovation process, it presents some drawbacks. For example, for our analysis we have collected data on the number of granted patents by the US Patent and Trademark Office. As previously highlighted, the United States account for almost half of the total granted patents. This unbalanced distribution is to be expected given the source of our data, i.e. the USPTO. At the same time, given the high costs and cumbersome procedures that inventors have to face when submitting a patent file application, it is likely that the same innovation has been patented in the country of origin of the inventor (Popp, Juhl, and D. K. Johnson, 2003). The large discrepancy in patents granted between developed and developing countries is attributable to the fact that inventors from emerging economies might not have enough resources to file their patents at the USPTO. Thus, it can be argued that some inventions are still patented in the country of origin but are not included in our data[50].

Our investigation highlights the importance of technological innovation in reducing carbon emissions. Several authors have argued in favour for an increase in the global effort to develop more advanced technologies with the aim to reduce the impact of economic development on the environment (see among others, Popp, 2011 and Raiser, Naims, and Bruhn, 2017). In fact, technology together with drastic changes in our consumption patterns, is the major ally in reducing carbon emissions. Given that the energy and transportation sector showed the most significant results, R&D expenditures should be directed toward these areas of innovation. At the same time, as we have discussed, developing countries need a large economic support to develop and adopt cutting-edge technologies on a wider scale. Thus, a strong international coordination is needed to increase the global adoption of cleaner technologies and reduce carbon emissions. Furthermore, international cooperation is required to reduce the technological gap between developed and developing countries (Copeland, Žarnic, and Cervantes, 2018). The fast growth rates of emerging economies will undoubtedly exert an increasing pressure on the environment (Capuano, 2018). Yet, as highlighted by Andersson and Karpestam (2013), the mere adoption of technologies from developed countries might not be sufficient to reduce carbon emissions. This entails the need of large investments in the development of low-carbon technologies with a higher reduction potential compared to the ones already developed.

According to Raiser et al. (2017), green policies and intellectual property rights are paramount in the role of spreading technological innovation and its implementation. The role of patents is two-fold. First, since patents aim at protecting a technology, they incentivise innovation. Second, a patent grants a monopoly to the inventor, which is a barrier to technological diffusion (Raiser et al., 2017). The uneven distribution of climate change related patents shows the quasi-monopolistic position held by developed countries in the realm of climate change mitigation technologies (as argued, for example, by Dechezleprêtre et al., 2011 and Latif et al.,

[50] A more comprehensive measure of the global innovation process can be attained by using the Triadic Patent data from the OECD dataset. This includes all the patents filed at the three largest patenting offices, i.e. the USPTO, the EPO (European Patent Office) and the JPO (Japan Patent Office). However, this indicator only reports the number of patents applications and not the number of patents granted. Hence, given that granted patents provide a more meaningful and significant measure of technological innovation, we have opted for using the data from the USPTO. Further research should be directed toward a more comprehensive indicator of patent counts.

2011). Hence, top-down transfers of technology together with a global effort in the development of low-carbon technologies are paramount to generate a more effective action in mitigating the effects of climate change.

7 Conclusion

In our paper, we examined the relationship between technological innovation and emissions. The analysis was conducted on a sample of 47 countries over the period 1976-2012. In order to measure green innovation, we used the number of climate mitigation patents granted by the USPTO. We believe that granted patents provide a more relevant indicator of innovation compared to both R&D expenditures and number of patents applications. The empirical evidence based on the EKC framework showed a significant role of technological innovation in reducing both CO_2 and GHG per capita emissions. We also find evidence of a large heterogeneity in the impact of green technologies depending on the technological area examined. Similarly, the division of the sample into developed and developing countries provides additional support for the nonhomogeneous impact of technological innovation. The paper findings are in line with the previous literature. Our study however presents some limitations. The use of data from the USPTO entails that developed countries account for a disproportionally large share of total granted patents. Hence, this gap represents a shortcoming in a potential generalisation of our results, especially in the case of developing countries. Careful attention should be paid on the different impact of green innovation between low and high-income countries. Further investigations should rely on a more comprehensive indicator of technological innovation.

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Appendix

Table A1: List of selected countries

Argentina[a]	France	Luxembourg	Singapore
Australia	Germany	Mexico[a]	South Africa[a]
Austria	Greece	Netherlands	South Korea
Belgium	Hungary	New Zealand	Spain
Brazil[a]	Iceland	Norway	Sweden
Canada	India[a]	Peru[a]	Switzerland
Chile[a]	Indonesia[a]	Philippines[a]	Thailand[a]
China[a]	Iran[a]	Poland	Turkey[a]
Czech Republic	Ireland	Portugal	United Arab Emirates[a]
Denmark	Israel	Romania	United Kingdom
Estonia	Italy	Russia[a]	United States
Finland	Japan	Saudi Arabia[a]	

Note: *a* indicates developing countries

Table A2: OLS fixed effects estimation results for lagged CO_2 emissions per capita

Variables	(1)	(2)	(3)	(4)	(5)
L.co2_capita	-0.0435	-0.0437	-0.0435	-0.0435	-0.0436
	(0.0567)	(0.0568)	(0.0568)	(0.0568)	(0.0568)
cc_transport	-0.000453				
	(0.000321)				
cc_energy		-0.000420***			
		(0.000133)			
cc_buildings			-0.00115		
			(0.00103)		
cc_goods				-0.000198	
				(0.000356)	
cc_tot					-0.000179**
					(6.78e-05)
wdi_gdpcap	0.000261***	0.000261***	0.000261***	0.000261***	0.000261***
	(5.25e-05)	(5.24e-05)	(5.25e-05)	(5.26e-05)	(5.24e-05)
wdi_sq_gdp	-1.27e-09***	-1.26e-09***	-1.27e-09***	-1.27e-09***	-1.26e-09***
	(4.33e-10)	(4.34e-10)	(4.34e-10)	(4.35e-10)	(4.33e-10)
wdi_trade	0.00580	0.00580	0.00580	0.00581	0.00580
	(0.00464)	(0.00464)	(0.00464)	(0.00465)	(0.00464)
wdi_pop	-0.0440***	-0.0439***	-0.0444***	-0.0438***	-0.0440***
	(0.00657)	(0.00657)	(0.00659)	(0.00646)	(0.00658)
wdi_fossil	0.104***	0.104***	0.104***	0.104***	0.104***
	(0.0266)	(0.0265)	(0.0266)	(0.0265)	(0.0265)
polity	-0.0155	-0.0154	-0.0156	-0.0155	-0.0154
	(0.0105)	(0.0105)	(0.0105)	(0.0105)	(0.0105)
wdi_fdiin	-0.00270**	-0.00270**	-0.00270**	-0.00270**	-0.00270**
	(0.00133)	(0.00133)	(0.00133)	(0.00134)	(0.00133)
Constant	0.0413	0.0417	0.0409	0.0397	0.0414
	(0.0711)	(0.0710)	(0.0714)	(0.0708)	(0.0711)
Observations	1,421	1,421	1,421	1,421	1,421
N	47	47	47	47	47
R-squared	0.297	0.297	0.297	0.297	0.297
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A3: OLS fixed effects estimation results for lagged GHG emissions per capita

Variables	(1)	(2)	(3)	(4)	(5)
L.ghg_capita	0.0267	0.0268	0.0267	0.0267	0.0267
	(0.0331)	(0.0332)	(0.0331)	(0.0331)	(0.0332)
cc_transport	-0.000680**				
	(0.000323)				
cc_energy		-0.000419***			
		(0.000155)			
cc_buildings			-0.00231		
			(0.00154)		
cc_goods				-0.000364	
				(0.000515)	
cc_tot					-0.000228***
					(8.43e-05)
wdi_gdpcap	0.000646***	0.000645***	0.000646***	0.000646***	0.000646***
	(0.000224)	(0.000224)	(0.000223)	(0.000224)	(0.000224)
wdi_sq_gdp	-3.38e-09**	-3.38e-09**	-3.38e-09**	-3.38e-09**	-3.38e-09**
	(1.34e-09)	(1.34e-09)	(1.34e-09)	(1.34e-09)	(1.34e-09)
wdi_trade	0.00701	0.00701	0.00701	0.00701	0.00701
	(0.00604)	(0.00604)	(0.00603)	(0.00604)	(0.00604)
wdi_pop	-0.0243*	-0.0241*	-0.0251*	-0.0240*	-0.0242*
	(0.0126)	(0.0125)	(0.0126)	(0.0125)	(0.0126)
wdi_fossil	0.0882***	0.0880***	0.0881***	0.0878***	0.0881***
	(0.0315)	(0.0314)	(0.0314)	(0.0314)	(0.0314)
polity	-0.0257	-0.0257	-0.0258	-0.0257	-0.0256
	(0.0290)	(0.0290)	(0.0290)	(0.0290)	(0.0290)
wdi_fdiin	-0.00538*	-0.00538*	-0.00538*	-0.00538*	-0.00538*
	(0.00317)	(0.00318)	(0.00317)	(0.00318)	(0.00317)
Constant	-0.297	-0.298	-0.297	-0.300	-0.298
	(0.225)	(0.225)	(0.225)	(0.225)	(0.225)
Observations	1,421	1,421	1,421	1,421	1,421
N	47	47	47	47	47
R-squared	0.247	0.247	0.247	0.247	0.247
Country FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1