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Research paper

The relationship between technology and emissions: Evidence from different income level countries and economic sectors

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A R T I C L E I N F O

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A B S T R A C T

Each economic sector contributes differently to carbon emissions; hence the environmental impact of technological advancement may also differ across sectors; even more so, the same economic sectors might perform differently in different economic environments in countries.

This study investigates the heterogeneous effect of aggregate and green technology on sectoral carbon emissions in a sample of 45 countries divided into three income categories (high-income, upper middle income, and lower middle income) between 1999 and 2018. The focus is on carbon emissions from five sectors (power, manufacturing, transport, petrol, and building). To do so, the two steps DIFF-GMM and the Feasible Generalised Least Square (FGLS) econometric methods are used. We proxied technological progress by four commonly used indicators (patents applications, R&D expenditure, ICT, and science and technology publications) and an aggregated one combining them.

For the full sample analysis, results show that aggregate technology increases carbon emissions in all sectors except the building sector. Renewable energy significantly lowers emissions from all sectors, except the petrol sector. Aggregate technology is positively associated with carbon emissions across sectors in upper-middle-income and lower-middle-income countries, while negatively for the manufacturing and building sector in high-income countries.

1. Introduction

In recent years, the impact of technological progress on the environment and the climate has received increasing attention in the literature (Asongu et al., 2017; Cheng et al., 2019; Churchill et al., 2019; Milindi and Inglesi-Lotz, 2021). While some studies suggest that technology reduces overall CO_2 emissions by reducing energy intensity, others are concerned about the positive effect of technological progress on energy consumption and economic growth, which translates to higher carbon emissions. The data can also support this intense debate. According to a 2015 report by the Global e-Sustainability Initiative (GeSI, 2015), mobile communications technology and the internet are making a considerable contribution to action on climate change. Analyses revealed that mobile phones and other telecommunications devices save more than 180 million tons of CO_2 emissions per year in the U. S. and Europe. This amount of carbon emissions is more than the one produced annually by the Netherlands (GeSI, 2015). The positive impact of technology on CO_2 emissions can be illustrated by the boom in shale oil production in the 2000s in the United States, for example.

Given the methods and results obtained by studies that have examined the relationship between carbon emissions and technological progress, several important points can be underlined. First, as discussed above, in general, a clear consensus on the effect of technological progress on CO_2 emissions has not yet been reached. This is due to several reasons, such as the differences in sampling, study periods, or the methods used to estimate the results. The definition and quantification of technological progress also constitute a major obstacle that does not allow having refined results. Measuring and quantifying technology is challenging. Most studies used only one indicator of aggregate technology or green technology to assess its impact on carbon emissions (Du et al., 2019; Gu et al., 2019). However, as Milindi and Inglesi-Lotz (2021) argued, a single indicator often only reveals a few facets of this complex relationship. Second, most of these studies are conducted on carbon emissions emitted at the country level. Still, the effects of technological progress on carbon emissions from different economic sectors are not broadly discussed in the literature. We argue that as all sectors do not contribute to CO_2 emissions at the same level, the impact of aggregate or green technology on carbon emissions might vary significantly

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across sectors. Some economic sectors may be more sensitive to technological advancement than others, possibly due to differences observed in their production process, financial capacities to induce and spread innovations, their vulnerability to the rebound effect, and their compliance with strict environmental laws (Milindi and Inglesi-Lotz, 2021; Alatas, 2021).

Not all economic sectors contribute to carbon dioxide emissions at the same level. Based on the 2014 IPCC report (IPCC, 2014a,b), the contribution of various global sectors to total carbon dioxide emissions is shown in Fig. 1. According to the IPCC (2014a, b), the electricity that comes from burning oil, coal, and natural gas is the largest source of greenhouse emissions (25 per cent). Agricultural activities and deforestation are the second-largest sources of greenhouse gas emissions (24 per cent). Twenty-one per cent of total emissions come from the industry sector. The transportation sector (road, air, rail, and maritime transportation) and the building sector (energy serves to supply heating and air conditioning systems for buildings and food cooking in homes) constitute 14 per cent and 6 per cent of total greenhouse gas emissions, respectively.

Thirdly, the impact of technology on sectoral CO_2 emissions has not yet been comprehensively investigated on different "income level" scales. Given that the responses to environmental challenges mainly depend on each country's financial capacity, it is necessary to look at this relationship in countries at different levels of development.

Based on these, this study aims to investigate the multifaceted and intricate relationship between technological progress and CO_2 emissions by sector. The study makes a contribution to the literature that has not made a consensus in this relationship appreciating various perspectives and the fact that the relationship also changes over time and under different socioeconomic conditions. This study offers also the analysis on the hypothesis that this relationship differs for various economic sectors. Such distinction is to be useful for policymaking as these sectors contribution to the total emissions also differ and hence, a suite of policies needs to be considered for each. This inquiry extends to considerations of financial capacity, innovation propagation, the rebound effect, and regulatory compliance.

Furthermore, this study aims to investigate the connection between technology and sectoral emissions across a range of income levels because it is well known that environmental responses are inextricably related to a nation's economic progress. Our research aims to provide a comprehensive knowledge of the complex relationships between technology, income, and sectoral emissions by exploring these factors, significantly adding to the ongoing academic conversation on environmental sustainability and technological advancement. Two main research goals serve as the framework for this study. First, it looks into how much sectoral CO_2 emissions are impacted by overall and green technologies. It also seeks to determine whether this impact differs amongst nations that are divided according to their level of income.

To answer this question, this paper uses the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) theoretical framework applied to five selected economic sectors: power, manufacturing, transport, petrol, and building (accounting more than 75% of total greenhouse gas emissions, IPCC, 2014a,b). The STIRPAT model, an expansion of the IPAT model published by Ehrlich and Holdren in 1971, is the theoretical foundation for this research. It was first put forth by Dietz and Rosa in 1997. The IPAT model claims that population, wealth, and technology are the three main determinants of environmental effect, though it lacks the ability to test hypotheses because it is an accounting identity. In order to allow for elasticity calculations while include an error term, Dietz and Rosa created the STIRPAT model. In this regard, the model investigates the relationship between carbon emissions and urbanization, GDP per capita, and technology, taking into account both conventional and environmentally friendly technology.

Econometrically, this study employs two methodologies to estimate the results: the two steps DIF-GMM estimator (1991) and the Feasible Generalized Least Square methodology (FGLS). The research is carried out on a panel of 45 countries divided into three income groups: 15 high-income countries, 15 upper-middle-income countries, and 15 lower-middle-income countries. The study period runs from 1999 to 2018. Countries are allocated to their respective income group according to the World Bank classification of income per capita (Lower-middle, \$1026 to \$3995; Upper-middle income, \$3996 to \$12375; High income, \$12376 or more). To constitute our dataset, we have followed the sampling methodology used by Milindi and Inglesi-Lotz (2021). We have selected in each income category, the 15 countries that have produced the most carbon emissions during the years 2000–2018

The contribution of this study to the literature is threefold.

Firstly, to the best of our knowledge, no other studies have examined the relationship between carbon emissions and aggregate and green technology in more than one sector. This allowed us to determine which sector aggregate technology and green technology significantly impact CO_2 emissions and the reasons that can explain such impact. It will also help policy-makers identify the sector where more efforts must be made in terms of technological advancement to curb the CO_2 emissions curve.

Second, using four direct and indirect measures of technological development – R&D spending, patents, ICT, Science and technology publications (direct measures), manufacturing value added, and education level – we create a composite indicator of aggregate technology. The composite indicator is created using principal component analysis techniques and incorporates the majority of the data from the six variables. A worldwide picture of the effects of technology on carbon emissions in each industry and for each country's income group is made possible by creating an index, which lowers the number of technical indicators while retaining as much information as possible.

Thirdly, this study examines the connection between sectoral carbon emissions and technological advancement in three nations with varying economic levels. Most studies limit their study to only two categories of nations: developed and developing nations. This could also have useful outcomes. However, given the wide disparities in per capita income levels between nations and the crucial role that income plays in the interaction between technology and the environment, it is necessary to look at this relationship in regard to various income levels. Suppose we take the example of four countries, Benin, Jordan, Argentina, and South Korea, with a GDP per capita of \$700, \$2000, \$8000, \$25000 in 2016. One can expect that the environmental impact of technology will be different in these four countries because, among other things, they have very different income levels.

The remainder of this paper is structured as follows: Section 2 briefly review the literature; Section 3 presents the theoretical model. Section 4 describes technology's influence on carbon emissions in each energy sector selected in this study. PCA estimation and methodology and the dataset are presented in Section 5. In Section 6, the econometric results are presented and analyzed. Section 7 concludes the study.

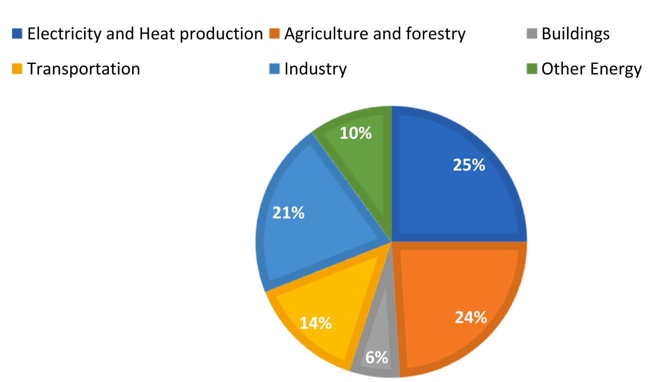

Fig. 1. GHG emissions by economic sectors.
IPCC (2014a, b) (2010 global emissions per sector) (IPCC, 2014a,b).

2. Literature review

Although many studies have been devoted to analyzing the relationship between technology and carbon emissions, less attention has been paid to examining the impact of technology on sectoral carbon emissions. Our literature review will be divided into four subsections. The first subsection summarizes recent studies investigating the nexus between technology and sectoral carbon emissions. The second, third, and fourth subsections present previous studies investigating the relationship between CO_2 emissions and economic growth, CO_2 emissions and urbanization, and CO_2 emissions and financial development. Hasanov et al. (2021) introduce a comprehensive theoretical framework to quantify the influence of technological progress, renewable energy consumption, and international trade on carbon emissions, distinguishing itself from prior research that often addresses these variables individually. Utilizing data from the BRICS countries spanning 1990 to 2017, the research accounts for panel data properties like integration, co-integration, cross-country interdependence, and heterogeneity, ensuring robust and grounded policy insights. The findings reveal that technological progress and renewable energy consumption contribute to carbon emission reduction, while GDP and import size increase pollution, emphasizing the importance of fostering technological advancements and sustainable energy transitions through regulatory measures and legislative frameworks. Gu et al. (2019) examine the complex relationship between China's energy technical development, energy use, and carbon emissions while considering a possible rebound impact. The results show an inverted U-shaped relationship between the development of energy technology and emissions, as well as a related trend for energy use. Turning points indicate an initial increase in emissions followed by a decrease, with the rebound effect continuing to have a favorable influence on emissions. Regional disparities are particularly noticeable in the direct and technical impacts of energy technological advancement on CO_2 emissions, which gives rise to useful policy suggestions.

2.1. Technology and sectoral carbon emissions

By evaluating how technological advancement affects carbon dioxide (CO_2) emissions in diverse sectors using national data for Pakistan from 1991 to 2017, Khan et al. (2020) quantile regression to identify sector-specific effects on emissions, demonstrating the negative effects of agriculture and services while highlighting the large contributions of the building, manufacturing, and transportation sectors. The study goes on to analyze emissions at the lower, middle, and upper percentiles, providing information about the distribution of impacts. Scenario studies provide useful direction for policymakers and planners looking to develop successful plans for emission reduction in the future by projecting probable CO_2 emission reductions in 2030, 2035, and 2040.

Erdoğan et al. (2020) investigated the impact of the innovation process on sectoral CO_2 emissions for 14 countries in the G20. The period of the study runs from 1991 to 2017. Patent applications are employed as a proxy for the innovation process. Results showed that innovations do not significantly impact carbon emissions from the energy and transport sector in the long term. However, innovation decreases carbon emissions from the industrial sector but increases carbon emissions in the construction sector. This paper is one of the scarce studies that have analyzed the effect of innovation on carbon emissions in different energy sectors (power sector, manufacturing sector, transport sector, and agriculture sector). Lee and Min (2015) analyze the impact of green R&D on carbon emissions and financial performance in Japan's firms. The researchers argued that existing studies have not clearly distinguished between R&D and green R&D and their influence on carbon emission and a firm's financial performance. They define green R&D as activities that promote operational efficiencies and eco-innovation in the production process. The results indicated that investment in green R&D negatively affects carbon emissions and positively affects the firm's financial performance.

Given that the construction industry is developing and expanding in developing countries, Erdogan (2021) proposed to analyze the effect of technological innovation on carbon emissions caused by the building sector in the BRICS countries between 1992 and 2018. After applying the Dynamic common correlated effects methodology, the findings indicated that technology innovation lowers carbon emissions from the building sector. Yang et al. (2021) have examined the impact of three technological progress channels (technology spillover from foreign direct investment, research and development expenditure, and interprovincial technology spillover) on carbon emissions from six energy sectors in China from 2000 to 2017. The authors argue that the relationship between technological progress on carbon emissions also depends on sectoral and regional heterogeneity. Therefore, they proposed a geographically and temporally weighted (GWR) model to estimate the results. After estimation, results revealed that R&D spending slows down carbon emissions caused by the industrial, agriculture and wholesale sectors.

However, R&D expenditure increases CO_2 emissions from the transportation, residential, and construction sectors. Li et al. (2021) have observed regional differences in green gas emissions in China's building sector. Therefore, they proposed investigating the drivers of carbon emissions in china's building sector at the provincial level. Results indicated that energy intensity, income, and energy mix explain regional differences in carbon emissions per capita in the building sector. Economic growth helps reduce regional disparities for residential buildings but does not significantly decrease regional disparities in public buildings. The authors conclude that energy intensity is the principal driver of emissions inequality in the building sector in China. Apergis and Payne (2017) extend the literature on the convergence of green gas emissions by investigating the presence of the convergence club of carbon emissions per capita, by sources of fossil fuel, and by sector of emissions, in 50 U.S. states for the period 1980 to 2013. After applying the Phillips and Sul club convergence approach, results revealed the presence of multiple convergence clubs in five sectors (electric power, commercial, transport, residential, and industrial). Carbon emissions convergence clubs have also been found for coal and natural gas. Sedat Alatas (2021) analyses green technology's impact on carbon emissions from the transport sector in 15 European countries. The period of the study ran from 1977 to 2015. The study considers that the increasing trend observed recently in the E.U. transport sector CO_2 emissions needs to be addressed by effective policies and strategies. They used the Common Correlated Effect Mean Group and the Augmented Mean Group to estimate the results empirically. Findings suggested that environmentally friendly technologies do have a significant impact on transport CO_2 emissions.

Robaina and Neves (2021) identify the main factors that explain variations in carbon emissions intensity in the E.U. transport sector from 2008 to 2018. The Complete Decomposition method has been used in this study to identify six different factors. Results identify two main drivers of carbon emissions intensity in Europe: change in total energy consumption (negative sign) and change in capital per inhabitant (positive sign). The authors argue that an adverse change in total energy consumption indicates that less and less energy is consumed in the transport sector due to more efficient motor vehicles. A positive change in per capita per inhabitant means that increasing carbon emissions in the E.U. is mainly driven by higher capital (mainly vehicles) per inhabitant. The authors proposed strengthening environmental regulations in the transport industries and promoting the development of electric vehicles. Isik, Ari, and Sarica (2021) use the Logarithmic Mean Divisia Index to identify the principal drivers of carbon emissions from the Turkish power sector. Findings indicated that energy efficiency has a negative but limited impact on power sector carbon emissions. However, changes in fossil fuel share have a bigger and more significant impact over time.

2.2. Economic growth and CO_2 emissions

The relationship between economic growth and carbon emissions has been extensively discussed in the literature. There is a consensus that economic growth has been related to environmental deterioration for decades (Hertin and Berkout, 2005; Bousquet and Favard, 2005; Sorrell, Dimitropoulos, and Sommerville, 2009). Greater economic growth leads to greater energy consumption to meet the growing energy demand of companies, industries, and households. Unfortunately, the energy developed and used globally is extracted mainly from fossil fuels. It is thus expected that economic growth will lead to higher CO_2 emissions.

However, as postulated by the Environmental Kuznets Curve (EKC) theory, many studies showed that economic growth is harmful to the environment in the early stages of development. But after reaching a certain level of wealth, economic growth would be accompanied by improved environmental quality (Borghesi, 1999). The enrichment of populations will meet the demand for a healthier environment, leading to higher standards and improved environmental quality in many areas (Shahbaz and Sinha, 2018). The EKC hypothesis has not yet reached a consensus in the literature. Some studies, such as Apergis and Ozturk (2015), have validated the EKC for 14 Asian countries. Jardón et al. (2017) have found similar results for 20 Latin America and Caribbean countries, and Kais and Hammami (2016) found support for the existence of an inverted U shape relationship between GHG emissions and economic growth for 58 countries from various regions between 1990 and 2012. In contrast, some other studies, such as the one by Holtz-Eakin and Selden (1995), Yang et al. (2015), and Narayan et al. (2016), did not find evidence of the EKC in their empirical results.

2.3. Urbanization and CO_2 emissions

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

2.4. Financial development and CO_2 emissions

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

This study differs from previous studies by constructing a technological progress index and evaluating its impact on sectoral carbon emissions in five primary sectors: power, manufacturing, transportation, petroleum, and the building sector. The paper also sheds some light on the role of technological progress induced by the private sector in successfully reducing CO_2 emissions in the manufacturing and building industries.

3. Theoretical framework

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

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

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

$$\mathrm{I} = \beta_i \mathrm{P}_{it}^{\theta} \mathrm{A}_{it}^{\alpha} \mathrm{T}_{it}^{\gamma} \mu_{it} \tag{2}$$

After log linearizing, the STIRPAT Eq. (2) takes the following form:

$$ln\mathrm{I}_{it} = \beta_i + \theta ln\mathrm{P}_{it} + \alpha ln\mathrm{A}_{it} + \gamma ln\mathrm{T}_{it} + \mathrm{u}_i + \mathrm{v}_{it} \tag{3}$$

In Eq. (3), *I* represents carbon emissions. *P* denotes population, represented in this study by urbanization (URB_{it}). *A* denotes affluence, represented by GDP per capita (GDP_{it}), and *T* stands for technology represented by aggregate and green technology (TECH_{it}). We augment model (5) by adding another important factor that can explain variations in carbon emissions: financial development ($\mathrm{FIN\_DEV}_{it}$). In addition, a quadratic term (GDP^2_{it}) is added to account for the potential nonlinearity association between carbon emission and GDP postulated by the Environmental Kuznets Curve (EKC) (Borghesi, 1999). Therefore, the final version of our theoretical model can be written as follows:

$$ln\mathrm{I}_{it} = \beta_i + \theta ln\mathrm{URB}_{it} + \alpha ln\mathrm{GDP}_{it} + \gamma ln\mathrm{TECH}_{it} + \mathrm{u}_i \quad + \omega\mathrm{FIN\_DEV}_{it} + \vartheta\mathrm{GDP}^2_{it} + \varepsilon_{it} \tag{4}$$

4. Overview of technological progress in each energy sector

This subsection describes technology's influence on carbon emissions in each energy sector selected in this study. Technology is an instrument that can be used to protect or damage the environment. So, we describe some channels by which technological development increases or decreases carbon emissions. The long-run impact of technology on CO_2 emissions often depends on balancing the technology's positive and negative effects (Milindi and Inglesi-Lotz, 2021).

4.1. Power sector

The way technology positively affects power sector carbon emissions can be split into two stages. The first stage is the generation of electricity. Most electricity generation technologies have been designed and constructed to produce electricity from fossil fuels (Hoffman, 2019). This is the case in coal-fired or oil and gas-fired power plants. Burning fossil fuels to satisfy the growing electricity demand of economies produces significant greenhouse gas emissions (IPCC, 2014a,b). The second stage is the utilization of electricity. Boosted by an increasing population and GDP, energy consumption continues to rise. A high standard of living translates into the acquisition of energy-intensive home appliances. Generally, the more prosperous and more developed people in a country are, the more emissions their lifestyle produces (Dietz and Rosa, 1997). So, on the one hand, technology raises CO_2 emissions, but on the other hand, technology can also serve as a tool to lower CO_2 emissions. It can negatively impact carbon emissions in the power sector through renewable energy development and the promotion of energy efficiency (IEA and IRENA, 2017). On one side, green technology's development allows for gradually replacing fossil fuel energies with clean energies such as solar, wind, hydraulic power, and nuclear. On the other side, energy efficiency brings energy savings by eliminating energy consumption waste (Hashmi and Alam, 2019; Gu et al., 2019). In the power sector, this mainly involves improving household appliances and the heating system, lowering device consumption in the house, and upgrading interior and exterior lighting systems. Therefore, in the power sector, technology can increase carbon emissions through the proliferation of fossil fuel power plants to meet the ever-increasing power sector energy demand. Technology can also lower CO_2 emissions through the expansion of renewable energies and the promotion of energy efficiency.

4.2. Manufacturing sector

Fig. 3 shows that the manufacturing sector is the sector that emits the most carbon emissions in upper-middle and lower-middle-income countries. This is not surprising because these economies are emerging, and their industries need the energy to expand their activities. The relationship between technology and manufacturing sector carbon emissions is similar to the one described in the power sector. Technology has a double effect on manufacturing sector emissions. First, the technology can increase CO_2 emissions in industries if most of the energy used in production comes from fossil fuels. Second, technology can reduce carbon emissions if industries progressively cut fossil fuel energy supply and increase clean energy usage. Industries can also embark on energy efficiency by identifying ways to use less energy to light and heat factories or run the equipment. Using natural gas instead of coal to run machinery, the former emits less CO_2 than the latter (IPCC, 2014a,b). Industries can also manufacture recycled materials rather than produce new products from raw materials (IPCC, 2014a,b).

4.3. Transport sector

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

4.4. Petrol sector

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

4.5. Building sector

Apart from construction operations, carbon emissions in the building sector are emitted through the heating, cooling, and lighting system (Bowen, 2021). These systems require a lot of energy to function. This situation can be improved using smart building technology and the internet of things which mitigate the amount of energy consumed (Bowen, 2021). The building sector has benefited greatly from digital and technical developments over the last few decades (Ahmed and Ridzuan, 2013). Several examples can be given to illustrate this. For instance, smart devices and sensors, which all share data and can be controlled from a central platform, can help determine when to increase or decrease power consumption and reduce the building's carbon footprint (U.K. Connect, 2021). An Internet of Things (IoT) platform provides energy-consumption analytics on use and overuse and the indicators of where adjustments are needed to save energy (Jones, 2020).

5. PCA estimation, empirical model, econometric methodology, and dataset

5.1. PCA estimation

We construct an index for aggregate technological progress using principal component analysis. In a similar fashion to the paper by Gupta and Modise (2012), using factor analysis, we extract one common factor from four indicators of technological progress, namely, patent applications, R&D expenditure, ICT, and science and technology publications. As shown in the correlation matrix presented in Table 1, these four variables are highly correlated, and extracting a common factor allows for solving the multicollinearity issue that may arise when all proxies of technology are included in the model (Jolliffe, 2002). Moreover, having one indicator of technological progress that encompasses most of the characteristics of several indicators will reduce the data's dimensionality, making the data analysis much easier and faster (Jolliffe, 2002). Many studies have shown that a country's quality and technology diffusion greatly rely on the quantity of a skilled labor force (Messinis and Ahmed, 2009; Toner, 2011). Achieving high academic standards for the largest proportion of school students within a country creates a workforce with greater potential to engage productively with innovation (Toner, 2011). To this end, the level of educational achievement is added to the index construction to reflect the quality of some technological proxies used in the study. For instance, the quality of patent application, and science and technology publication greatly dependent on the level of school education in a country (Milindi and Inglesi-Lotz, 2021) . In addition, we use manufacturing value-added as a share of GDP to reflect the level of industrialization. We argue that the more a country is industrialized, the more technology is needed, utilized, and spread. Therefore, the technological index will be a function of the following factors:

$$\mathrm{Tech\_index}_{\mathrm{it}} = \mathrm{f}(\mathrm{ICT}_{\mathrm{it}}, \mathrm{PAT}_{\mathrm{it}}, \mathrm{RD}_{\mathrm{it}}, \mathrm{Scien\_tech}_{\mathrm{it}}, \mathrm{Educ}_{\mathrm{it}}, \mathrm{MV\ A}_{\mathrm{it}}) \tag{5}$$

ICT_{it} denotes information and communication technology represented in this study by internet users per 100 people, PAT_{it} represent the number of patent applications per 1000 people, RD_{it} stands for Research & Development expenditure as a percentage of GDP, $Scien\_tech_{it}$ represent science and technology publication per 1000 people, $Educ_{it}$ represent the enrolment ratio in tertiary education, MVA_{it} stands for the manufacturing value-added as a percentage of GDP. The PCA procedure consists of five steps. First, the dataset is standardized so that each variable contributes equally to the analysis. Second, the covariance matrix is calculated for the whole dataset. The third step consist of calculating eigenvalues and eigenvectors of the covariance matrix. The number of eigenvectors is equal to the number of principal components, and the number principal component equals the number of variables included in the PCA estimation. Fourth, sort eigenvectors and their corresponding eigenvalues by ascended order, the highest to the lowest. In the fifth and last step, we multiply the original matrix dataset (the dataset that contains technological proxies) with the eigenvectors matrix to obtain the transformed matrix which constitute the matrix of index. An orthogonal transformation is performed to convert the set of variables correlated into a set of values of linearly uncorrelated variables (Jolliffe, 2002).

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

$$\mathrm{index} = [\mathrm{pc1} - min(\mathrm{pc1})]/[max(\mathrm{pc1}) - min(\mathrm{pc1})] \tag{6}$$

Where pc1 represents principal component one.

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

Fig. 2 displays the mean value of the technological index on the vertical axes and the mean value of total carbon emissions on the vertical axes from 1999 to 2018. As expected, high-income countries are more advanced in technology than upper-middle-income and lower-middle-income countries. In our sample, the US, South Korea, Australia, Germany, Canada, Japan, and the Netherlands have the highest average technological index of 80, 73, 72, 71, 68, 65, and 58, respectively.

Table 1
Correlation table of technological indicators.

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

5.2. Empirical model

A dynamic panel data approach is adopted in this study to examine how to aggregate and green technology impact sectoral carbon emissions. We employ a dynamic panel approach because many studies have established that carbon emissions depend on emissions from the last period and that environmental impacts present some dynamic sustainability (Kais and Sami, 2016; (Zhang et al., 2017)). The first-panel model will examine the effect of the aggregate technological index, obtained by summarizing the information in Eq. (5) on sectoral CO_2 emissions.

The first-panel model is as follows:

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

Where the subscripts i and t refer to countries and time. u_i is the unobservable country-specific characteristics and $v_{i,t}$ is the i.i.d. disturbance terms. SCE_{it} refers to sectoral carbon emissions in metric tons. Sectoral carbon emissions from the power sector ($Power_{it-1}$), the manufacturing sector ($Manuf_{it-1}$), the transport sector ($Transp_{it-1}$), the petrol sector ($Petrol_{it-1}$), and the building sector ($Building_{it-1}$). $X^{'}_{it}$ represents a vector of control variables, including GDP per capita (GDP_{it}), GDP per capita square (GDP^2_{it}), urbanization rate (URB_{it}) and financial development (FIN_DEV_{it}). $TECH_{it}$ is our variable of interest; it represents the aggregate technological index. Following the number of sectors, model (7) will be divided into five different sub-models, and this will allow us to estimate the long-run elasticities of each sectoral carbon emission with regard to the technological index:

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

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

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

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

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

The second-panel model will investigate the influence of green technology represented by renewable energy on sectoral CO_2 emissions.

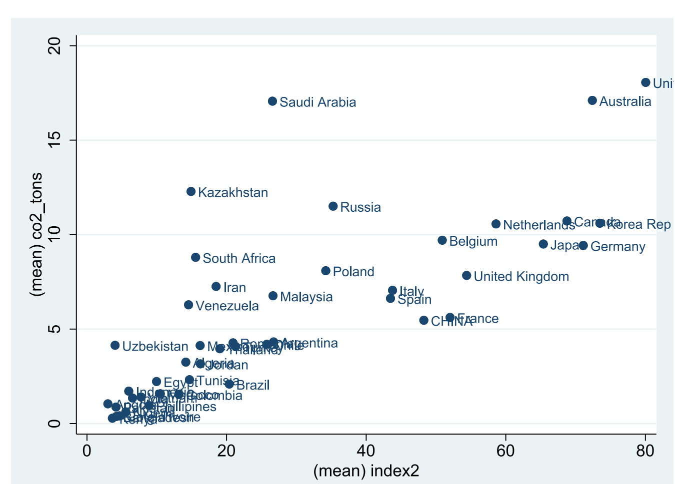

Fig. 2. Aggregate technological index.

$$lnSCE_{it} = ln(GTECH_{it-1})\delta + ln(TECH)_{it}\beta + X'_{it}\rho + u_i + v_{i,t} \quad (8)$$

Where $ln(GTECH)_{it}$ denotes green technology represented by renewable energy consumption.

5.3. Econometric methodology

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

Both the Feasible Generalized Least Squares methodology (FGLS) and the Two-Step System Generalized Method of Moments (2S-GMM) estimator are commonly used econometric methodologies for various reasons. The 2S-GMM estimator performs well in cases in which some independent variables are linked with the error term because it can handle endogeneity by employing lagged values as instruments. Additionally, it effectively uses the available instruments, producing accurate estimates even when only a few weak ones are used, and it is resistant to both heteroscedasticity and autocorrelation. In contrast, the FGLS approach is preferred when the traditional OLS assumptions are broken since it takes into account heteroscedasticity and autocorrelation through the use of optimal weighting matrices, producing parameter estimates that are more accurate. Furthermore, FGLS is especially well suited to dealing with serial correlation in time series data, offering reliable estimates in circumstances where other corrections might be less successful.

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

$$\Delta SCE_{i,t} = \sum_{s=1}^{s} \delta_s \Delta SCE_{i,t-s} + (\Delta TECH)_{i,t}\beta + \Delta X'_{i,t}\rho + \Delta v_{i,t} \quad (9)$$

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

$$E[SCE_{i,t-j}\Delta v_{i,t}] = 0 \quad \text{and} \quad E[X_{i,t-j}\Delta v_{i,t}] = 0 \quad (10)$$

$$for \quad t = s+2, \ldots, j \geq s+1 \quad (11)$$

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

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

5.4. Data

This study covers 45 economies consisting of 15 high-income, 15 upper-middle-income, and 15 lower-middle-income countries. The dataset provides a period of 20 years, from 1999 to 2018. In 2018, the 45 economies selected in this study represented 90 per cent of global GDP and 88 per cent of global CO_2 emissions (World Bank, 2019). The variables used in this study were collected from different sources. The descriptive statistics table for the full sample is presented in Appendix. Data on sectoral CO_2 emissions comes from the Emissions Database for Global Atmospheric Research (EDGAR, 2021). EDGARD estimates sectoral carbon emissions according to the classification guidelines proposed by the (IPCC, 2006) for national greenhouse gas inventories. CO_2 emissions (metric tons); GDP per capita (in constant 2010 US$), renewable energy consumption (percentage of total energy consumption), financial development (represented by the domestic credit to the private sector as a percentage of GDP), and urbanization (percentage of the total population) were drawn from the World Bank's Development Indicators (World Bank, 2019).

Fig. 3. shows the evolution of sectoral carbon emissions across income-group countries from 1999 to 2018 and the share of each sectoral carbon emission in total carbon emissions. The power industry is the first source of emissions in the full sample and the first in high-income countries. It can also be observed that emissions from the power, manufacturing, and building sectors are decreasing. In contrast, in high-income countries, emissions from the transport sector are pretty stable after 2009. The manufacturing industry is the first source of emissions in upper-middle-income and lower-middle-income countries. CO_2 emissions from all sectors are rising in these two groups of countries. However, it is essential to note that emissions from lower-middle-income countries have the steepest positive slope. It means the rate at which emissions increase is higher in lower-middle-income countries than in upper-middle-income countries.

6. Empirical results and discussion

We employ the following empirical strategy to check our dataset and estimate the results: First, we determine the order of integration of each

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

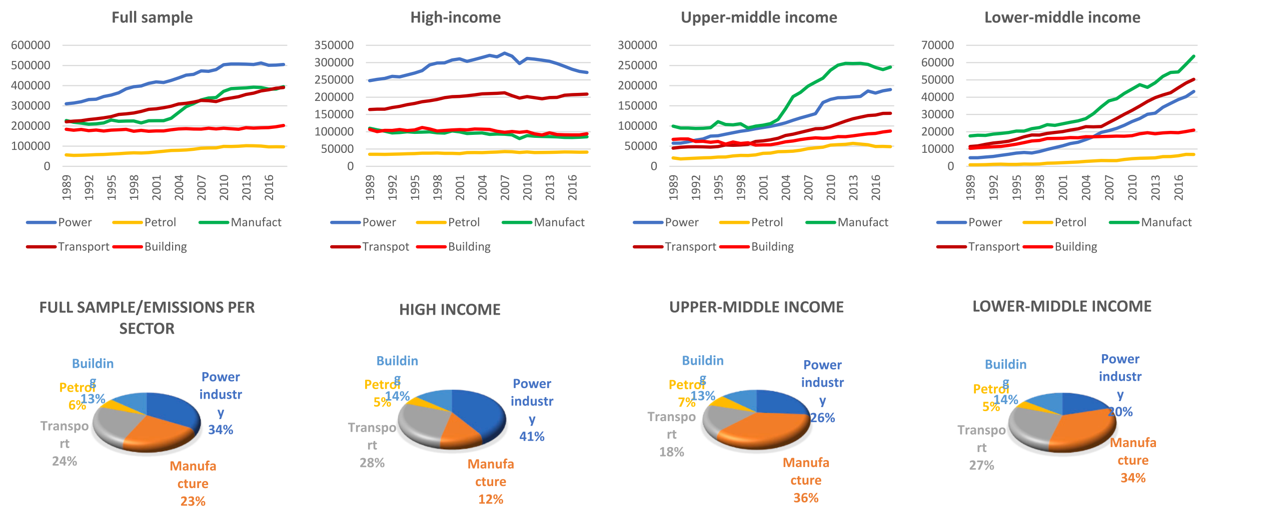

Fig. 3. Evolution of sectoral carbon emissions from 1989 to 2018 and share of emissions per sector in total CO_2 emissions.
Data used in this graph comes from EDGAR (2021).

variable included in our empirical model with different panel unit root tests proposed by Im, Pesaran, and Shin (IPS) (2003), Fisher-ADF (Augmented Dickey–Fuller) (Choi, 2001), and Fisher-PP (Phillips–Perron). Second, we investigate the cointegration in our model using panel cointegration tests proposed by Johansen (1999) and Pedroni (1999). Also, we check the presence of cross-sectional dependence using a Pesaran (CD) (2004), Frees (1995), and Friedman (1937) CD test. Third, we use a more appropriate estimation technique for short-period dynamic panel models with a high number of cross-sectional observations, namely the GMM methodology (Judson and Owen, 1999). We employ the FGLS methodology for robustness check, which allows controlling for heteroscedasticity, serial correlation, and cross-sectional dependence in data (Bai, Hoon Choi, & Liao, 2021).

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

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

Unit root test results are displayed in Table 2. Results show that for at least two types of unit root tests, we fail to reject the null hypothesis of unit root for all variables except renewable energy consumption and building sector carbon emissions. After differencing variables that are not stationary to eliminate the non-stationary trend, the results show that the null hypothesis of unit root is rejected at a 5 per cent level. Thus, it can be concluded that all variables are integrated into order one.

The cointegration test is performed by using the Westerlund (Westerlund, 2005), Pedroni (1999, 2004), and Kao (1999) tests. Cointegration in the models tested means that the results of the regressions are not spurious, and there is a long-run relationship among variables. The Kao and Pedroni test verified the alternative hypothesis that the variables are cointegrated in all panels. The Westerlund test checks the hypothesis that the variables are cointegrated in some or all panels.

Cointegration results are presented in Table 3. In the full sample, except for the Dickey–Fuller t-statistic in panel models (7b) and (7c) and the variance ratio in model (7a), all other t-statistics are statistically significant at least at a 10% level. Other sample cointegration tests (high-income, upper-middle, and lower-middle-income samples), which can be found in the Appendix, also exhibit similar results. Thus, our study concludes that cointegration exists in all sample models.

This study applies three different tests procedure to test the presence of cross-sectional correlation in the dataset, namely the Pesaran (2004), Frees (1995), and Friedman (1937) CD test. These tests are more

Table 2
IPS, Fisher-ADF, and Fisher-PP unit root tests.

Full sample						
Variables	IPS		Fisher-ADF		Fisher-PP	
	With trend	Differenced	With trend	Differenced	With trend	Differenced
$lnCE_{it}$	1.5606	−4.3002***	95.2055	83.3279***	100.77	155.66***
$lnPWR\_IND_{it}$	2.1271	−4.5643***	73.8950	90.1828***	124.79***	128.89***
$lnMANUF\_IND_{it}$	−0.1792	−6.0138***	115.672*	105.299**	99.6745	161.84***
$lnTRANSP\_IND_{it}$	5.1396	−1.9741***	70.8309	89.2264***	71.2893	92.631***
$lnPETRO\_IND_{it}$	1.5244	−5.0025***	98.9253	75.5956***	119.41**	153.02***
$lnBUILD\_IND_{it}$	1.3362*	−5.0649***	87.7577*	131.16***	121.83**	215.91***
$lnGDP_{it}$	3.6098	1.4042**	109.907	55.5775***	173.651	48.306***
$lnFIN\_DEV_{it}$	3.6072	6.4215***	2.8497**	9.87895***	8.75931	11.251***
$lnURB_{it}$	6.3822	6.8864***	19.4804	28.1855***	58.8921	30.8353**
$lnREN_{it}$	4.6751*	−2.7984***	84.7386	69.1020***	85.2476**	103.870**
$INDEX_{it}$	3.2451	3.6955***	111.636	76.6753***	96.2049	33.5493***

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

Table 3
Cointegration tests.

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

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

adapted to detect the presence of cross-sectional dependence in panels with many cross-sectional units and few time-series observations (De Hoyos and Sarafidis, 2006). Table 4 reports the results of the cross-sectional dependence test. The frees test indicates the presence of cross-sectional dependence in all empirical equations. However, the Pesaran detects cross-sectional dependence only in model (7a). De Hoyos and Sarafidis (2006) argue that Pesaran's test remains valid in dynamic panels under various estimation methods, including fixed effect and random effect (even if the estimated parameters are biased). Therefore, it may be the preferred choice since the properties of the other cross-sectional dependence tests in dynamic panels are not yet known.

6.2. Empirical results

This section estimates and discusses the impact of aggregate and green technology on sectoral carbon dioxide emissions. Aggregate technology is represented by a composite technological index developed in this study, following Higon, Gholami, and Shirazi's (2017) approach. Green technology is proxied by renewable energy following the approach of Nguyen and Kakinaka (2019); Milindi and Inglesi-Lotz, (2022). We apply the two steps DIFF-GMM, considered in this study as the benchmark model, because this methodology eliminates the Nickel bias, and it is more appropriate for the short-period panel dynamic model (Judson and Owen, 1999). The section is divided into two subsections. The first subsection examines the relationship between aggregate technology and sectoral carbon emissions in the full sample and the three subsamples (high-income, upper-middle-income, and lower-middle-income countries). We evaluate if the composite technological index influences the trend in CO_2 emissions in the power sector, manufacturing sector, transport sector, petrol sector, and building sector. In the second subsection, we examine the effect of green technology on sectoral $C0_2$ emissions. In the last subsection, we perform a robustness check of the results found in previous subsections using the FGLS methodology.

Table 4
Cross-sectional dependence test.

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

6.2.1. Aggregate technology and sectoral carbon emissions

(a) Power sector

The results from the two steps GMM estimator reported in Table 5 show that, in the full sample, aggregate technology increases carbon emissions in the power sector. A 1 per cent increase in technology increases CO_2 emissions by 0.011 per cent in the GMM model. The results are statistically significant at a 10 per cent level. It is not surprising that technology increases CO_2 emissions in the power sector globally. Fossil fuels are the most significant energy source for electricity generation (IEA, 2020b). In 2018, electricity generation from fossil fuels accounted for 65 per cent of total electricity generation (IEA, 2020b). The remaining 35 per cent belongs to nuclear and renewable energy. Even if there is a gradual decrease in the share of fossil fuels in electricity production in developed economies, many emerging countries continue to invest heavily in these energies to produce electricity (IEA, 2020b). And this is facilitated by the evolution of technology. Another important reason that can explain the positive association between aggregate technology and power sector CO_2 emissions is the lack of a competitive electricity market in the electricity sector. In many countries, notably in developing economies, electricity generation is entrusted to a state-owned company that has a monopoly on the production and distribution of electricity. The prevalence of state-owned companies in electricity production is based on the principle that energy is primarily a public good. As such, its management cannot remain in the hands of private companies. The main reasons for a monopoly in electricity production are the high initial costs of producing electricity on a regional or national scale and the need to find a "fair" price for consumers. However, several studies have shown that promoting competition in the electricity sector can be beneficial for reducing electricity costs and prices. It also benefits the environment by promoting energy efficiency (Hibbard et al., 2017).

In the GMM model, technology increases power sector carbon emissions in upper-middle and lower-middle-income countries. However, it does not have a significant effect in high-income countries. The nonsignificant impact of technology on carbon emissions in the high-

Table 5
DIF-GMM results estimations.

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

[a] Assume B1 is the coefficient on GDP, and B2 coefficient on GDP_SQ, the turning points are calculated using the following formula: T = exp ($-B_1/2B_2$).

income countries' power sector can be explained by the considerable disparity in the evolution of fossil fuel shares in electricity generation across countries. Some countries associate technological advancement with a greater investment in fossil fuels for electricity generation, while others favor renewable energies. During the previous decade, countries such as UK and Spain have sensibly reduced their dependence on electricity from fossil fuels. From 2008 to 2018, the share of fossil fuel electricity dropped from 80% to 47% in the UK and 61% to 41% in Spain (BP, 2021). Other high-income countries such as Germany and Italy have also experienced similar changes in their energy mix.

On the contrary, some countries have increased their production of fossil-fuel electricity. This share rose from 64% to 75% in Japan from 2008 to 2018. South Korea's share increased from 64% to 73% during the same period. Regarding other high-income countries selected in this study (e.g., France, Canada, Belgium, and Saudi Arabia), the share of fossil-fuel electricity has remained generally stable during our study period (BP, 2021). The intuition behind all these figures is that, in the electricity sector, technology development has been at the same time used to increase the exploitation of fossil fuel energy for electricity generation and to expand the development of renewable energy. So we have both a positive and a negative effect of the technology on the CO_2 emissions in this sector. This balancing effect has resulted in an insignificant impact of technology on sectoral carbon emissions from the power sector. The two effects seem to have the same magnitude and cancel each other out.

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

(b) The manufacturing sector

Results show that technology increases CO_2 emissions from the manufacturing sector in the full sample and upper-middle-income countries but decreases CO_2 emissions in high-income countries. The industrial sector requires a lot of energy, particularly in developing countries that have seen their energy demand explode in recent decades. Three main reasons can explain the positive coefficient of technology in the full sample. First, the growing energy demand from manufacturing industries in developing countries. Second, the reliance on fossil fuel energy to power these industries. The last main reason is the weak impact of measures taken by the industrial sector to lower energy consumption and, thus, reduce carbon emissions (Khoshnevis and Dariani, 2019).

Regarding high-income countries, technology turns out to have a negative impact on carbon emissions. High-income countries are progressively diversifying their energy supplies by increasing the share of renewable energies in the energy mix. The industrial sector seems to take advantage of this energy mix by favoring the supply of renewable energy instead of fossil fuel. Also, industrial equipment and machinery are constantly improved to make them more efficient. Promoting energy efficiency leads to identifying procedures and techniques that reduce energy consumption.[2] Therefore, it seems that in high-income countries, the negative effect of technology on carbon emissions has outweighed its positive impact, resulting in a negative relationship between technology and CO_2 emissions.

(c) **The transport sector**

Technology is positively related to carbon emissions in the transport sector in the full sample and upper-middle and lower-middle-income countries. The relationship between aggregate technology and transport sector carbon emissions is negative but statistically insignificant in high-income countries. We consider the main reason for this positive relationship is the insufficient stock of global low-carbon vehicles (electric vehicles, hydrogen vehicles, etc.). The stock of electric vehicles worldwide is far too low to affect carbon emissions significantly. In 2018, electric cars accounted for only 1 per cent of global car stock (IEA, 2020). Another reason is that energy consumption in the transport sector continues to increase despite technological innovations implemented to save energy and reduce combustion engines' carbon footprint. A typical illustration of this is the continued popularity of Sport Utility Vehicles (SUVs), offsetting some of the benefits of increased electric vehicles in the last decade (IEA, 2021a). The IEA (2021a) notes that despite the increased availability of electric SUV models and improved fuel efficiency in new SUV models, an average SUV still consumes around 20% more energy than medium-sized vehicles. This implies more carbon emissions as the sale of SUVs is on the rise worldwide.[3]

(d) Petrol sector

There is a positive and significant relationship between technology and petrol sector carbon emissions in the full and upper-middle-income samples. This relationship is also positive in high-income and lower-middle-income countries but not statistically significant. The petroleum industry is the sector that supplies other sectors with fossil fuel energy; unsurprisingly, technologies used in this sector are mostly directed towards the discovery of new oil and gas fields,[4] hence expanding petrol and gas production.[5] Green technologies used in this sector can only have a limited impact on CO_2 emissions. A promising technology that can allow extracting petrol or gas while not sending carbon emissions into the atmosphere is carbon capture and storage technology (Beuttler and Wurzbacher, 2019). There is still the challenge of developing this costly technology on a large scale to impact the petrol sector's carbon emissions significantly. Stopping routine flaring in the petrol sector is another important measure that should be implemented in the petroleum and gas extraction industries. Masnadi et al. (2018) note that burning unwanted gas associated with oil production – called flaring – remains the most carbon-intensive part of producing oil. According to Masnadi et al. (2018), eliminating routine flaring and cutting methane leaks and venting could cut as much as 700 megatons of emissions from the oil sector's annual carbon footprint - a reduction of roughly 43 per cent.

(e) Building sector

Aggregate technology significantly reduces carbon emissions in the building sector only in high-income countries. The relationship between aggregate technology and carbon emissions is statistically insignificant in all other samples. Some of the main reasons that decrease energy consumption and, thus, carbon emissions in high-income countries' building sector are as follows. Firstly, the growth rate of urbanization is relatively lower than other income groups, allowing the construction sector to also focus on building smart cities and renovating and refurbishing existing buildings with more efficient systems that can significantly reduce energy consumption. Secondly, energy-consuming building systems such as heating, cooling, and lighting systems in private homes, office buildings, and public buildings (schools, hospitals, campuses, etc.) are becoming more efficient with technological advancement. Thirdly, energy efficiency investment in buildings has constantly increased in high-income countries over the past decade. From 2015 to 2020, efficiency investment in Europe and the US building increases from USD 100 billion to USD 130 billion (IEA, 2021a).

(f) Consistency of estimates and other key drivers

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

Concerning other key drivers of sectoral carbon emissions, generally, GDP per capita elevates sectoral carbon emissions in all samples. Urbanization is positively related to sectoral carbon emissions in upper-middle and lower-middle-income countries. These results are consistent with Wu et al. (2016), who have demonstrated that a higher urbanization rate leads to higher carbon emissions in developing countries. In high-income countries, urbanization reduces sectoral CO_2 emissions. As Wang et al. (2021) noted, high-income countries progressively diversify and expand urban public transport, reducing the number of vehicles on the roads. The construction of smart cities also brings optimal use of energy sources. Efficiency and economy of scale in public infrastructure and well-functioning waste management also create a better environment (Moreno and Lee-Gosselin, 2011).

Financial development leads to higher carbon emissions in all samples except the lower-middle-income sample. In lower-middle-income countries, financial development seems negatively related to sectoral carbon emissions. However, this negative relationship is only statistically significant in the building sectors.

In terms of the presence of an inverted U-shape relationship between sectoral CO_2 emissions and GDP per capita in the full sample, the coefficients on GDP per capita and GDP per capita squared have the expected signs in the power, manufacturing, and building sector. Thus, supporting the presence of an Environmental Kuznets Curve in these three sectors. As mentioned above in the transport and petrol sector results subsections, we argue that the lack of EKC evidence in these two sectors is probably related to their nature. The petrol sector is primarily a carbon-intensive sector, and the transport sector dramatically relies on the consumer's individual choice of the type of vehicle to purchase. Despite income increase, solutions for carbon reduction have a limited impact on the petrol sector's CO_2 emissions. Although GDP per capita is increasing worldwide, electric vehicles are still expensive to attract middle-class consumers. Therefore, we think EKC will probably be

[2] Identifying the ways that manufactures can use less energy to light and heat factories or to run equipment. Industries can also switch to fuels that result in less CO_2 emissions but the same amount of energy, when combusted (e.g. using natural gas instead of coal to run machinery).

[3] The share of SUVs in total passenger car sales was around 40% in US, 20% in Europe, 30% in China, 25% in South Africa, and 30% globally (IEA, 2021a).

[4] The proved oil reserved in the world increased from 1277 billion of barrel in 1999 to 1736 in 2018.

[5] Oil production increased from 3448 million of tons in 1999 to 4500 tons in 2018. An increase of 30 per cent. Gas production went from 2310 billion cubic meters in 1999 to 3857 billion of cubic meters in 2018.

detected in the future thanks to technological advancements bringing game-changing solutions such as large-scale carbon capture storage in the petrol sector and cost-cutting technologies for electric vehicles.

6.2.2. *Green technology and sectoral carbon emissions*

Table 5 reports the GMM estimation results for model (4). Results reveal that renewable energy is associated with a decline in CO_2 emissions in all sectors except the petrol sector for the full sample. Subsample results estimation also reveals similar findings. Thereby endorsing the findings of Saidi and Omri (2020), Akram et al. (2020), and Dogan et al. (2021). The effect of renewable energy on sectoral carbon emissions is negative but becomes nonsignificant in many sectors in upper-middle and lower-middle-income countries. Generally, all samples show a nonsignificant relationship between renewable energy consumption and petrol sector CO_2 emissions. This result is not surprising because the petrol sector is naturally carbon-intensive; fossil fuels come from this sector. Also, as noted by the IEA (2020), carbon emissions from the petrol sector have been dramatically increasing over the past decades despite renewable energy development. While some regions have experienced a significant decline in oil extraction investments (e.g., Europe), other regions have increased their investments in gas extraction over the past decades (e.g., shale gas in the USA, gas extraction in Russia) (Azam et al., 2021). Gas is considered less polluting than other fossil fuels (Zárante and Sodré, 2009). So this suggests that the development of renewable energies has, for the moment, little influence on carbon emissions from the oil sector, which continues to develop, particularly with natural gas exploitation (see Table 6).

6.2.3. *Robustness check and extension*

(a) FGLS methodology

The FGLS results are reported in Table A.1 in Appendix. According to the diagnostic test results, problems of cross-sectional dependence are found in the dataset. The FGLS methodology allows controlling for cross-sectional dependence. In addition, it also deals with heteroscedasticity and serial correlation (Bai, Hoon Choi, & Liao, 2021). The results reported by FGLS are generally similar to those obtained with GMM. Generally, aggregate technological progress positively influences carbon emissions in all energy sectors, and green technology is associated with a decrease in carbon emissions (see Table A.2). FGLS also confirms that the technological index is negatively associated with CO_2 emissions in high-income countries' manufacturing and building sectors.

However, unlike the GMM, FGLS results suggest that Aggregate technology increases carbon emissions in the power sector in high-

Table 6
Estimation results for green technology.

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

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

(b) Extensions

In this subsection, we analyze further the results obtained in the high-income country's sample. Findings indicate that the technological index developed in this study decreases carbon emissions in the manufacturing and building sectors. These two sectors account for more than a third of total carbon emissions, and most companies that operate in these two sectors belong to the private sector. From the result obtained in Table 7, it can intuitively be deduced that enterprises take climate change challenges into account in their expansion strategies. They use the skills acquired through investing in technological progress to decarbonize the production process of goods and services. Model (8) is established to check this hypothesis. Model (8) aims to provide empirical evidence of the effects of business R&D expenditure on the manufacturing and the building sector CO_2 emissions in high-income countries. R&D expenditure is an essential upstream technology push instrument that helps develop, design, and enhance companies' products, technologies, and processes.

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

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

Model (8a) investigates the effect of manufacturing R&D expenditure on manufacturing carbon emissions, and model (8b) examines the influence of construction R&D expenditure on building sector carbon emissions. Data on these two distinct types of R&D expenditure comes from the OECD (2020). Period (a) refers to the full period (1999–2018), and period (b) refers to twelve years (2007–2018).

Table 7 shows that a 1 percent increase in manufacturing R&D spending decreases manufacturing carbon emissions by 0.10 percent. When taking 2004–2018, this reduction increases from 0.10 to 0.22 percent. Similarly, a 1 percent increase in construction sector R&D reduces building sector CO_2 emissions by 0.01 percent from 1999–2018 and 0.02 from 2004–2018.

This result demonstrates how the private sector is critical in climate mitigation and the transition to a low-carbon world. These findings suggest that companies are progressively integrating climate change and market opportunities that may arise from it among their priorities. In the manufacturing sector, it is done by progressive decarbonization of the production and supply chain processes. Also, by replacing the supply of fossil fuels with renewable energies, encouraging energy efficiency, and implementing a circular economy to optimize the use of materials and energy. Companies are seizing colossal investment opportunities in constructing green buildings and smart cities. Green buildings impact climate change and people's lives by reducing energy bills through innovative technics and technologies, such as solar panels and insulation. As an illustration, the Environmental Protection Agency (EPA) estimates that homeowners in the US can save an average of 18% on heating and cooling costs by making proper home insulation (EPA, 2021).

Table 7
Manufacture and building sector R&D results.

Two-step DIFF-GMM with orthogonal deviations				
Dependent variable: sectoral carbon emissions				
High-income sample				
	Period (a)		Period (b)	
	Manuf (8a)	Building (8b)	Manuf (8a)	Building (8b)
Lag term	.4202*** (8.64)	.6165*** (12.63)	.4838*** (18.7)	.5207*** (10.32)
GDP	.2507 (1.22)	.0931** (2054)	.5051*** (3.14)	.1136** (2.39)
Urbanization	−.3635 (−1.20)	−.5082** (−2.13)	−.2334** (−2.22)	−2.757** (−2.13)
Fin_Dev	.2614 (1.55)	.1538 (0.66)	.4303** (2.30)	.0358 (0.45)
R&D Man	−.1093** (−2.08)		−.2271*** (−12.65)	
R&D BUILD		−.0159*** (−3.02)		−.0201** (−2.45)

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

7. Conclusion

Global warming poses a serious threat to our ecosystem and our future. In this regard, reducing the use of fossil fuels by limiting energy consumption or improving energy efficiency is considered a critical path to combat climate change and environmental degradation. Among the main factors for reducing carbon emissions, technological progress's environmental impact has recently received considerable attention. A growing number of existing studies in the broader literature have examined the relationship between technology and CO_2 emissions. However, these studies have generally neglected differences in carbon emissions per energy sector. We argue that because each sector's contribution to total carbon emissions varies, the environmental impact of technological advancement may also differ across sectors. This study investigates the heterogeneous impact of aggregate technology and green technology on sectoral carbon emissions in 45 countries divided into three income categories (High-income, upper-middle, and Lower middle-income) between 1999 and 2018. The study uses the theoretical framework of the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) with sectoral carbon emissions as the dependent variable and technology, GDP per capita, urbanization, and financial development as explanatory variables. Five energy sectors are selected (The power sector, manufacturing sector, transport sector, petrol sector, and building sector). These five sectors generally account for more than 75% of carbon emissions across countries (IEA, 2020).

We employ principal component analysis to construct an aggregate technology index from four usual technological progress indicators (Patents, R&D expenditure, ICT, and science and technology publications). Renewable energy consumption is employed as an indicator of green technology development. We have adopted dynamic panel models and implemented two econometrics methodologies to empirically estimate the results: DIFF-GMM and the Feasible Generalized Least Square (FGLS) methodology. The full sample results indicate that, on the one hand, aggregate technology increases carbon emissions in the power sector, manufacturing sector, transport sector, and petrol sector. However, aggregate technology fails to affect the building sector's CO_2 emissions significantly.

On the other hand, renewable energy significantly lowers emissions in all five energy sectors. Findings also suggest that urbanization and financial development generally lead to higher carbon emissions in all sectors in the full sample. Results from subsamples indicate that, generally, aggregate technology is positively associated with carbon emissions in all sectors in upper-middle-income and lower-middle-income countries. However, aggregate technology is negatively related to carbon emissions in high-income countries' manufacturing and building sectors. We further demonstrate that technological progress induced by the private sector significantly reduces CO_2 emissions in these two sectors.

The results highlight the crucial role that private sector activities play in reducing climate change and accelerating the shift to a low-carbon global economy. From both short- and long-term perspectives, the reported decreases in carbon emissions linked to increased R&D spending in the manufacturing and construction sectors serve as an example of how firms are increasingly incorporating climate-conscious strategies into their fundamental priorities. This calls for a gradual decarbonization of production and supply chain operations in the industrial sector, a switch to renewable energy sources, and the promotion of energy efficiency and circular economy principles.

Regarding the control variables, it is concluded that income and financial development lead to more air pollution and environmental degradation in all samples. However, urbanization is positively related to CO_2 emissions in lower-middle-income countries but negatively associated with carbon emissions in high-income countries. These findings are similar to several studies that have found that urbanization can negatively influence the ecosystem (deforestation, air pollution, waste management, etc.) (Liddle, 2014; Wu et al., 2016; Khoshnevis and Dariani, 2019). Urbanization can also positively affect the environment by promoting public transport and reducing traffic congestion (Pachauri and Jiang, 2008; Barla et al., 2011).

This study also investigated the presence of EKC in sectoral carbon emissions in the full sample. We wanted to check if CO_2 emissions decline after reaching a certain income level. We found evidence of EKC in the power, manufacturing, and building sector. However, we could not find evidence of EKC in the transport and petrol sector.

The research's findings highlight how there are differences across industries and socioeconomic levels in how technology innovation affects emissions. Although the impact of aggregation technology on emissions in the power, manufacturing, transportation, and petroleum sectors may be cause for concern, its unfavorable impact on the construction sector points to the necessity for sector-specific initiatives. On the other hand, the large decrease in emissions brought on by the use of renewable energy sources emphasizes the significance of shifting to cleaner energy sources.

Using quantile regression to identify the impact of technical advancement on emissions within particular sectors, Erdogan et al. (2020) examine sectorial disparities within Pakistan. It demonstrates that whereas transportation, manufacturing, and construction all have a major impact on carbon emissions, agriculture and services have a negative impact on emissions. Contrarily, our study uses econometric techniques and a variety of technical progress indicators to examine the varied effects of technology development across 45 nations divided into income categories. It demonstrates that while overall technology raises emissions in the majority of sectors, renewable energy significantly lowers emissions, with varying effects depending on income level. Fundamentally, both studies stress the importance of technology, but their differences in breadth, concentration, and conclusions underline the necessity for sophisticated sector- and income-level-specific emissions reduction measures.

Some important policy implications can be drawn from these empirical findings.

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

(1) Concerning the power sector, the authorities should liberalize the electricity sector in addition to massive investments in renewable energies. This should be done especially in low-income countries, which often fail to meet the energy needs of their economies. Liberalizing the electricity sector will bring competition, encouraging the acquisition and adoption of innovative technologies and thus increasing energy efficiency in the power sector.
(2) Regarding the transport sector, the major solution is the development and deployment of electric vehicles. Even though the electric car market is rapidly expanding in high-income countries, it is still underdeveloped in the rest of the world. In general, one of the significant challenges in the transportation sector is the cost of buying an electric vehicle. The price of an electric vehicle is still much higher than a combustion engine one. These challenges can only be met through a collaborative effort between governments and industries. The government could adopt a set of incentive policies. Measures such as reducing taxes for the production of electric cars and — primarily purchase subsidies and/or vehicle purchase and registration tax rebates for consumers. Another major challenge for all countries is to invest in a sustainable network of charging stations and ensure that this network is powered by renewable energy.
(3) Carbon capture storage technologies (CCS) constitute a promising solution to reduce CO_2 emissions in the petrol sector. However, CCS projects require a lot of capital and a highly skilled workforce. Oil and gas companies, as well as other large emitters, will not invest in these projects if they significantly impact the profitability of their operations. It is also worth noting that many CCS technologies are either new or not commercially viable. Public R&D funding for emerging CCS technologies can help strengthen CCS development across countries and contribute to developing important future technologies. Governments should seek to strike the right balance between early-stage public investment in CCS projects and better regulation, with the ultimate goal of encouraging increasingly market-oriented CCS investment.

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

Thirdly, implementing effective emissions trading systems such as the European Union Emissions Trading System (EU ETS) across countries will also help to boost the competitiveness of carbon-neutral technologies compared to traditional technologies. A system where CO_2-intensive generation will gradually become more expensive due to the rising cost of emissions. This system will strongly encourage incentives for energy-intensive industries to shift to low-carbon technologies to remain competitive.

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

Table A.1
Descriptive statistic: full sample.

Variables	Observations	Mean	Stand dev	Min	Max
GDP per capita	899	15 502.76	17 088.77	508.3852	56 842.3
Financial credit (% GDP)	854	69.27214	48.66821	5.388089	221.2885
Urbanization	900	64.95143	19.54564	19.55	98.001
lnPWR_IND$_{it}$	900	156 920.4	374 663.2	113.85	2560374
lnMANUF _IND$_{it}$	900	108990	350 501.9	377.79	3039591
lnTRANSP _IND$_{it}$	900	111 087.4	255 247.4	1037.4	1772939
lnPETRO _IND$_{it}$	900	28 388.13	54 846.98	87.44	388 857.6
lnBUILD _IND$_{it}$	900	62 675.45	115230	36.26	680 413.8

Table A.2
FGLS estimation (Aggregate technology).

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

and enabling the growth of an environmentally friendly economy.

From a methodological standpoint, this study has a number of shortcomings. First off, the choice of proxy indicators for technological growth, such as patents, R&D investment, ICT, and publications in the field of science and technology, may not accurately reflect the intricate and varied character of technical development. Other factors that could have an impact on carbon emissions but were not taken into consideration by the models exist. We have tried to accommodate such issues by estimating the PCA index and considering the variety of these proxies. Additionally, the study ignores potential feedback loops and dynamic interactions with other environmental and economic issues in favor of concentrating solely on the effect of technological advancement and green technology on carbon emissions. It is crucial to recognize that this study does not fully represent the complex web of interconnected factors that the environmental impact of technology is embedded within. Future studies should delve into the specific type of technology and its impact for each of the sectors, taking into consideration their particular production techniques and type of energy used.

CRediT authorship contribution statement

Chris Belmert Milindi: Conceptualization, Methodology, Software, Data curation, Writing – original draft. **Roula Inglesi-Lotz:** Supervision, Visualisation, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

See Tables A.1 and A.2.

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