Technological Forecasting & Social Change 198 (2024) 123024

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

The effects of environmental innovations and international technology spillovers on industrial and energy sector emissions – Evidence from small open economies.

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A R T I C L E I N F O

JEL classifications:
O33
O44
Q54
Q5

Keywords:
Greenhouse gases
Emissions
Environmental technologies
Diffusion of technology
Nordics

A B S T R A C T

Environmental innovations hold promise for cutting greenhouse gas (GHG) emissions, but most technology investments are made in large technologically leading countries. Thus, emission reductions in small open economies, such as the Nordic countries, depend on not only domestic technological development, but also technology spillovers from foreign countries. The present study analysed how the development of climate change technologies affected the Nordic countries' GHG emissions from the industrial and energy sectors during a particular time frame. Consequently, while controlling for economic growth and population, domestic and foreign technological development's effects on industrial and energy sector GHG emissions were examined from the 1990–2019 period. The results revealed that both domestically developed environmental technologies and technology spillovers from foreign economies mitigated GHG emissions from these nations' energy and industrial sectors, thereby providing an efficient pathway to achieving sectoral environmental sustainability. In particular, domestic environmental technologies were found to be more efficient in driving environmental sustainability in the industrial sector, whereas impacts from domestic and foreign technological development did not differ significantly in the energy sector. Furthermore, given that economic growth plays a vital role in GHG emissions, environmental Kuznets curve (EKC; inverted U-shaped and U-shaped) relationships have been observed in the energy and industrial sectors, respectively. This suggests that the examined countries' industrial sectors have more environmental quality hurdles to overcome.

1. Introduction

The climate crisis and the urgent problems that it poses for Earth's natural systems and human societies are viewed as the largest global challenges of our time. Consequently, more and more countries are setting ambitious targets to become carbon neutral. Simultaneously, many countries have struggled to improve their populations' economic well-being. Within current environmental discourse, development and diffusion of environmental technologies are viewed as the most cost-effective ways to reduce environmental and climate pressures without compromising economic well-being. Thus, achieving carbon neutrality is expected to depend heavily on the development of new climate change mitigation technologies and the efficient transfer of these technologies globally (Popp et al., 2010; Popp, 2020). Simultaneously, economists have pointed out the risk of a rebound effect, i.e., that improvements in resource efficiency due to environmental innovation fail to elicit expected resource savings and environmental benefits, and may even lead to increasing resource use and environmental degradation in some instances, an effect also known as 'backfire' (Alcott, 2005).

Therefore, to shape climate policies, it is fundamentally important to clarify the impacts of environmental technological change on greenhouse gas (GHG) emissions. Accordingly, prior empirical studies have set out to analyse environmental technological development's effects on carbon dioxide (CO_2) and other GHG emissions (Du et al., 2019; Hashmi and Alam, 2019; Puertas and Marti, 2021; Toebelmann and Wendler, 2020; Yıldırım et al., 2022; Zhang et al., 2017). While these studies

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https://doi.org/10.1016/j.techfore.2023.123024
Received 15 April 2023; Received in revised form 11 September 2023; Accepted 12 November 2023
Available online 23 November 2023

generally have indicated that environmental innovations reduce emissions, the results have not been uniform and have not indicated climate benefits in all circumstances. Thus, more empirical evidence that analyses different contexts is needed. Moreover, although domestic technological development matters, how climate technologies diffuse internationally and how these technology spillovers impact emissions from receiving countries also are important. Theoretical studies have recognised the key importance of environmental technology spillovers (Gerlagh and Kuik, 2014; Hübler et al., 2012). Few empirical studies have analysed environmental technology spillovers' impacts on environmental productivity and emissions on the sectoral and regional levels, whereas other prior studies have examined trade or foreign direct investments (FDI) as indicators of knowledge transfer (Costantini et al., 2017; Jiao et al., 2020; Cui et al., 2022; Balsalobre-Lorente et al., 2022a). Nevertheless, extant literature is scant on international environmental technology spillovers' impact on country-level emissions. Finally, emission-reduction pathways differ across sectors, and sectoral characteristics need specific analyses (Erdoğan et al., 2020). These are empirical literature gaps that the present study aims to address.

The global diffusion of climate change technologies (CCT) is particularly important for small open economies, including the Nordic countries, that depend on international trade and foreign developed technologies, thereby magnifying the importance of using environment-related trade policy measures to curb potential diffusion of environmentally hazardous technological innovations. However, the Nordic countries also have set stringent targets to reduce their emissions and reach net zero emissions (OECD, 2016). Since these economies' pioneering implementation of energy taxation in 1990s, primarily to soften the effects from economic woes at the time, the countries have remained global leaders in terms of environmental policy stringency and green growth approaches. Notably, given the Nordic countries' administrative and governance characteristics in terms of transparency, decentralisation and rule-based governance (Sääksjärvi, 2020), a more consistent implementation of environment-related measures among these countries is not surprising. These measures have positioned the Nordic countries as prime research subjects through which to examine domestic and foreign environmental technological development's effects.

Globally, the energy and industrial sectors produce the most GHG emissions. Energy production is also crucial for countries' economic and social development. Furthermore, the industrial sector is highly relevant to economic growth in developed economies, given that the sector includes construction and manufacturing. Given the above motivation, this study examined the Nordic countries' GHG emissions from their industrial and energy sectors, and how domestic and foreign CCT development influences GHG emissions. To achieve the investigation's objective, we applied econometric approaches that include cross-sectional dependency, stationarity, cointegration tests and autoregressive distributed lag panel data set analysis that covers the 1990–2019 period in Denmark, Finland, Norway and Sweden. Using a novel perspective, the study contributes to prior empirical literature by examining domestic and foreign CCT spillovers' emission-reducing effects and how these effects differ across industrial and energy sectors. Furthermore, economic growth's role in GHG emissions from the energy and industrial sectors also is examined, thereby providing evidence of the environmental Kuznets curve's (EKC) (in)validity. This study also makes additional contributions by deploying the recently developed Granger causality approach, by Juodis et al. (2021), for robustness estimates. Moreover, the focus is on GHG emissions as an environmental indicator, rather than more commonly analysed CO_2 emissions.

The study proceeds as follows. Section 2 provides a literature review. Section 3 explains the data and empirical methods. Sections 4 and 5 present the investigation's results and conclude the investigation with policy recommendations, a discussion of the study's limitations and suggestions for future research directions.

2. Literature review

This section discusses the existing literature. The investigation's theoretical and modelling underpinnings are examined first, then several related empirical studies are discussed critically from the perspective of empirical approaches and results.

2.1. Theoretical literature

Environmental technological development is characterised by a double externality (Barbieri et al., 2016). First, environmental technological innovations help reduce negative environmental externalities from production and human activities. Second, like all innovations, they can produce positive knowledge spillovers that benefit other individuals and countries in addition to the initial innovator. The first externality implies that climate change technological development should lead to a reduction in CO_2 and other GHG emissions. However, the rebound effect and the Jevons paradox imply that part or even all of these climate gains may be offset, as an innovation that improves resource efficiency leads to a decrease in the effective price of that resource and, thus, demand and use of the resource will tend to increase (Alcott, 2005). Overall, large uncertainties surround macroeconomic rebound effects' size (Gillingham et al., 2016), implying that the environmental and climate impacts from environmental technological change are theoretically ambiguous and call for empirical research. Moreover, environmental technological development's second externality, positive knowledge spillovers, implies that environmental innovations also may make environmental and climate impacts in other countries aside from the original innovator.

The empirical research on environmental innovation's impacts dovetails with the environmental Kuznets curve (EKC) literature, following Grossman and Krueger (1995) and research on the IPAT model that Ehrlich and Holdren (1971) introduced. The EKC hypothesises an inverted U-shaped relationship between environmental indicators and per capita income. Despite the extensive literature on EKC, the validity of the hypothesis remains under scrutiny (Stern, 2017; Sarkodie and Strezov, 2019). Meanwhile, the IPAT model and its stochastic version, Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT), model the environmental impact as a function of population, affluence and technology (Dietz and Rosa, 1994; York et al., 2003).

2.2. Empirical literature

Following the theoretical literature lines, recent studies have investigated environmental innovations' impacts on emissions at national and regional levels. Most of these studies have relied on data on environmental or CCT patent applications, and in some cases R&D data. Generally, these studies have found that environmental patents help reduce CO_2 and GHG emissions (Hashmi and Alam, 2019; Puertas and Marti, 2021; Toebelmann and Wendler, 2020; Zhang et al., 2017). They analysed, e.g., European countries, Organisation for Economic Cooperation and Development (OECD) countries and Chinese provinces. However, other studies have provided more complex results. Weina et al. (2016) reported that while environmental patents have improved Italian regions' environmental productivity, they did not reduce the regions' CO_2 emissions. Yıldırım et al. (2022) demonstrated that green patenting makes a nonlinear impact on energy sector CO_2 emissions from OECD countries. Furthermore, Du et al. (2019) analysed panel data comprising 71 countries and reported that green patents do not reduce CO_2 emissions in low- and middle-income countries, but do so in high-income countries. Thus, the empirical literature has not yet reached a comprehensive consensus on the relationship between environmental technological change and GHG emissions.

Moreover, the second externality produced by environmental technological development, i.e., positive knowledge spillovers that impact other individuals and countries, has received considerably less attention in the literature analysing determinants of GHG emissions. The theoretical studies following the path of endogenous growth models have recognised technology spillovers' important role in emissions (Gerlagh and Kuik, 2014; Hübler et al., 2012), and international technology diffusion's role in the context of climate change has also been examined and noted generally (Popp, 2011). However, few empirical studies have examined this channel of impact in the CCT and emissions context.

Costantini et al. (2017) examined several European industrial sectors and reported that sectoral environmental patents, as well as domestic and foreign environmental technology spillovers from vertically related sectors, reduced sectoral emission intensity. Similarly, Ghisetti and Quatraro (2017), Jiao et al. (2018) and Jiao et al. (2020) found that environmental technology spillovers influence environmental and carbon productivity among vertically related sectors in Italy and China. While these studies have indicated that international or interregional environmental technology spillovers can be important in mitigating GHG emissions, we are not aware of studies that have analysed international environmental technology spillovers' effects on country-level emissions. In the energy efficiency context, Sun et al. (2021) found that international technology spillovers improve other countries' energy efficiency. Their analysis used patent data to measure technological innovation directly.

Some related studies have examined spillovers' role in general and have analysed their impacts on environmental or carbon productivity and energy intensity. Pan et al. (2020) interpreted outward foreign direct investment (FDI) as technology transfer and found that such transfers improve carbon productivity in Chinese provinces, while Zhou et al. (2019) reported that such technology spillovers make a positive, but very limited impact, on green total factor productivity in China. They also reported that the effects indicate large heterogeneity across provinces. Furthermore, Wang et al. (2021) examined Chinese provinces and found that international R&D spillovers influence environmental productivity. Pan et al. (2021) found that interregional technology spillovers reduce energy intensity in China, but that the effects depend on absorptive capacity. Similarly, Balsalobre-Lorente et al. (2022a) found that FDI dampens energy use, which indicates potential technology transfer. However, Cui et al. (2022) and Lv et al. (2021) reported mixed environmental impacts from FDI and trade openness among OECD countries and China.

Beyond the (aggregate) economy-level investigation of environmental-related R&D's role in carbon emissions, related sectoral perspective studies can be found in the literature (Jiao et al., 2018; Yang et al., 2021; Jiang et al., 2022; Kassouri and Alola, 2023). For instance, Yang et al. (2021) implemented an approach that combines geographically and temporally weighted regression (GTWR) and STIRPAT models to investigate how CO2 emissions are impacted across six sectors in China during the 2000–2017 period. Three aspects of technology spillovers were considered in the investigation, i.e., spillovers from international technology arising from FDI inflow, inter-provincial technology spillovers and domestic R&D investment. The investigation's results indicated that R&D investment hinders carbon emissions from the wholesale, industrial and agricultural sectors, but triggers carbon emissions across the residential, construction and transportation sectors. Furthermore, with the exception of the transportation sector, international technology spillovers arising from FDI worsen carbon emissions across the sectors. Moreover, the findings revealed that inter-provincial technology spillovers mitigate carbon emissions from the agricultural, construction and wholesale sectors, but worsen CO2 emissions from the transportation, residential and industrial sectors. In addition to technology-related indicators discussed above, economic (i.e., income) and other socioeconomic (i.e., population) factors also have proven to influence the economic sectors' environmental quality aspects (Chen et al., 2022; Balsalobre-Lorente et al., 2022b; Alola et al., 2023).

To sum up, most of the aforementioned studies analysed overall FDI impacts and largely failed to provide a clear distinction between environmental and nonenvironmental R&D. Moreover, the spillovers from different climate change technologies also have not been examined from sectoral perspectives. Considering this obvious literature gap, the present study contributes to the literature by examining the critical drivers of energy and industrial sector emissions given climate change technologies' development domestically and international spillovers alongside economic and socioeconomic factors.

3. Materials and empirical methods

In this section, the materials and empirical techniques employed for the investigation are described in detail. Specifically, the details on relevant data computations are presented first, followed by the preliminary and main estimation approaches.

3.1. Materials and computations

In this investigation of the Nordic countries (Denmark, Finland, Norway and Sweden), Iceland is excluded given data availability issues and the nation's seemingly heterogeneous characteristics compared with other Nordic economies. To achieve the study's objective, data on gross domestic product (denoted as *GDP* and measured in constant 2015 prices, expressed in U.S. dollars), population (denoted as *POP* and measured as the number of people in millions), energy sector GHG emissions[1] (denoted as *EGHG* and measured in thousands of tonnes), industrial sector GHG emissions[2] (denoted as *IGHG* and measured in thousands of tonnes) and patent application statistics were used to measure technological innovation as described in detail in the next section. The examined data set covered only the 1990–2019 period, given that patent applications are published with considerable time lags, which vary across applications. GDP and POP data were retrieved online from the World Bank database, and sectoral GHG emission data were retrieved from the Eurostat online database. The selection of variables was motivated by the previous literature, summarised in Section 2.2 (see, e.g., Costantini et al., 2017, Jiao et al., 2020, Chen et al., 2022; Balsalobre-Lorente et al., 2022b; Alola et al., 2023).

3.1.1. Computations

Climate change technology was measured using patent data, which was retrieved from the OECD's REGPAT database. Consequently, two distinct computations were made for domestic climate change technology stock (CC), which captures a country's climate change mitigation and adaptation technologies, and climate change technology spillover stock (SCC), which accounts for diffusion of climate change-related technologies from other countries to a country in question. Climate change patents were counted as the number of patent applications in technology classes Y02E and Y02P based on patent applications filed with the European Patent Office (EPO) (Angelucci et al., 2018).[3] Class Y02E comprises energy generation-, transmission- and distribution-related CC technologies, i.e., technologies related to the energy sector, and Y02P comprises CC technologies related to the production and processing of goods, i.e., technologies related to the industrial sector. Following prior studies, we relied on patent applications filed at the

[1] Energy sector GHG accounts for CO_2, N_2O in CO_2 equivalent, CH_4 in CO_2 equivalent, HFC in CO_2 equivalent, PFC in CO_2 equivalent, SF_6 in CO_2 equivalent and NF_3 in CO_2 equivalent.

[2] Industrial sector GHG emissions comprise emissions from industrial processes and product use (IPU), including mineral products, chemical industry, metal production, other solvent and product use, other industrial production, wood processing, production of POPs, consumption of POPs and heavy metals, other production and consumption, storage and transportation or handling of bulk products.

[3] This study considers energy sector- and industrial sector-related CC patents, not the broader category of environmental patents.

EPO, thereby avoiding problems tied to differing patent regimes in various countries and because Nordic countries are EPO members. Patents are allocated to countries based on the inventor's resident country. In the case of multiple inventors from several countries, fractional counting was applied to avoid double counting of patents.

Given that new technologies are expected to exert an effect over a longer period, the accumulated CC patent stocks using the annual patent counts were constructed. Thus, CCE and CCI stocks, i.e., domestic climate change-related technologies, were computed as follows:

$$\mathrm{CCI}_{it} = \mathrm{CCI}_{it-1} \text{ x } (1-\delta) + \mathrm{CI}_{it} \tag{1}$$

$$\mathrm{CCE}_{it} = \mathrm{CCE}_{it-1} \text{ x } (1-\delta) + \mathrm{CE}_{it} \tag{2}$$

in which CI and CE are the number of patent applications in year t in country i in industrial activity- and energy-related technologies, and CCI and CCE are the respective accumulated stocks. δ is the depreciation rate, which is set at 15 % (Hall et al., 2010). EPO patent data are available as early as 1978; thus, we did not estimate starting values separately, as our estimation period begins in 1990.

Moreover, climate change-related technologies' spillovers also were calculated. As technological innovations in one country diffuse over national borders, they create technology spillovers, which are expected to benefit countries beyond the country of origin. The computation of technology spillovers could be performed through a weighted (by imports, FDI or distance) or unweighted approach. Previous studies have indicated that knowledge spillovers occur between regions and countries situated near each other, and that spillover probability diminishes as distance increases. Thus, following prior studies (e.g., Costantini et al., 2013; Grafström, 2018), we adopted the distance-weighted approach. The distance-weighted spillover stocks for energy sector- and industrial sector-related climate change technologies, i.e., DSCCE and DSCCI, are computed as follows:

$$\mathrm{DSCCI}_{it} = \sum\nolimits_k d_{ik}\mathrm{CCI}_{kt} \tag{3}$$

$$\mathrm{DSCCE}_{it} = \sum\nolimits_k d_{ik}\mathrm{CCE}_{kt} \tag{4}$$

Table 1
Statistics of the variables.

	GDP	POP	EGHG	IGHG	CCE	CCI	DSCCE	DSCCI
Denmark								
Mean	2.69E+11	5,440,864.	51,127.37	2637.06	497.26	185.92	10.51	6.98
Median	2.77E+11	5,411,978.	53,751.49	2579.27	207.59	120.99	7.31	6.04
Maximum	3.35E+11	5,814,422.	74,038.28	3698.25	1459.41	481.81	22.24	13.11
Minimum	2.02E+11	5,140,939.	30,052.42	1835.17	28.12	22.93	2.62	2.59
Std. Dev.	3.74E+10	200,289.7	11,121.46	593.80	519.32	155.26	7.61	3.57
Skewness	−0.28	0.29	−0.29	0.27	0.66	0.60	0.51	0.42
Kurtosis	2.17	2.02	2.25	1.74	1.75	1.82	1.58	1.75
Jarque-Bera	1.25	1.60	1.11	2.36	4.15	3.54	3.80	2.85
Finland								
Mean	2.06E+11	5,264,458.	53,780.71	5888.27	128.13	127.44	6.75	4.23
Median	2.20E+11	5,237,134.	53,726.42	5803.24	66.10	108.50	4.58	3.62
Maximum	2.55E+11	5,521,606.	69,369.55	7696.77	307.91	256.32	14.80	8.16
Minimum	1.41E+11	4,986,431.	38,922.22	4704.42	21.11	26.71	1.54	1.47
Std. Dev.	3.85E+10	163,690.1	7917.34	724.87	113.10	82.40	5.06	2.26
Skewness	−0.49	0.12	−0.19	0.66	0.66	0.38	0.52	0.45
Kurtosis	1.73	1.82	2.35	3.27	1.66	1.62	1.60	1.78
Jarque-Bera	3.20	1.82	0.71	2.24	4.44	3.10	3.81	2.87
Norway								
Mean	3.21E+11	4,706,821.	35,855.79	11,194.24	81.04	46.83	9.11	5.72
Median	3.33E+11	4,607,601.	37,172.51	11,418.26	62.64	37.17	6.02	4.88
Maximum	4.06E+11	5,347,896.	39,687.40	15,376.57	175.09	86.67	20.10	11.05
Minimum	2.11E+11	4,241,473.	27,785.10	8371.14	5.86	13.62	2.09	2.01
Std. Dev.	5.92E+10	354,258.9	3353.136	1810.17	64.74	27.85	6.91	3.07
Skewness	−0.40	0.45	−1.18	0.23	0.26	0.17	0.54	0.45
Kurtosis	2.00	1.85	3.21	2.16	1.38	1.35	1.61	1.77
Jarque-Bera	2.02	2.67	6.99	1.14	3.61	3.56	3.87	2.92
Sweden								
Mean	4.04E+11	9,195,494.	47,276.63	7902.88	270.57	146.09	7.80	5.01
Median	4.10E+11	9,011,552.	48,743.80	7899.66	207.29	119.30	5.10	4.28
Maximum	5.50E+11	10,278,887	58,376.54	8948.81	514.48	325.72	17.45	9.62
Minimum	2.83E+11	8,558,835.	34,995.89	6387.09	81.12	54.66	1.67	1.70
Std. Dev.	8.42E+10	485,665.7	6573.75	622.73	151.74	84.08	6.07	2.71
Skewness	0.06	0.80	−0.43	−0.16	0.36	0.82	0.54	0.42
Kurtosis	1.76	2.51	1.94	2.65	1.60	2.42	1.61	1.72
Jarque-Bera	1.96	3.48	2.30	0.27	3.12	3.79	3.89	2.93
Panel								
Mean	3.00E+11	6,151,909.	47,010.13	6905.61	244.25	126.57	8.54	5.48
Median	2.89E+11	5,343,756.	48,091.79	7036.72	142.13	82.56	5.89	4.66
Maximum	5.50E+11	10,278,887	74,038.28	15,376.57	1459.41	481.82	22.24	13.11
Minimum	1.41E+11	4,241,473.	27,785.10	1835.17	5.86	13.62	1.54	1.47
Std. Dev.	9.28E+10	1,814,427.	10,290.94	3293.75	319.22	109.67	6.56	3.07
Skewness	0.64	1.09	0.17	0.27	2.29	1.33	0.68	0.68
Kurtosis	2.98	2.50	2.10	2.39	7.73	4.05	2.02	2.43

Note: Jarque-Bera statistics is the statistics for normality and std. Dev is the standard deviation.

in which d = 1/distance in kms between the capital cities of countries i and k, and CCI and CCE are the domestic CC technology stocks in country k in year t.

3.1.2. Descriptive statistics and correlation

These variables' common statistics for each country and the correlation statistics are presented in Tables 1 and 2, respectively. As observed in Table 1, the countries exhibited similar statistical properties across the data set. Clearly, and as presented visually in Fig. 3, GHG emission volume from the energy sector was significantly larger than from the industrial sector in all the countries and the overall panel. A similar pattern occurred with domestic CC technological development and foreign technology spillovers, in which climate change technologies in the energy sector were more abundant than in the industrial sector (see Figs. 1 and 2). Specifically, as depicted in Fig. 1, the disparity in energy and industrial domestic climate change technologies is more significant in Denmark. Moreover, the statistical evidence indicates that CCE, CCI, DSCCE and DSCCI are correlated negatively with EGHG and IGHG (see Table 2). While a negative correlation was found between EGHG and GDP, a positive correlation was found between IGHG and GDP. Meanwhile, population exhibited a positive association with EGHG, while the correlation between population and IGHG was not statistically significant.

3.2. Models and empirical methods

3.2.1. Empirical model

Given that this study examined economic growth's effects alongside domestic and foreign development of climate change technologies on energy and industrial sector GHG emissions, the investigation was designed to follow the empirical literature on the EKC hypothesis and STIRPAT model. The EKC hypothesises an inverted U-shaped connection between environmental indicators and income. Meanwhile, human impact on the environment is represented as a function of population, affluence and technology in a STIRPAT model (Dietz and Rosa, 1994; York et al., 2003).

In the present study, GHG impacts within this framework are modelled for the energy and industrial sectors as:

$$\text{Energy Model} : \text{EGHG} = f\ \{\text{GDP}, \text{GDPsq}, \text{POP}, \text{CCE}\ (\text{DSCCE})\ \} \tag{5}$$

$$\text{Industrial Model} : \text{IGHG} = f\ \{\text{GDP}, \text{GDPsq}, \text{POP}, \text{CCI}\ (\text{DSCCI})\ \} \tag{6}$$

and the respective econometric models are modelled as:

$$EGHG_{it} = \gamma_0 + \gamma_1 GDP_{it} + \gamma_2 GDPsq_{it} + \gamma_3 POP_{it} + \gamma_4 CCE_{it}/DSCCE_{it} + \epsilon_{it} \tag{7}$$

$$IGHG_{it} = \delta_0 + \delta_1 GDP_{it} + \delta_2 GDPsq_{it} + \delta_3 POP_{it} + \delta_4 CCI_{it}/DSCCI_{it} + \epsilon_{it} \tag{8}$$

in which CCE_{it} and $DSCCE_{it}$ in Eq. (7) and CCI_{it} and $DSCCI_{it}$ in Eq. (8) are incorporated into the respective models one at a time. Furthermore, i, t and ϵ stand for countries (i = Denmark, Finland, Norway and Sweden), period (t = 1990, 1991, 1992, …, 2019) and error terms, respectively.

3.2.2. Empirical methods

Given that this was a panel investigation, several preliminary tests were conducted ahead of the coefficient estimation. First, tests were conducted to investigate cross-sectional dependence (CSD) in the panel, i.e., for each variable and proposed model. This aimed to ascertain whether changes in macroeconomic, economic and/or socioeconomic factors in one country can impact those in another country. Therefore, a variable-wise CSD test was conducted following Pesaran (2021), and the results suggested the presence of CSD. In the models, the combination of the Breusch-Pagan Lagrange Multiplier Test (Breusch and Pagan, 1980) and Pesaran Scaled Lagrange Multiplier Test (Pesaran, 2021) also provided evidence of CSD in the outlined models. Given the evidence of CSD in Table 3, a stationarity test was conducted, with the results indicating that the variables were all stationary at most after first difference. Two distinct approaches to stationarity tests – i.e., Pesaran (2007), which accounted for CSD, and Levin et al. (2002) – were conducted, and the results are documented in Table A (appendix). However, Pedroni's (1999) cointegration test and Pesaran and Yamagata's (2008) slope homogeneity test provided evidence of cointegration (see Table 4). Meanwhile, as indicated in Table 5, slope homogeneity was rejected for the energy model, but the test failed to reject the null hypothesis for the industrial model.

Concerning coefficient estimations, the appropriateness of Pooled Mean Group (PMG) autoregressive distributed lag (ARDL) by Pesaran et al. (1999) is relied upon for the long run and short run. The choice of PMG was guided by its suitability to estimate coefficients with cross-sectional short-run heterogeneity and long-run homogeneity. Furthermore, the PMG-ARDL approach was deployed, given the mixed evidence of slope homogeneity, as the two models in Table 5 indicate. Finally, the aforementioned technique is effective at providing short- and long-run coefficient estimates. Given that the step-by-step procedure is documented widely in the literature, details on the process are excluded here for space considerations. However, a robustness investigation was conducted to ascertain Granger causality direction among the variables in the panel. Specifically, the recently developed Granger noncausality approach by Juodis et al. (2021) was employed. For the aforementioned empirical approaches, the step-by-step descriptions were not documented here to avoid unnecessary replication and because of space constraints.

4. Discussion of findings

4.1. Main results

The results from coefficient estimation through the PMG-ARDL approach for both the energy and industrial sector GHG models from Eqs. (7) and (8) are provided in Table 6. As for the drivers of energy sector GHG emissions, the short- and long-run results are presented on the left-hand side of Table 6. Notably, the results affirm the validity of the EKC hypothesis for energy GHG emissions, particularly in the long run. This desirable outcome suggests that although economic growth was detrimental to environmental quality in the energy sector, these countries' environmental quality began to improve significantly over

Table 2
Correlation evidence.

Variables	GDP	POP	EGHG	IGHG	CCE	CCI	DSCCE	DSCCI
GDP	1.00							
POP	0.69[a]	1.00						
EGHG	−0.46[a]	0.04	1.00					
IGHG	0.29[a]	0.01	−0.51[a]	1.00				
CCE	0.31[a]	0.19[b]	−0.35[a]	−0.48[a]	1.00			
CCI	0.35[a]	0.28[a]	−0.29[a]	−0.48[a]	0.92[a]	1.00		
DSCCE	0.52[a]	0.09	−0.51[a]	−0.22[b]	0.75[a]	0.79[a]	1.00	
DSCCI	0.53[a]	0.07	−0.50[a]	−0.26[a]	0.78[a]	0.80[a]	0.98[a]	1.00

Note: a = probability value <0.01 and b = probability value <0.05.

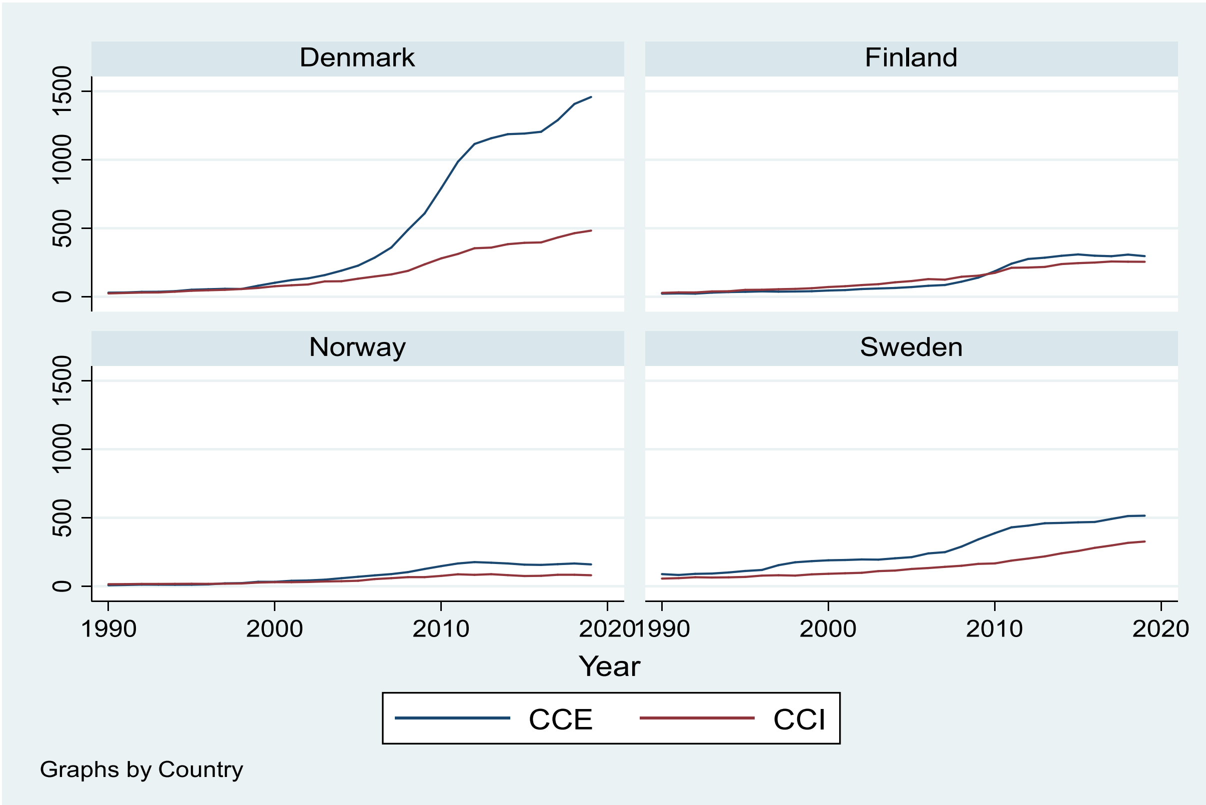

Fig. 1. The trend in energy (CCE) and industrial (CCI) climate change technologies across the Nordic countries.

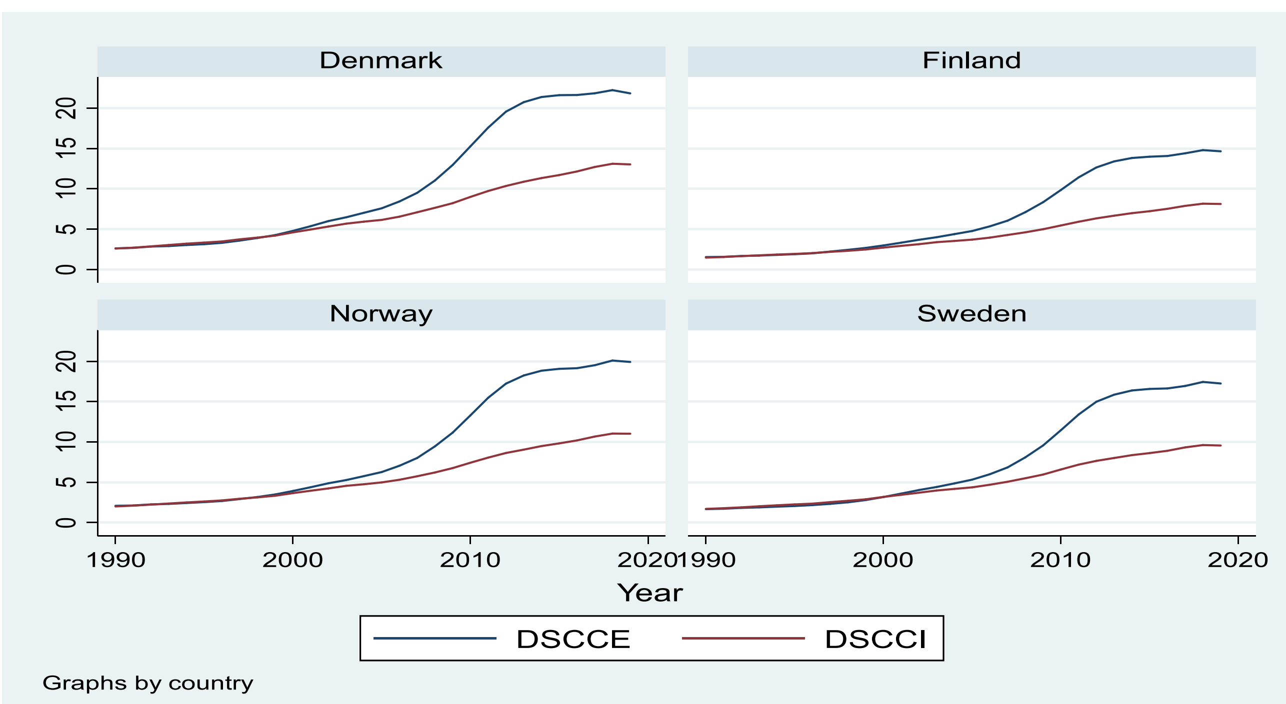

Fig. 2. The trend in distance-weighted energy (DSCCE) and industrial (DSCCI) spillovers of climate change technologies across the Nordic countries.

time, particularly after attaining a certain threshold of economic performance. Specifically, economic growth elicited less environmental degradation from a surge in energy GHG emissions, i.e., a percentage increase in economic growth began to mitigate energy GHG by 0.41 % in the long run. The current evidence partly aligns with the validly of the EKC hypothesis in the literature (Urban and Nordensvärd, 2018; Alola and Onifade, 2022). While Urban and Nordensvärd (2018) validated the EKC hypothesis for Denmark, Iceland and Sweden, Alola and Onifade

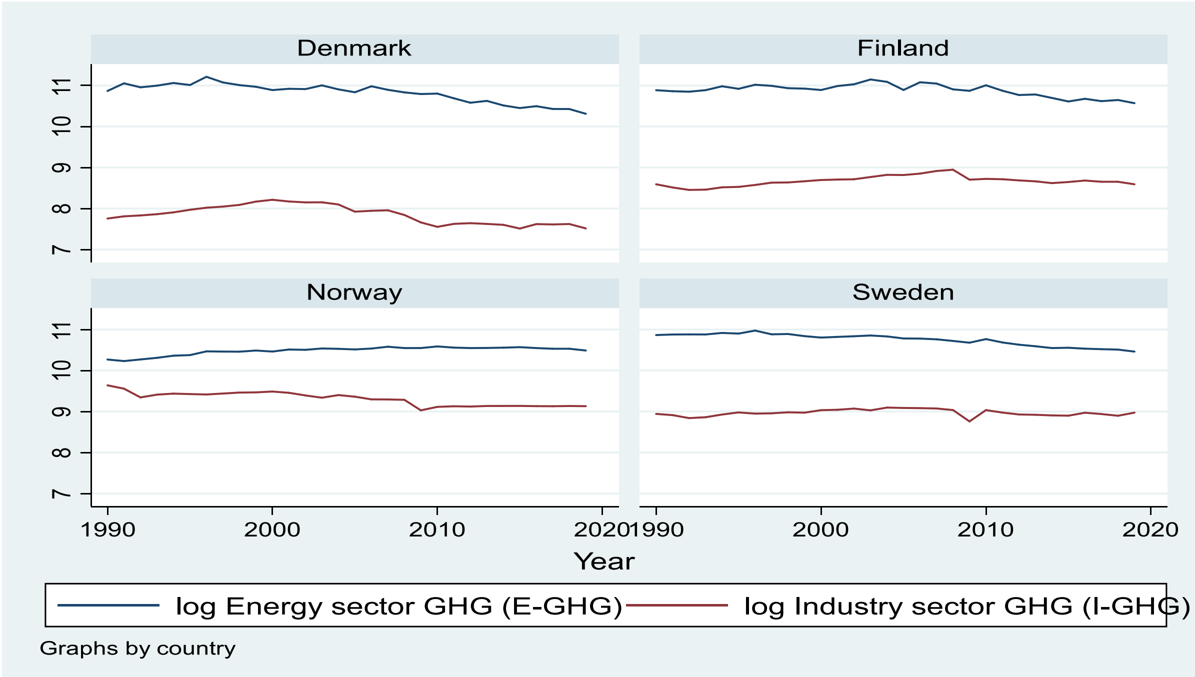

Fig. 3. The trend in greenhouse gas emissions across the Nordic countries.

Table 3
Cross sectional dependence tests.

Cross section dependence in panels by Pesaran (2021)									
Variables	GDP	GDPsq	POP	EGHG	IGHG	CCE	CCI	DSCCE	DSCCP
CD-test statistics	13.07[a]	12.07[a]	13.23[a]	3.44[a]	4.78[a]	13.08[a]	12.90[a]	13.41[a]	13.42[a]

Cross section dependence in models	With domestic climate technology			With international climate technology (spillover)		
	B-P LM	PS LM	P CD	B-P LM	PS LM	P CD
Energy model	54.09[a]	13.88[a]	4.66[a]	54.10[a]	13.89[a]	4.71[a]
Industrial model	60.27[a]	15.67[a]	-1.16	21.43[a]	4.45[a]	0.49

Note: a = probability value <0.01, b = probability value <0.05, and c = probability value <0.10. B—P LM is Breusch-Pagan Lagrange Multiplier by Breusch and Pagan (1980). Then, PS LM which represents Pesaran scaled Lagrange Multiplier and P CD the Pesaran cross sectional dependence are reported in Pesaran (2021).

Table 4
Cointegration by Pedroni (1999).

Pedroni cointegration statistic	Domestic climate technology		International climate technology (spillover)	
	Within the panel	Entire panel	Within the panel	Entire panel
Energy model				
Modified Phillips-Perron t	-0.91	-1.41[c]	-0.86	-1.88
Phillips-Perron t	-4.66[a]	-4.10[a]	-4.74[a]	-4.03[a]
Augmented Dickey-Fuller	-3.53[a]	-3.33[a]	-3.71[a]	-3.29[a]
Industrial model				
Modified Phillips-Perron t	0.52	-0.29[c]	0.47	-0.27
Phillips-Perron t	-1.95[b]	-2.09[b]	-1.77[b]	-1.78[b]
Augmented Dickey-Fuller	-2.09[a]	-2.16[b]	-1.51[c]	-1.68[b]

Note: a = probability value <0.01, b = probability value <0.05, and c = probability value <0.

Table 5
Slope homogeneity.

	Domestic climate technology		International climate technology (spillover)	
	Delta	Adjusted delta	Delta	Adjusted delta
Energy model	4.88[a]	5.46[a]	-0.23	-0.26
Industry model	3.25[a]	3.63[a]	-0.13	-0.14

Note: HAC kernel with bartlett with average bandwidth 3. The null hypothesis, H_0 is slope coefficient are homogenous.

(2022) validated it for Finland.

Furthermore, for energy sector GHG emissions, both climate change technological development domestically and CC technologies' spillovers diffusing from other countries mitigated GHG emissions across the panel, thereby improving environmental sustainability. Specifically, a 1 % increase in locally produced CC technologies and CC technology spillovers from foreign states mitigated energy GHG emissions by 0.16 % and 0.13 %, respectively, particularly in the long run. Notably, in the energy sector, locally produced environmental technologies and

Table 6
PMG Long-run coefficient estimates.

With climate change energy technologies			With climate change industrial technologies		
Variables	E-Model	E-Model with s	Variable	I-Model	I-Model with s
Long run					
GDP	22.06[a]	44.15[b]	GDP	-57.42[a]	-45.41[a]
GDPsq	-0.41[a]	-0.83[b]	GDPsq	1.10[a]	0.87[a]
POP	-1.21[c]	-4.48[c]	POP	-1.50[a]	-2.24[a]
CCE	-0.16[a]		CCI	-0.34[a]	
SCCE		-0.13[c]	SCCI	-0.18[a]	
Short run					
GDP	21.25	8.36	GDP	-55.03[a]	-48.64
GDPsq	-0.40	-0.15	GDPsq	1.07[a]	0.95
POP	9.03	13.25[b]	POP	1.84	-2.97
CCE	0.13[b]		CCI	-0.04	
SCCE		0.28	SCCI	0.15	
Adjustment	-0.53[a]	-0.51[b]		-0.44[b]	-0.47[b]
log likelihood	198.07	199.70		212.95	209.39

Note: Take [a, b, and c] as the $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively. E-Model and I-Model are respectively energy and Industrial models.

international technology spillovers exerted roughly similar impacts on emissions. Although there is almost no previous study that compares sector-wide GHG emissions from locally produced environmental technologies and spillovers, Wang et al.'s (2021) study on Chinese provinces and Costantini et al.'s (2017) examination of European industrial sectors both aligned with the evidence that environmental technology spillovers and international R&D spillovers improve environmental productivity and mitigate sectoral emission intensity. The positive result for local CC technologies is in line with Du et al. (2019) and Yıldırım et al. (2022), but not Erdoğan et al. (2020). However, Erdoğan et al. (2020) did not focus on environmental or climate patents, unlike Du et al. (2019), Yıldırım et al. (2022) and the present analysis, which may be one reason for the differences. Meanwhile, as the population has increased by 1 %, energy GHG emissions declined by ~1.2 %, particularly in the long run.

The model for the industrial sector GHG emissions is slightly different, particularly from the perspective of the economic growth and GHG emission nexus (see the right-hand side of Table 6). Specifically, it is surprising that the EKC hypothesis was not valid. Instead, a U-shaped hypothesis was established in both the short and long runs, thereby indicating no evidence that economic growth improves environmental quality. Specifically, increases in economic activity initially continued to mitigate industrial sector GHG emissions until emissions were reduced to a certain minimum level, after which the sector's GHG emissions surged in the long run. Meanwhile, for the separate models with domestic and spillover environmental technologies, population increases played a desirable environmental role.

Notably, locally produced environmental technologies and environmental technologies' spillovers mitigated GHG emissions from the industrial sector in the panel. However, unlike the energy sector, locally produced environmental technologies reduced industrial sector GHG emissions by almost twice as much as environmental technologies' spillovers in the long run. Domestic environmental technologies' impact on GHG emissions is also clearly higher in the industrial sector than in the energy sector. This finding also is in line with Erdoğan et al. (2020), who found that innovations reduced emissions from the industrial sector, but not from the energy sector. The evidence from this investigation also partly aligns with the literature indicating that technology spillovers exert significant effects on emissions. However, Sun et al. (2021) demonstrated that international spillovers make a greater impact on energy efficiency than domestic innovations. Moreover, on the sectoral level, Costantini et al. (2013) and Jiao et al. (2020) also indicated that technological spillovers exert a greater impact on environmental performance than technological development, contradicting both energy and industrial sector results in Table 6. Spillovers' lesser importance in our aggregate-level results can be due to differences in countries' industrial structures, implying that not all foreign developed technologies are technologically relevant and applicable to domestic industrial activities, thereby limiting the potential to benefit from international technology spillovers. Another interpretation of these differences is that domestic inventive activities are particularly important in the industrial sector, but less so in the energy sector. This interpretation is also in line with Sun et al. (2021).

4.2. Robustness evidence

Although the cross section under investigation was small (a panel of four countries), the Granger noncausality approach by Juodis et al. (2021) was found to be most suitable for the robustness analysis, considering its suitability for homogeneous or heterogeneous coefficients. Given the results presented in Table 7, significant evidence indicates that all the variables, with the exception of population, exerted a significantly negative impact on energy sector GHG emissions, i.e., these Granger variables caused energy sector GHG emissions from the Nordic states, in line with the results from the PMG-ARDL approach. Similarly, the Granger causality results from industrial sector GHG emissions supported the PMG-ARDL approach. Specifically, GDP and the square of GDP Granger elicited industrial sector GHG emissions with positive coefficients. Furthermore, locally produced environmental technologies and environmental technologies' spillovers from foreign states also Granger cause industrial sector GHG emissions, but with negative coefficients. Overall, the results from Juodis et al.'s (2021) approach largely supported the PMG-ARDL results, thereby indicating significant robustness.

5. Conclusions and policy recommendations

In the present investigation, the drivers of energy and industrial sector GHG emissions were examined through a panel of small open economies in the Nordic region (i.e., Denmark, Finland, Norway and Sweden) from the 1990–2019 period. As such, environmental technologies' roles through the domestic development of climate change technologies and spillovers from foreign climate change technology development were considered. Furthermore, the contributions of population and economic growth were also investigated. Regarding economic growth's role, this investigation contributes to the literature by examining the EKC hypothesis with energy and industrial sector GHG emissions as environmental indicators.

Notably, the results indicate that domestic climate change technological development and international climate change technology spillovers mitigate energy and industrial GHG emissions across the panel. Although this indicates that both types of climate change technological development are useful in improving the energy and industrial sectors' environmental quality, the findings indicate that domestic

Table 7
Granger non-causality approach.

	Half-Panel Jackknife Estimation		Half-Panel Jackknife Estimation	
	With energy sector		With industrial sector	
	Wald test	Coefficient	Wald test	Coefficient
GDP	1074.18[a]	-0.41[b]	204.33[a]	1.76[a]
GDPsq	1037.23[a]	-0.01[b]	227.61[a]	0.03[a]
POP	12.21[a]	-9.25	61.71[a]	-14.85[c]
CCE	190.55[a]	-0.08		
DSCCE	272.77[a]	-0.46[a]		
CCI			180.89[a]	-0.22[b]
DSCCI			349.01[a]	-0.29[b]

Note: Number of lags = 2, BIC.

environmental technologies exert a greater impact on the industrial sector's GHG emissions, while their impacts do not significantly differ in the energy sector. While the EKC, i.e., inverted U-shaped hypothesis, was validated based on the GHG emissions from the energy sector, U-shaped evidence of GHG emissions also was found in the industrial sector. Therefore, given economic performance, these results suggest that the energy sector in the examined countries has a more reliable pathway to environmental sustainability than the industrial sector. This is a positive finding, particularly as the energy sector accounts for the lion's share of total GHG emissions. Interestingly, it also has been observed that population growth across the panel mitigates GHG emissions from the energy and industrial sectors.

5.1. Policy recommendations

As both domestic environmental technological development and international technology spillovers have been demonstrated to reduce sectoral GHG emissions, national R&D and climate policies need to incorporate both aspects. R&D-related policies should be conceived from the perspective that environmental technological development has the potential to drive both economic and environmental benefits, thereby justifying wider policy interventions towards environmental R&D investments. Beyond considering wider policy interventions, environment-related measures, particularly for domestic and internationally imported technologies, should reflect the elements of the Nordics' nationally determined contributions (NDCs) significantly. Furthermore, because international technology spillovers appear to be an important mechanism for emission reductions, public policies should support international technology and R&D collaboration. Furthermore, to utilise foreign knowledge spillovers, countries' absorptive capacity could also be improved through further human capital development and technology investment programmes. Differences in absorptive capacity also may explain why technology spillovers' importance appears to vary across sectors and countries, but further research is needed to clarify this. However, further research is also needed to pinpoint the exact channels of foreign spillovers and to enable more targeted policy responses to support international climate change technology diffusion. The identified international technology spillovers could also backfire and provide countries with incentives for free-riding, which could lead to suboptimal environmental R&D investments globally. Thus, international coordination of climate change technology subsidies and support policies is also warranted.

Considering the evidence of a U-shaped relationship between economic growth and GHG emissions, particularly in the industrial sector, the results suggest that adoption of green economic and environmentally friendly practices in the sector is highly deficient. To improve the industrial sector in this regard, more stringent environmental policies that promote resource productivity, resource reuse and circularity, and green and clean content development should be promoted further. Specifically, such stringent environmental policy should span the sector's value chain, from the manufacturing and distribution of capital goods, to end-users' information through product labels. Furthermore, as domestic technology development's emission-reducing effects are highlighted in particular, the industrial sector's environmental performance in the Nordic countries will benefit from more investment in environmental R&D through more public-private partnerships that further encourage development of environmental technologies and innovations. Moreover, green entrepreneurial activities through increased access to credit facilities and relevant environmental sustainability trainings should be encouraged across economic sectors.

5.2. Study limitations

Although this study's results are exciting and offer significant policy insight, the investigation contained limitations that could be improved upon in future research. One limitation is that the patent data used only covered technological inventions; thus, many important service-related innovations were ignored in the analysis. While patent data arguably are fit for analyses of energy and industrial sectors, other approaches are needed for more service-oriented sectors.

A future study could extend the scope to GHG emissions from other sectors to provide a more holistic approach to achieving environmental and climate sustainability. Aside from a comprehensive sector-wide analysis, given data availability, future studies also could include intra-sector analysis. This approach should help channel organisations' green management approaches further, thereby providing a pathway for micro- to macro-level climate sustainability and a green economy. While climate change technologies' spillovers were measured via a distance-weighted approach, we do not argue that geographical closeness is the only mechanism for technology diffusion. Thus, future studies also could consider other technology spillover channels. Such an analysis also could provide a deeper understanding of why international environmental technology spillovers' role differs markedly between the energy and industrial sectors.

CRediT authorship contribution statement

Andrew Adewale Alola: Methodology, Formal analysis, Writing – original draft. **Jaana Rahko:** Conceptualization, Writing – original draft.

Data availability

Data will be made available on request.

Appendix

Table A
Panel unit root tests.

Variables	LLC with adjusted t-		Pesaran	
	Level	First difference	Level	First difference
IGHG	-0.177	-9.890***	-1.882	-4.683***
EGHG	-2.1059	-9.251***	-1.175	-6.190***
GHG	-1.451	-10.001***	-2.501**	-5.832 ***
GDP	-2.098*	-7.524***	-1.259	-3.572***
POP	-1.479	-4.068*	0.996	-2.668***
CCE	-1.768	-4.328*	-0.579	-3.470***
CCI	2.683	-4.306*	-2.238	-5.544***
DSCCE	-2.928***	-3.063***	0.581	-3.834***
DSCCI	-0.177	-6.779***	-2.805*	-5.551***

LLC: H_0 (panels contain unit roots) against H_1(panels are stationary) in Levin et al. (2002) and Pesaran: H_0 (homogeneous non-stationary) against H_1(homogeneous stationary) in Pesaran (2007). *, **, and *** are statistically significant levels for $p < 0.1$,

$p < 0.05$, and $p < 0.01$ respectively. Maximum number of lags implemented for the variables is 1 but 3 for POP.

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