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Examining green productivity amidst climate change technological development and spillovers in the Nordic economies

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ABSTRACT

The common ground of both critics and proponents of green productivity is arguably hinged on the main role of environmental technological advancement. Considering the drive for climate-neutral economy among the Nordic states, the current study examines the role of climate change technological development within the countries and technological spillovers across countries in the pursuit for green economy. By using a combination of pooled mean group approach of autoregressive distributed lag (for coefficient estimation) and the recently developed Granger non-causality approach by Juodis et al. (2021) for the panel dataset analysis over the period 1990–2018, the results reveal that both domestic technological development and spillovers from abroad promote long-run green productivity growth in the panel and country-specific estimations. In both estimations, the impact of international diffusion of climate change technologies on green productivity is found to be larger. Additionally, the influence of these two dynamics of climate change-related technologies on attaining greening economy is the most impactful in Sweden. In the remaining Nordic economies, climate change technology spillovers in Denmark are more impactful than in Finland and least in Norway, while climate change technological development in Norway drives green productivity more than in Finland and least in Denmark. As a robust insight, the Granger causality techniques revealed causality from climate change technologies within the countries, climate change technology spillovers, and population to green productivity. Consequently, public policies should promote green innovativeness and especially learning and knowledge transfer from other countries to achieve climate neutrality targets.

1. Introduction

After the Paris Agreement in 2015 and amidst the growing global awareness of climate risks, increasing number of countries have published targets to become carbon or climate neutral. The Nordic countries have set some of the most ambitious goals, such as reducing greenhouse gas (GHG) emissions and achieving carbon neutrality. Nevertheless, meeting these targets and achieving sustainable economic growth depends crucially on the development of new climate change mitigation technologies and the efficient transfer of these technologies globally (Popp et al., 2010; Popp, 2011). According to the current understanding, developing and adopting green technologies is considered the most cost-effective way to reduce environmental pressures without compromising economic competitiveness. New technologies are expected to reduce emissions and decouple economic activity from environmental impacts.

Accordingly, one key element in the public policy mixes for climate neutrality is support for green technology development. For example, the European Union (EU) has implemented the Eco-Innovation Action Plan. This policy approach finds support in the academic literature. Studies have provided evidence of the importance of domestic environmental or climate change technology (CCT) innovations in reducing emissions and promoting green productivity growth, although the evidence is more ambiguous for poorer countries (e.g., Töbelmann and Wendler (2020), Zhang et al. (2017), Du and Li (2019) and Puertas and Marti (2021)).

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According to OECD,[1] ten largest R&D-funding countries account for about 85% of global R&D investments and the situation is similar for CCT innovations (Amoroso et al., 2021). This implies that for most countries the foreign sources of technology account for a vast majority of technological development. Therefore, it is essential to examine more evidence on how CCT innovations diffuse internationally and how these spillovers impact emissions and productivity in the receiving countries. This understanding can inform local climate change policies but also provide justification for cross-governmental R&D coordination as international technology spillovers may lead to free-riding problems. Currently, the existing empirical studies have analysed the role of interregional or interindustry vertical green technology spillovers (e.g., Ghisetti and Quatraro, 2017; Costantini et al., 2013, 2017; Jiao et al., 2020) and the effects of foreign direct investment (FDI) and outward foreign direct investment (OFDI) on green productivity in China (e.g., Li and Ouyang, 2020; Pan et al., 2020; Zhou et al., 2019). Moreover, Aldieri et al. (2022) analyse the environmental performance and role of R&D and R&D spillovers at the firm level. However, to our knowledge, there are no prior studies that analyse the impact of international green technology spillovers on country-level green productivity. The present study aims to fill this gap in the literature. Moreover, studies have shown that the effects of domestic CCT innovations are heterogeneous across countries (see, e.g., Többelmann and Wendler (2020)), which warrants further studies analysing different countries. Thus, as the second contribution to the empirical literature, the present study provides evidence of the role of domestic green technology development on green productivity by analysing the case of Nordic countries.

Given the above motivation, this study examines the green productivity of the Nordic countries with respect to the role of CCT development within the countries and CCT spillovers across the countries in promoting green productivity. In particular, this study contributes to the literature by studying the green productivity effects of trade-transmitted CCT spillovers, analysing the case of the Nordic countries and focusing on aggregate GHG emissions rather than CO_2 emissions. The main CCTs in the Nordic countries vary somewhat by country and include technologies in energy generation, energy efficiency of transport and industrial processes as well as GHG emission reducing technologies in industrial production.

The Nordic region is considered for this investigation because of the peculiarity of the countries' commitment to climate and energy technologies, thus projecting the region as a decisive leader in long-term energy technology and climate targets (International Energy Agency, 2013; Carbon Commentary, 2022). Moreover, while Stoknes and Rockström (2018) probed the criticality of green growth and touted the Nordics' genuine green growth, the recent study by Tilsted et al. (2021) noted the complexity in the pathway to attaining genuine green growth even for the Nordic economies. Thus, with the intention of extending the aforementioned literature by implementing econometric approaches, the role of climate change technology dimensions in the panel of Denmark, Finland, Norway, and Sweden alongside country-specific analyses are examined so that relevant policies can be outlined for decision-making purposes.

Proceeding from this section are other important parts of the study. Specifically, related studies alongside the hypotheses of the study are detailed in section 2, while the materials and empirical methods employed are outlined in section 3. In section 4 and 5, the result of the investigation and the conclusion from the investigation are presented respectively.

2. Literature review and research hypotheses

Economic growth theories place innovation and knowledge diffusion at the centre in explaining long-term productivity and economic growth (Aghion and Howitt, 1992; Romer, 1990). While this literature studies the change in labour or total factor productivity, environmental economists have moved towards analysing green productivity, i.e., economic output per environmental measure such as emissions or resource use (Ghisetti and Quatraro, 2017; Huppes and Ishikawa, 2005).

Furthermore, green technological development is especially characterized by a double externality (Barbieri et al., 2016). First, new green technologies reduce the negative environmental externalities of production. Second, like all innovations, they also produce knowledge spillovers that benefit other individuals and countries besides the original innovator. Thus, when studying new green technologies, we may expect them to reduce the environmental impact of economic activities or, in other words, to improve the green productivity of the economy. As such, they appear to be a key requirement for green productivity growth and decoupling economic activity and environmental impact. However, there are also critics of the green growth objective (Antal & Van Den Bergh, 2016; Hickel and Kallis, 2020), who state that the target is not feasible on a global scale.

Accordingly, researchers have attempted to identify the effect of green technologies and innovations on environmental performance and green productivity in various settings. Earlier empirical literature found that advances in environmental technology tend to improve the environmental productivity, although contradictory findings have also been presented. Jung (2015) finds that the six core aspects of South Korea's climate technology programs are projected to offer new pathways to economic growth while mitigating climate change challenges. Ghisetti and Quatraro (2017) and Weina et al. (2016) find that patented green technologies support green productivity, i.e., valued added produced per emissions in Italian regions; however, there is no significant impact on the level of CO_2 emissions. Zhang et al. (2017) find that green patents reduce CO_2 emissions in Chinese provinces and Puertas and Marti (2021) report that green innovation activities reduce GHG emissions among the OECD countries. Furthermore, Többelmann and Wendler, 2020 report that green patents reduce CO_2 emissions in European countries, but less so in poorer countries. This heterogeneity is also supported by Du and Li (2019) and Yan et al. (2020), who find that CCT patents and renewable energy technology innovations do not improve green productivity in general, but only lead to an improvement in richer countries and regions.

Based on the earlier theoretical and empirical literature, and considering the level of economic development in the Nordic countries, we hypothesize the following:

H1. Climate change technological development improves the green productivity in the Nordic countries.

Moreover, there is the second externality of green technical change that needs to be considered: new climate change technologies are developed in countries that invest in climate change R&D, and these technologies diffuse over time to other countries. The importance of international technology spillovers and technology transfer in the context of climate change is also widely recognized; see Popp (2011). The literature on international knowledge spillovers has identified different channels through which technological knowledge diffuses from one country to another (Keller, 2021; Clark et al., 2011). International trade and foreign direct investments are typically seen as central channels.

Empirical studies have analysed green technology spillovers in various contexts. Costantini et al. (2017) study emissions (GHG, CO_2, NO_x SO_x) in European industrial sectors and find that sectoral green innovations as well as domestic and foreign technology spillovers from vertically related sectors reduce the emission intensity. Jiao et al. (2020) analyse the carbon intensity of Chinese industries and argue that the effects of domestic interindustry spillovers are positive and even larger than the effect of technological development within sector. The above-mentioned studies analyse vertical technology spillovers at the industry level, but spillovers are not expected to be limited to these cases. E.g.,

[1] OECD dataset: Gross domestic spending on R&D.

Costantini et al. (2013) study GHG emissions in Italian regions. They find that regional spillovers have a stronger negative impact on emissions than do own innovations in the region. Similarly, Ghisetti & Quatraro (2017) find evidence of green technology spillovers among vertically related sectors among Italian regions. In contrast, Wang et al. (2021a) find that regional green technology spillovers may have insignificant or negative effects on green productivity in China.

Considering also nongreen technologies, the vast empirical literature on international technology spillovers has found them to be important for growth and productivity at the country, regional and firm levels (Keller, 2021; Clark et al., 2011). In the context of green productivity, Pan et al. (2020), Li and Ouyang (2020) and Zhou et al. (2019) show that inward and outward foreign direct investments create technology spillovers that improve carbon and green productivity in China and Wang et al. (2021b) also argue that international R&D spillovers positively influence green productivity. However, Cui et al. (2022) and Lv et al. (2021) report mixed environmental impacts from FDI and trade openness among OECD countries and China.

Thus, the industry level studies on green technology spillovers mostly conclude in favour of green spillovers, whereas the green productivity effects of trade and FDI mediated spillovers appear more ambiguous. This could be because the latter studies do not separate green and nongreen technologies. However, we also know that green patents are cited more often than nongreen patents, which suggests even larger spillovers from green technologies than nongreen technologies (Barbieri et al., 2020; Popp and Newell, 2012). Hence, we hypothesize the following:

H2. International climate change technology spillovers improve the green productivity in the Nordic countries.

In the empirical section, we focus on international technology spillovers mediated through imports. While the prior literature indicates that technology spillovers can take place through international trade, FDI, personal mobility and other channels, we focus on the import channel of spillovers for the following reasons. First, the related industry-level studies argue that sourcing intermediate inputs from vertically related sectors acts as a channel of technology spillovers (Costantini et al., 2017; Jiao et al., 2020). Thus, considering the import channel of international technology spillovers is in line with this argumentation. Second, data on international trade covers wider range of countries and years than, e.g., FDI or other alternative datasets.

Theoretical research on endogenous growth and technology diffusion highlights the importance of international trade for the technological development of small open economies (Grossman and Helpman, 1991; Buera and Oberfield, 2020). Specifically, Keller (2004) discusses how foreign technology has a larger impact on productivity growth than domestic technological development in small open economics. Furthermore, earlier studies on green technology spillovers, e.g., Costantini et al. (2013) and Jiao et al. (2020), indicate that technological spillovers exert a larger impact on environmental performance than own technological development, whereas Costantini et al. (2017) report that the relative importance varies by field of technology. Moreover, the results of Zhou et al. (2019) and Pan et al. (2021) indicate that absorptive capacity as measured with R&D or education explains why some Chinese regions benefit from international or inter-regional spillovers and some do not. Thus, it appears that the relative importance of domestic technological development and international technology spillovers may vary by technology and country characteristics. The Nordic countries are small open economies, where the role of international trade is central. Furthermore, they invest considerably in green innovation activities. As also suggested by the theoretical literature, the role of international technology spillovers mediated through international trade is thus expected to be especially important to the environmental performance of Nordic countries and we expect that technology spillovers are more important than national innovation. Therefore, we hypothesize the following:

H3. Climate change technology spillovers have a larger impact on green productivity than domestic climate change technological development in the Nordic countries.

3. Material and empirical methods

3.1. Variable formation and data sources

In this investigation, variables were collected and restricted to only four Nordic countries (Denmark, Finland, Norway, and Sweden) over the period 1990–2018. Iceland was excluded because of the reasons of data availability and obviously distinct features of the country in comparison with other Nordic economies. The material employed to achieve the study objective include the gross domestic product i.e. GDP (proxy for economic growth which is measured in U.S. dollars for constant 2015 prices and denoted as Y), financial development i.e. FD which is represented by financial system deposit and measured as a percentage of GDP, population i.e. POP is the number of people in millions, and green growth (denoted as GY) which is computed as the ratio of GDP to GHG emissions (computed by authors as a proxy for green productivity), where GHG emissions are the total GHG emissions excluding memo items and are measured as thousand tonnes. The World Bank database is the source of GDP and POP, the Eurostat is the source of GHG emissions while FD was retrieved from the International Financial Statistics of the International Monetary Fund (IMF).

Importantly, we obtained patent data from the Organisation for Economic Co-operation and Development (OECD) Regpat database. Following prior studies (e.g., Többelmann and Wendler, 2020; Costantini et al., 2017), we rely on patent applications filed at European Patent Office (EPO), which avoids the problems due to differing patent regimes in different countries.[2] Again, following prior studies, we focus on patents in climate change technologies, as these technologies are expected to have direct impact on GHG emissions and green productivity.[3] Thus, based on the patent database, we form the following variables: climate change technology stock (CCTS) which captures the climate change mitigation and adaption technologies patented in a country and climate change technology spillover stock (CCTSS) which captures the diffusion of climate change-related technologies from other countries. We use climate change patents as a proxy for climate change technology. Climate change patents are counted as the number of patent applications in technology classes Y02 and Y04 (Angelucci et al., 2018).[4] These technology classes include, e.g., renewable energy technologies, energy efficient heating and transport technologies, technologies improving the efficiency of industrial processes as well as climate change technologies related to improved waste management. The patents are allocated to countries based on the country of the inventor. In case of multiple inventors from several countries, fractional counting is applied in order to avoid double counting of patents.

Because the new technologies are expected to have an effect over a longer time period, we construct the accumulated CCT stock using the annual patent counts. Thus, the CCT stocks, i.e. countries' own climate change-related technologies, are calculated as follows:

[2] The Nordic countries are members of EPO and vast majority of their trade partners are other European countries. Furthermore, EPO patents are also expected to have higher average value than national patent applications (Deng, 2007).

[3] Wurlod and Noailly (2018) and Lee and Min (2015) report that the environmental effects of green technological development are stronger and more consistent than the environmental effects of nongreen technological development, which provides a further empirical motivation for our approach.

[4] Unlike some prior studies, we focus on CCT patents and not on a broader category of environmental patents; however, there is a large overlap between the two categories. Categories Y02 and Y04 identify patents that have potential to mitigate climate change. As we analyse green productivity, i.e., output per GHG emissions, these technologies appear the most relevant for our study.

$$\mathrm{CCTS}_{it} = \mathrm{CCTS}_{it-1} \text{ x } (1 - \delta) + \mathrm{C}_{it} \quad (1)$$

where C is the number of patent applications in year t in country i and CCTS is the accumulated stock. δ is the depreciation rate, which is set to 15%, which is typical in the R&D and patent literature (Hall et al., 2010). EPO patent data start from year 1978 and thus we do not separately estimate the starting values as our estimation period starts from 1990.

Moreover, as a technology developed in one country moves over national borders, it creates technology spillovers benefiting also other countries than the one which originally developed it. As argued in section 2, international trade is an important channel of these international knowledge spillovers. Hence, we construct the CCT spillover stock (CCTSS) as follows:

$$\mathrm{CCTSS}_{it} = \sum_j \mathrm{m}_{ijt}\ \mathrm{CCTS}_{jt} \quad (2)$$

where CCTSS is the CCT spillover stock available for country i in year t. CCTS_{jt} is the CCT stock in a foreign country j in year t. m_{ij} is the country i's import share from country j (Keller, 2021). The import shares are calculated based on the UN international trade data that covers over 99% of global merchandise trade.

3.2. Dataset statistical inference

Table 1 displays the descriptive statistics of the aforementioned variables. The statistics reveal that CCT stock is highest in Sweden (mean is ∼181), followed by Denmark (mean is ∼159), while CCT spillovers are highest in Denmark (mean is ∼546), followed by Sweden (mean is ∼519). While CCT stock in Norway (mean is ∼40) is the lowest among the Nordic countries, CCT spillovers to Finland are the lowest (mean is ∼481). Given that Sweden[5] has the highest mean value of GY, i.e., 18368061, followed by Norway (6464936), this finding points to the leadership of the two countries in terms of green productivity. This evidence of economic growth amidst a decline in GHG emissions is visually corroborated by the graphics in Figs. 1–3. Moreover, the correlation evidence in Table 2 shows that the variables of interest, i.e., CCT stock and CCT spillover stock, and the control variables exhibit statistically significant and positive associations with green productivity in the panel of the Nordic countries.

3.3. Empirical methods

3.3.1. Empirical model and preliminary tests

Proceeding to the empirical analysis, the first step involves preliminary tests that seek to examine evidence of cross-sectional dependency (CD) and slope homogeneity in the panel. Importantly, the empirical model formulation of the investigation is crucial to the pretests. Although the literature reveals several modifications to the production function, the baseline concept hinges on traditional economic growth theory, as documented by Solow (1956). By modifying the model with the stock of climate change technologies and the stock of climate change technology spillovers, the adopted empirical model offers a feasible alternative to the traditional growth model. Whereas the traditional growth model focuses mainly on economic growth as the exclusive productive output, the alternative perspective that classifies productive outputs as economic (in this case, GDP) and environmental (in this case, GHG emissions) is gaining traction in the literature (Färe, et al., 1989; Chung et al., 1997; Wang et al., 2020). Moreover, this perspective, which later offers a hint on green productivity, can be traced to the studies of Debreu (1951) and Shephard (2015) on the theory of production for efficiency evaluation. Specifically, this line of argument model productivity, P such that $P = (x, y, z) \mid x$, where the input vector of production x can produce y (desirable output, i.e., GDP) and z (undesirable output, i.e., GHG).

For instance, Wang et al. (2020) further extended the Slack Based Measures-Directional Distance Function (SBM-DDF) by incorporating the three important goals of energy saving, pollution abatement, and industrial growth to present a green productivity approach. This also aligns with the OECD's "Green Growth Strategy" which is based on the principle of balancing the long-run interdependence of economic growth and ecological environmental protection. Thus, the current approach considers economic growth and emission abatement as represented by the ratio GDP/GHG (assuming the economic growth and declining GHG emission of the case countries). Meanwhile, Stoknes and Rockström (2018) opine that carbon productivity provides the deep decarbonization pathway to achieving a genuine green growth (Wiedenhofer et al., 2020), and in this case, the GHG productivity. Then, given that the production process enables these output (desirable and undesirable) patterns, the green productivity, GY could be modelled as:

$$GY_{it} = [\mathrm{A}_{it}\ \mathrm{POP}_{it}]^{\mu}\ FD_{it}^{\alpha}\ CCTS_{it}^{\beta}\ CCTSS_{it}^{\Psi} \quad (3)$$

After a logarithmic transformation, the function is presented as

$$lnGY_{it} = \mathrm{Z} + \mu\ lnPOP_{it} + \boldsymbol{\alpha} \ln FD_{it} + \beta \ln CCTS_{it} + \Psi \ln CCTSS_{it} + \epsilon_{it} \quad (4)$$

where the variables are transformed to logarithmic forms and the elasticities of response of green productivity (GY) to POP, FD, CCTS, and CCTSS are respectively (μ, α, β, and Ψ). Moreover, Z is the constant term representing the intercept and the white noise is ϵ for the panel cross-sections ($i = 4$) over the period ($t = 1990, \ldots, 2018$).

We include population and financial development as important control variables in the model. Given foremost literature that presents economic growth as a function of main inputs i.e., capital (such as mechanization and financial instrument) and labour (human capita), financial instrument such as FD and human capita such as POP have been often employed to respectively proxy for capital and labour (Prochniak, 2011; Dawson, 2003; Cuaresma et al., 2014; Pradhan et al., 2016). Furthermore, although related studies deploy per capita income or population and sometimes both variables to empirically model green growth and productivity (Fernandes et al., 2021), the current study employs POP as a control variable for following reasons: (i) including income per capita and population in the same model could increase the potential of serial correlation in the model, (ii) since the dependent variable, i.e., GY is measured as the ratio of GDP to GHG emissions, this ordinarily suggests a pre-determined effect of the per capita income and (iii) we focus on green productivity and not emissions per capita intensity in which case the use of GDP per capita would be theoretically motivated (Costantini et al., 2017). Thus, we assume that green growth effect of POP is less likely to be pre-determined and, thus, aligns with the augmented growth and green growth models (Mankiw et al., 1992; Brock and Taylor, 2010).

The aforementioned CD and slope homogeneity tests provide a foundation for the adoption of appropriate stationarity and cointegration tests that precede the use of the coefficient estimation technique. The Breusch−Pagan Lagrange Multiplier test by Breusch and Pagan (1980) together with the Pesaran (2015) test reject the null hypothesis of non-dependence, as implied in Table 3. Additionally, slope homogeneity was tested by Pesaran and Yamagata (2008), with the result suggesting rejection of the null hypothesis of homogeneous slope coefficients, as indicated in the upper part of Table 4. Moreover, there is no multicollinearity in the model, as indicated by the relevant test and other diagnostics, the results of which are not provided here because of space limitations.

Following the evidence of CD, stationarity and cointegration tests are performed. Although the results of the stationarity tests are not provided

[5] Large negative emissions from land use and forestry are a significant contributor to this situation. Emissions from land use and forestry are also negative in Finland and Norway but less so than in Sweden.

Table 1
Statistics of the variables.

Statistics	Y	GY	GHG	FD	POP	CCTS	CCTSS
Denmark							
Mean	2.71E+11	3208145	71013.99	53.119	5453462	159.445	546.651
Std. Dev.	3.83E+10	1986294	14615.48	4.660	209042.6	133.530	260.375
Skewness	−0.281	0.834	−0.338	0.781	0.280	0.438	0.110
Kurtosis	2.150	2.488	1.840	3.868	1.974	1.576	1.509
J-Bera	1.342	3.930	2.328	3.858	1.765	3.613	2.934
Probability	0.511	0.140	0.312	0.145	0.414	0.164	0.231
Finland							
Mean	2.07E+11	3788433	50379.03	54.906	5273009	90.548	480.503
Std. Dev.	3.86E+10	2070616	9938.278	7.700	167833.5	61.866	194.383
Skewness	−0.533	0.758	−0.306	0.170	0.088	0.545	−0.080
Kurtosis	1.773	2.541	1.892	1.627	1.770	1.949	1.646
J-Bera	3.411	3.237	2.069	2.418	1.994	2.959	2.402
Probability	0.182	0.198	0.355	0.300	0.369	0.228	0.301
Norway							
Mean	3.24E+11	6464936	35369.84	52.000	4728520	40.960	531.404
Std. Dev.	6.00E+10	3172398	4035.000	4.697	368662.0	26.247	254.569
Skewness	−0.414	0.025	−0.333	0.490	0.413	0.175	0.217
Kurtosis	2.012	1.520	2.534	2.670	1.785	1.761	1.520
J-Bera	2.146	2.831	0.852	1.290	2.787	2.141	3.071
Probability	0.341	0.243	0.653	0.525	0.248	0.343	0.215
Sweden							
Mean	4.09E+11	18368061	25929.80	35.565	9232847	181.0351	519.258
Std. Dev.	8.60E+10	17019820	9711.157	24.681	520828.0	116.3682	226.542
Skewness	0.0244	2.276	−0.158	−0.236	0.778	0.444	0.137
Kurtosis	1.716	9.638	1.755	1.480	2.413	1.762	1.584
J-Bera	2.133	83.674	2.132	3.060	3.571	3.000	2.687
Probability	0.344	0.000	0.344	0.217	0.168	0.223	0.261
Panel							
Mean	3.03E+11	7957394	45673.17	48.897	6171959	117.997	519.454
Std. Dev.	9.43E+10	10632835	19889.37	15.305	1826755	108.965	233.837
Skewness	0.643428	4.261831	0.556792	−1.925	1.094932	1.1334	0.188
Kurtosis	2.956582	27.79245	2.637622	6.396	2.534	3.069	1.675

Note: J-Bera is Jarque-Bera statistics.

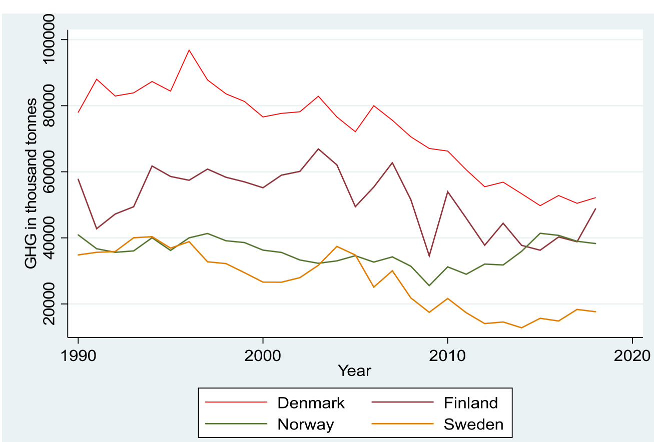

Fig. 1. Illustration of the trend in GHG emission in the Nordic countries.

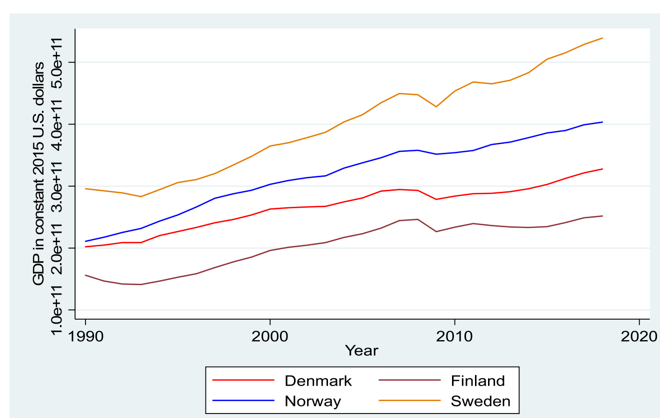

Fig. 2. Illustration of the trend in GDP in the Nordic countries.

here due to space constraints, they indicate that the variables are all stationary at most after the first difference. Furthermore, as implied by the cointegration result in Table 4 (lower part), the Westerlund (2007) panel cointegration test could not sufficiently reject the no cointegration null hypothesis evenly among G_a, G_t and P_a, P_t. However, cointegration based on error correction by Persyn and Westerlund (2008) and Kao's (1999) modified Dickey-Fuller cointegration estimation were applied, and the results validate cointegration in the examined panel (see Table 5).

3.3.2. Coefficient estimation

Backing the error correction-based cointegration evidence, the autoregressive distributed lag (ARDL) that is based on the error correction form is found to be suitable to provide a long-run coefficient estimate. Following Pesaran and Smith (1995) and Pesaran et al. (1999),

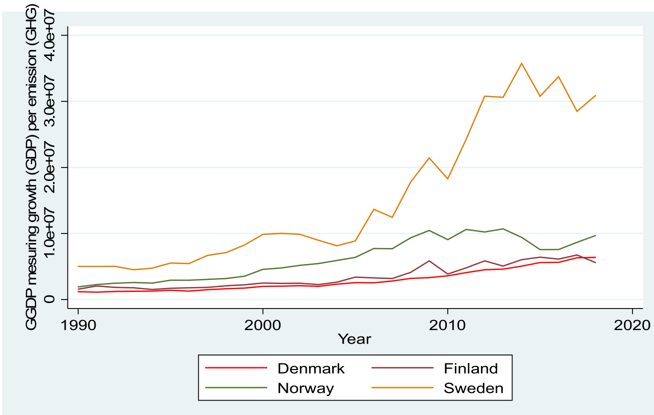

Fig. 3. Illustration of the trend in GY i.e. green productivity in the Nordic countries. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Correlation evidence.

Probability	GY	POP	FD	CCTS	CCTSS
GY	1.000				
POP	0.709[a]	1.000			
FD	0.193[b]	−0.380[a]	1.000		
CCTS	0.674[a]	0.522[a]	0.305[a]	1.000	
CCTSS	0.423[a]	−0.004	0.444[a]	0.447[a]	1.000

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

Table 3
Cross sectional dependence in the variables.

	Breusch-Pagan LM	Pesaran scaled LM	Pesaran CD
Model	52.685[a]	13.4477[a]	−0.069

Note: a = probability value < 0.01.

Table 4
Further test for cointegration and slope homogeneity.

Slope homogeneity		Delta			Adjusted Delta
Model		4.55[a]			5.10[a]
Cointegration	Gt	Ga	Pt	Pa	Lag type
Model	−7.10[a]	−0.37	−8.25[a]	−0.41	AIC (3.0)

Note: a = probability value < 0.01 and b = probability value < 0.05. AIC and () are respectively the Akaike information criterion and the lag length.

Table 5
Cointegration.

Model		
Error-correction- panel cointegration tests		
Critical value	−1.382	0.083[c]
All panels	−0.876	0.191
Kao test for cointegration	Statistics	Probability
Modified Dickey-Fuller	−3.648	0.000[a]
Unadjusted modified Dickey-Fuller	−4.795	0.000[a]
Dickey-Fuller	−3.033	0.001[a]
Unadjusted Dickey-Fuller	−4.427	0.000[a]

Note: a = probability value < 0.01, b = probability value < 0.05, and c = probability value < 0.10.

the advantages of the three main proposed estimators, i.e., dynamic fixed effect (DFE), mean group (MG), and pooled mean group (PMG), are priorities in the consideration of the techniques. For instance, implementing the MG and PMG estimators does not necessarily require tests for stationarity and cointegration in estimating the long-run relationship among the variables. Moreover, the issue of endogeneity[6] is also accounted for by the above-mentioned estimators, and especially the PMG approach. Specifically, as detailed in Pesaran et al. (1999), the PMG approach assumes that the error terms to be serially uncorrelated and are distributed independently of the regressors. Additionally, for individual basis, the PMG provides coefficients for adjustment speed to the long run alongside the short run and estimates. However, the estimator is restricted to homogeneity in long-run slope coefficients in the panel, unlike the MG, which allows coefficients to differ, i.e., be heterogeneous in the short and long run. Meanwhile, the DFE estimator is similar to the PMG since it also exhibits the homogeneity limitation of coefficient estimation and the speed of adjustment. Irrespective of the differences in the efficiency of these estimators, the Hausman test is employed to test the significance of the differences among the estimators as well as to suggest the most appropriate estimator. Thus, the null hypothesis of no significant difference between the PMG and MG is tested with a Hausman approach, and the PMG is selected in case of failure to reject the null hypothesis. The step-by-step empirical approach that covers the equations and parameterization of the estimators is not provided here since it is widely covered in the literature. Meanwhile, Pesaran et al.'s (2001) approach of ARDL bound-testing to cointegration was further employed to provide country-specific long-run coefficient estimation.

3.3.3. *Robustness estimation: Granger causality and dynamic ordinary least square*

To ensure robustness of the coefficient estimates, the recently developed Granger noncausality (known as the JKS causality test) is employed following Juodis et al. (2021). This causality approach implements the Half-Panel Jackknife (HPJ) Wald-type test to provide power performance and a superior size through a pooled estimator with a (NT)^(1/2) rate of convergence. Considering that the approach is appropriate for multivariate systems while accounting for homogeneous and heterogeneous situations, it has been employed to offer insights into robustness. Moreover, Dumitrescu and Hurlin's (2012) Granger causality approach is further employed given its robustness to endogeneity drawback. Finally, dynamic ordinary least square (DOLS) by Pedroni (2001) is also employed due to its suitability for panel cross-section dependence and slope heterogeneity. DOLS method takes endogeneity into account by including leads and lags of first differences of the regressors.

4. Empirical results and discussion

4.1. *Panel results*

The results of panel estimation with MG, PMG, and DFE, as displayed in Table 6, are the first aspect of the coefficient estimation, followed by the country-specific results in section 4.2 and Table 7. Although the panel investigation offers important insight into the green productivity prospects of the Nordic region, country-specific investigation is also considered important to note potential differences and possibly provide country-specific policy suggestions.

Three specifications with the selection of PMG are explored: the first

[6] The novelty of our study is to study the effect of CCT spillovers. As these spillovers emanate from the innovation activities of other countries, the endogeneity concern appears to be less marked in the case of CCT spillovers than regarding own CCT innovations. Nevertheless, we conduct robustness tests as described in section 3.3.3.

Table 6
Long-run coefficient estimates.

	DFE	MG	PMG	DFE	MG	PMG	DFE	MG	PMG
ECT	−0.40[a]	−0.84[a]	−0.57[b]	−0.39[a]	−0.76[a]	−0.49[b]	−0.20[a]	−0.69[a]	−056[b]
POP	−0.92	7.27	4.67[b]	−0.97	7.53	9.52[a]	−7.99	3.25	5.17[b]
FD	0.01[a]	−0.00	0.01[b]	0.01[a]	−0.01	0.00	0.01	−0.02	0.01[b]
CCTS	0.61[a]	0.50	0.10	0.61[a]	0.64	0.22[a]			
CCTSS	−0.03	0.20	0.64[a]				1.68[b]	1.23[b]	0.85[a]
H-T	PMG is selected			PMG is selected			PMG is selected		

Note: a = probability value < 0.01, b = probability value < 0.05, and c = probability value < 0.10. Also, H-T denotes Hausman test.

Table 7
Country-specific long-run coefficient estimates (ARDL Bound-test).

	Denmark Coefficient		Finland Coefficient		Norway Coefficient		Sweden Coefficient	
POP	9.81[a]	0.42[a]	0.75[a]	0.36[a]	0.90[a]	0.82[a]	0.56[a]	0.26[b]
FD	0.00	0.01	0.01[b]	0.01	−0.03[b]	−0.09	−0.00	0.00
CCTS	0.22[a]		0.46[a]		0.69[a]		1.13[a]	
CCTSS		1.19[a]		1.11[b]		1.07[b]		1.72[a]
ECT (−1)	0.72[a]	0.82[a]	0.94[a]		0.45[a]	0.14[a]	0.58[a]	0.69[a]
R^2	0.99	0.80	0.96	0.99	0.98	0.97	0.97	0.97
J-Bera	7.80	0.79	0.55	0.24	0.52	0.73	0.92	1.27
F-Bounds Test	11.81[a]	12.01[a]	7.89[a]	9.29[a]	6.37[a]	3.83[b]	5.13[a]	4.40[c]
B-G SR LM Test	(0.57)	(0.50)	(0.92)	(0.36)	(0.31)	(0.80)	(0.76)	(0.79)
B–P-G H Test	(0.79)	(0.21)	(0.55)	(0.63)	(0.52)	(0.56)	(0.35)	(0.64)
CUSUM Test	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUSUM of Squares	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable

Note: a = probability value < 0.01, b = probability value < 0.05, and c = probability value < 0.10. The B-G SR LM Test is Breusch-Godfrey Serial Correlation LM Test and B–P-G H Test is Breusch-Pagan-Godfrey Heteroskedasticity Test. Also, () encloses the probability value.

involves the estimation of the main model (represented in Equation (2)), while the second and third involve incorporating CCTS and CCTSS one at a time. In the first specification (leftmost side of Table 6), there is a short-run adjustment by a speed of 57 percent annually. For the role of climate change technological development within the countries and the spillovers of climate change technologies to these countries, the positive contribution to green productivity is observed which supports the hypotheses 1 and 2. Despite criticism of green growth (e.g., Antal & Van den Bergh, 2016; Hickel and Kallis, 2020), the results presented here clearly show that green technologies and green technology spillovers support green productivity and are associated with a reduction in total GHG emissions.

Importantly, when domestic CCT and CCT spillovers are considered together, technological spillovers exert a statistically significant positive impact on green productivity in the long run, while the contribution of CCT stock within the countries is statistically insignificant. However, upon considering the role of the climate change technologies one at a time, green productivity responds to climate change technologies within the country and CCT spillovers with statistically significant elasticities of 0.22 and 0.85, respectively. Notably, the panel investigation reveals that the transfer and diffusion of climate change technologies promotes green productivity in the Nordic region far more (approximately three times more) than climate change technological development within the countries. This result provides empirical support for hypothesis 3 and confirms that for the Nordic countries, as examples of small open economies, the green productivity is more strongly generated by foreign technological development than domestic innovations. Thus, our results extend and reassert the earlier findings of Keller (2004) regarding relative importance of domestic and foreign technological development in general.

Furthermore, the results show that the Nordic economies grow with declining GHG emissions by ~4.7 percent when there is an increase in the region's population. This result could ordinarily be justified in terms of both economic prosperity and the decline in GHG emissions in these countries in recent years. For instance, this outcome could be because society is well educated and knowledgeable about the environmental challenges of the 21st century, such as the issues of climate change; therefore, the people (irrespective of the change in the population) are already taking responsibility for their economic choices and activities, such as the increasing adoption of low carbon cars, adoption of energy efficiency practices, consumption choices, reuse and recycling of material resources, etc. On the other hand, the desirable impact of the population on green productivity could be explained by strong economic development amidst a relatively low increase in the human population, especially due to the demographic influence (older population) among the Nordic countries. Of course, this issue has increasingly become an economic concern among the Nordic countries. Generally, although there is a (traditional) notion that population largely exerts an adverse effect on the environment (Dietz and Rosa, 1997; Holdren and Ehrlich, 1974), this assertion has since produced two different augments in the literature considering that urbanization is believed to play an ambiguous role (Rosa and Dietz, 2012). For instance, Xu et al. (2019) examined the case of 28 EU member states and found that population density caused a decline in energy-related per capita GHG emissions over the period 2000–2012. This result also aligns with the finding of Alola et al. (2019) that the fertility rate mitigates the ecological footprint, improving environmental sustainability across selected EU member countries from 1997 to 2014. However, an earlier study by Hamilton and Turton (2002) established that population growth spurred energy-related GHG emissions across the entire panel of the Organisation for Economic Co-operation and Development (OECD) during period 1982–1997.

Meanwhile, the results show that financial development engineers a green productivity pathway in the Nordic region. As indicated in Table 6, financial development in the Nordic economies appears to be a statistically significant driver of economic productivity while achieving low-carbon emissions. The implication of this observation is that financial development not only promotes growth but also potentially yields desirable outcomes when deployed through financing of low-carbon technologies. This result also aligns with earlier studies (Acheampong et al., 2020).

4.2. Country-specific results

For the country-specific results displayed in Table 7, there is no significant deviation from the aforementioned panel results. This is in line with the understanding that the Nordic economies share many similarities, e.g., the level economic development, climate policy ambition and international trade policies, which could have induced more heterogenous results.

To properly account for the roles of climate change technologies in each country while minimizing potential econometric error, the estimation was conducted with each climate change technology variable incorporated in the model one at a time. As shown in Table 6, population plays a statistically significant role in promoting greening productivity in each of the examined countries, while the role of financial development is subjective. For instance, financial development significantly promotes green productivity in Finland but not in Norway, while its impact in Denmark and Sweden is statistically insignificant. Moreover, both the development of climate change technologies and the diffusion of climate change technologies promote green productivity in each country. Importantly, a larger impact is again exerted by the diffusion of climate change technologies than the development of climate change technologies within each country. Sweden shows the highest benefits arising from both the development of climate change technologies and the diffusion of climate change technologies, which aligns with the visual illustration in Fig. 3. While the development of climate change technologies promotes greening productivity more in Norway than in Finland (with an elasticity of 0.69 against 0.46) and is the lowest in Denmark, the diffusion of climate change technologies in Denmark exerts a larger impact (elasticity of 1.19) than in Finland (elasticity of 1.11) and has the lowest impact in Norway.

4.3. Diagnostic and robustness results

Following the implementation of the ARDL technique for the country-specific investigation, the diagnostic results of the technique are displayed in the lower part of Table 7. Specifically, there is statistically significant evidence of a short-run relationship in the examined model, while tests reveal failure to reject the null hypotheses for no serial correlation and homoskedasticity. Additionally, cumulative sum and cumulative sum of square tests affirm the stability of the examined model. Moreover, along with the JKS causality evidence in Table 8, there is a statistically significant Granger causality from all indicators (except financial development) to green productivity in the panel of Denmark, Finland, Norway, and Sweden. Additionally, to further circumvent the problem of endogeneity, cross sectional dependence, and slope heterogeneity, robustness results for both panel Granger causality and coefficient estimations are provided. Clearly, the panel DOLS in Table A (see the appendix) strongly aligns with the PMG result and the Granger causality approaches i.e., HPJ (Table 8) and Dumitrescu and Hurlin (see the appendix) are also strongly assertive.

Table 8
JKS Granger non-causality results.

	Coefficient	Standard error	Z	Probability
POP	-4.15^{a}	0.45	−9.12	0.00
FD	−0.08	3.50	−0.02	0.98
CCTS	0.76^{c}	0.43	−1.76	0.08
CCTSS	-0.60^{a}	0.14	−4.35	0.00

Note: a = probability value < 0.01 and c = probability value < 0.1. BIC selected lags (2) = −471.38142 from the maximum lag of 3 i.e lags (1) = −471.07147, lags (2) = −471.38142, and lags (3) = −458.41469. JKS is the Juodis et al. (2021) Granger non-causality test which is estimated by computing the sum of Half-Panel Jackknife (HPJ) Wald test coefficients across lags. The hypotheses are: H_0: Selected covariates do not Granger-cause GY and the H_1: H_0 is violated.

5. Conclusions and policy recommendations

This study examined the growth path of the Nordic countries with respect to the region's progress in mitigating environmental degradation vis-à-vis GHG emissions. Considering the case of Denmark, Finland, Norway, and Sweden, i.e., the Nordic countries (with the exception of Iceland), this study examines whether the domestic stock of climate change technologies and climate change technology spillovers contribute to green growth over the period 1990–2018. Additionally, the contributions of population and financial development to the greening growth are examined by employing econometric panel and time series tools to offer both regional and country-specific insights.

Prior to examining the main results, necessary pre-tests, such as the CD, homogeneity, stationarity, and cointegration tests, were performed, which provided justification for the chosen empirical techniques. Importantly, the investigation revealed that the stock of climate change technological development within the countries and the international diffusion of climate change technologies promote green growth in the panel analysis. Moreover, the country wise investigations align with the panel findings. Importantly, we observed a larger impact from international climate change technology diffusion on green growth than from domestic technological development in each country as well as in the panel.

In the panel investigation, both population and financial development had a statistically significant contribution in promoting economic growth without necessarily causing an upsurge in GHG emissions. Specifically, the population exerts a statistically significant and positive impact on green growth in each country, while the impact of financial development is only positively significant in Finland. Last, the recently developed Granger causality approach by Juodis et al. (2021) shows causality only from the population, climate change technology spillovers, and climate change technological development within the countries to green growth.

5.1. Policy recommendations

The results of this investigation enable propositions for relevant policies in the Nordic countries. As international technology diffusion appears to be the key channel to achieve green productivity growth, public policies should provide support for international technology and R&D cooperation. Considering the desirability of both domestic climate change technological development and the international spillovers of climate change technologies, the Nordic countries would also need to scale up the domestic development of climate change technologies. International coordination of climate change technology subsidies and support policies is also warranted, as the identified strong international technology spillovers can provide free-riding motives leading to suboptimal R&D investments globally. In the European context, this provides motivation for the European Union to coordinate R&D policies in order to avoid free-riding. Due to the double externality related to green technological development, these policy concerns appear even more pertinent than for technological development in general.

National climate change technology support policies can also provide double benefits as domestic technology investments may provide crucial absorptive capacity needed to better profit from technologies developed abroad. As literature has shown regarding overall R&D spillovers (Coe et al., 2009; Seck, 2012), differences in absorptive capacity could also explain the observed differences in how the countries benefit from foreign technology spillovers. Further research could provide insight on this aspect. Furthermore, we have analysed technology spillovers as transmitted by international trade. While important, we do not expect this to be an exhaustive channel of technology spillovers. Further studies could explore the different channels of international climate change technology diffusion in more detail. Another question left to future studies is to verify whether the same national characteristics and policies, such as strong intellectual property protection and educational system, support green spillovers as they do other technology spillovers (Coe et al., 2009; Seck, 2012).

Moreover, the desirable role of financial development and population louds the need to deploy more financial instruments such as providing credit and incentives for entrepreneurial activities through public and private engagements. Concerning the role of population, government of these economies should further consider measures that encourages birth-rate among families and promotion of skilled migration policy to buffer the effect of population ageing.

5.2. Limitations and recommendations

One obvious limitation of the present analysis is that we have not analysed the differences between climate change technology fields. There are differences in the technological specialization among the Nordic countries, which may reflect on our estimation results.

There are also potential drawbacks of the dependency on imported environmental-related technology, which have been exemplified in the recent situation of EU's dependency on Russian energy. Thus, the result of this investigation should inspire the Nordic countries to rather increase investment in home-made climate change technology development. Investment in clean technologies could be scaled up through public-private partnerships across economic sectors, deployment of fiscal policy such as subsidy or targeted tax relief, and increase in research funding to relevant institutions.

CRediT authorship contribution statement

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

The used data is freely available from online sources.

Appendix

Table A
Robustness estimation for the panel analysis.

DOLS results	P	P_w	P	P_w	P	P_w
	effect	*effect*	*effect*	*effect*	*effect*	*effect*
POP	−2.966	−3.201	−0.326	0.522	−4.555[c]	−0.999
FD	0.003	0.004	0.002	0.003	0.007[c]	0.007[a]
CCTS	0.350[a]	0.304[b]	0.571[a]	0.527[a]		
CCTSS	0.690[c]	0.775[c]			1.569[a]	1.281[a]

Granger causality by Dumitrescu and Hurlin.
POP does Granger cause GY (reject null hypothesis with w-statistics = 4.506, p-value = 0.000).
FG does not Granger cause GY (fail to reject null hypothesis with w-statistics = 0.309, p-value = 0.344).
CCTS does Granger cause GY (reject null hypothesis with w-statistics = 7.844, p-value = 0.000).
CCTSS does Granger cause GY (reject null hypothesis with w-statistics = 5.499, p-value = 0.000).
Note: [a], [b], and [c] are respectively $p < 0.01$, $p < 0.02$, and $p < 0.1$. Additionally, P and P_w respectively pooled and weighted pooled estimates.

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