Journal of Environmental Management 370 (2024) 122972

Contents lists available at ScienceDirect

Journal of Environmental Management

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

Research article

The effects of climate change technology spillovers on carbon emissions across European countries

Jaana Rahko[a,b,*], Andrew Adewale Alola[c]

[a] Department of Economics, School of Accounting and Finance, University of Vaasa, 65200, Vaasa, Finland
[b] Vaasa Energy Business Innovation Centre, University of Vaasa, 65200, Vaasa, Finland
[c] CREDS - Centre for Research on Digitalization and Sustainability, Inland Norway University of Applied Sciences, 2418, Elverum, Norway

ARTICLE INFO

Keywords:
Climate technology
Green innovation
Technology spillovers
Carbon dioxide emissions
Environmental sustainability

ABSTRACT

To unravel the challenges in the global diffusion of climate-friendly technologies, this investigation analyzes the diffusion of climate change-related technologies across countries. By using an unbalanced panel of selected European countries over the period 1990–2020, this investigation quantifies the carbon dioxide (CO2) emission effects of the diffusion of climate change-related technologies that are mediated by imports, geographical and technological proximity and free diffusion of technologies. In this study, the effects of domestic development of climate change-related technologies, population and affluence are also accounted for, and the emission effects are estimated using a fixed-effects panel model with instrumental variables. The instrumental variable for foreign technology spillovers is based on the technology support policies adopted in foreign countries. As expected, international spillovers of climate-friendly technologies are negatively linked to CO2 emissions, thus promoting emission reductions across the region. Importantly, emission reductions in Europe are more strongly influenced by international technology spillovers than by domestic innovation activities. Moreover, while all the analyzed technology diffusion channels appear relevant, the results are the most robust regarding import-mediated technology spillovers. Insights from this study support policy recommendations, especially in the trade policy context.

1. Introduction

Technological development and technology diffusion are vital to economic development. In the context of climate change mitigation, there is a clear indication that technological innovations offer a dual solution, i.e., geared toward improving economic output (Acemoglu, 2012; Ferreira et al., 2019; Aldieri et al., 2022) alongside combating climate change challenges (Probst et al., 2021; Milindi & Inglesi-Lotz et al., 2022). Nevertheless, according to Amoroso et al. (2021) and Probst et al. (2021), the development of climate change mitigation technologies (CTs) is heavily concentrated in few countries. Thus, for most countries, foreign sources of technology account for a vast majority of green technological development. Given this perspective, the Paris Agreement and the Intergovernmental Panel on Climate Change (IPCC) clearly highlighted the need for climate-resilient sustainable development pathways through the vast development of climate-related technologies and their diffusion to mitigate climate change (UNFCCC, 2020). Thus, the post-Kyoto climate era is critically saddled with the promotion of the global application of low-carbon or climate-friendly technologies. Nevertheless, the pace of the global diffusion of CT innovations remains limited due to, e.g., lack of information, financial costs of technology adoption, reluctance to share intellectual assets, and inadequate investment in research and development (R&D) among countries (Dechezleprêtre et al., 2011; Kassouri and Alola, 2023; Touboul et al., 2023). Moreover, while the abovementioned challenges to CT diffusion on a global scale remain an area of interest to researchers and policymakers, the patterns of diffusion should also raise interesting research questions.

Considering the criticality of CT diffusion for improving environmental sustainability and decarbonization of the energy sector, the current study advances the literature from the perspective of diffusion mechanisms. While Verdolini and Galeotti (2011) showed that foreign technology spillovers mediated by geographical and technological proximity contribute to domestic environmental innovativeness, there are gaps in our understanding of whether and how these spillovers also contribute to domestic environmental outcomes. Therefore, in addition

* Corresponding author. Department of Economics, School of Accounting and Finance, University of Vaasa, 65200, Vaasa, Finland.
E-mail addresses: jaana.rahko@uwasa.fi (J. Rahko), andrew.alola@inn.no (A.A. Alola).

https://doi.org/10.1016/j.jenvman.2024.122972
Received 6 March 2024; Received in revised form 9 September 2024; Accepted 16 October 2024
Available online 19 October 2024

to considering the role of domestic CT (as in prior studies such as Du and Li (2019), Töbelmann and Wendler (2020), Erdoğan et al. (2020) and Cheng et al., 2021), this study especially analyzes the roles of the different international spillover mechanisms of CT and their effects on carbon emissions. Specifically, the mechanisms of climate change-related technology spillovers under consideration include technology diffusion mediated through imports, geographical and technological proximity and free diffusion. We estimate their CO_2 emission effects using a fixed-effects panel model with instrumental variables to address the potential endogeneity of technology spillovers. We propose an instrument for technology spillovers that is formed based on the technology support policies of foreign countries. Our empirical approach allows us to control for global time trends in technology support policies and to control for possible policy spillovers by controlling for domestic support policies, which lends support to the exogeneity of our instrumentation strategy. Furthermore, the present study contributes to the literature by providing novel country-level evidence on the CO_2 emission effects of technology spillovers.

While there is considerable literature that shows how international R&D spillovers influence economic performance (Ang and Madsen, 2013; Keller, 2010, 2021), prior studies on the emission impacts of green technology spillovers focus on the regional or firm level or on a smaller set of countries (Aldieri et al., 2022; Alola and Rahko, 2024; Costantini et al., 2013; Chen et al., 2023; Huang et al., 2018). In addition, Sun et al. (2021) provide a country-level analysis of the energy efficiency impacts of technology spillovers. Meanwhile, by considering the case of China, Huang et al. (2018) examine how the country's carbon intensity responds to domestic R&D investment and spillovers through international trade and foreign direct investments. Given this evidence from a country-specific investigation, we nevertheless lack comparative evidence on the importance of other spillover channels, particularly across a large panel of countries, which is another contribution of the present study.

Our empirical results indicate that CO_2 emission reductions in Europe arise more strongly from international CT spillovers than from domestic CT innovations. Moreover, while all the analyzed technology diffusion channels appear relevant, the empirical results are the most robust regarding import-mediated technology spillovers, highlighting trade contacts as a key technology diffusion channel. In addition to allaying the skepticism associated with the challenges of diffusing climate change-related technologies, the current study offers a novel perspective on climate change discussion. In addition to providing rare insight into the literature, European countries are the focus of investigations given the heterogeneity in economic and socioeconomic aspects across the continent. Moreover, Europe is globally significant in terms of both economic climate- and climate change-related issues, i.e., the share of Europe's global greenhouse gas (GHG) emissions and the region's technology drive.

Moving ahead to the other sections of this study, the literature is described in detail in Section 2. In Sections 3, 4, and 5, the description of the dataset, the empirical methods, the discussion of the findings, and the conclusion of the investigation are presented, respectively.

2. Literature review

The efforts to mitigate greenhouse gas (GHG) emissions and improve the environmental sustainability of energy and industrial sectors are largely associated with climate change mitigation technologies (CTs) and environmental innovations. Nevertheless, the rebound effect suggests that part of the climate change mitigation gains of innovations may be canceled when an environmental innovation that improves resource efficiency also leads to a decrease in the effective price of that resource and, hence, demand for the resource increases (Alcott, 2005). Thus, the climate impacts of environmental technological change remain theoretically ambiguous. However, the empirical literature provides some, although not ubiquitous, evidence of the climate benefits of CTs (Du and Li, 2019; Du et al., 2019; Töbelmann and Wendler, 2020; Yıldırım et al., 2022; Erdoğan et al., 2020). In particular, the studies of Töbelmann and Wendler (2020) and Yıldırım et al. (2022) affirmed this perspective for the panels of the European Union (EU) and Organization for Economic Cooperation and Development (OECD) countries, respectively. In the case of the EU, during the period 1992–2014, Töbelmann and Wendler (2020) show that environmental innovations have significant but modest contribution to a reduction in CO_2 emissions. Similarly, Du et al. (2019) examined the climate change effects of green technology innovations in a panel of 71 countries over the period 1996–2012. The findings showed that the role of green technology innovations in CO_2 emission mitigation is conditioned on income level and that green technology innovations have no mitigating effect on CO_2 emissions in economies that are below a certain income threshold but mitigate CO_2 emissions in economies that surpass such an income threshold. The results by Jiang et al. (2022) support the same conclusion. Moreover, Erdoğan et al. (2020) find that innovations reduce emissions only in one of the sectors that they study. This heterogeneity in results underscores the need for more research on the impacts of climate innovations and their diffusion.

Theoretical studies further emphasize the importance of CT diffusion for cost-effective emission abatement (Hübler et al., 2012; Huang et al., 2017). Different approaches have been applied to evaluate the role of climate-friendly technologies in mitigating climate change as reported by Huang et al. (2017) and Mandel et al. (2020). Specifically, evidence from Huang et al. (2017) shows that welfare losses and long-term abatement costs arising from the mitigation of carbon emissions can be minimized by the diffusion of the abovementioned technology designs.

By investigating the trend in both the development and diffusion of CTs, Probst et al. (2021) showed a 10 percent annual growth over the period 1995 to 2012 and a 6 percent decline in growth between 2013 and 2017 in CT inventions. Furthermore, the results show high concentrations by geographical location, especially in Germany, Japan, and the United States. Thus, the study reiterates the significant disparity in the international diffusion of CT inventions compared to their potential highlighted in more theoretical studies.

The role of CTs is further conditioned on the diffusion mechanisms of these technologies, which may provide insight into the limited scope of international technology diffusion. In the broader literature on technology diffusion and R&D spillovers, diffusion channels have been studied widely. Ang and Madsen (2013) summarize different channels of R&D spillovers as follows: imports, exports, foreign direct investments (FDI), geographic proximity, foreign patents and free diffusion of knowledge. This literature is also reviewed by Keller (2010, 2021). In micro-level studies, the role of technological proximity, as suggested by Jaffe (1986), is highlighted. In line with this literature, Verdolini and Galeotti (2011) and Kim and Verdolini (2023) show that a lack of trade borders and geographical, linguistic and technological proximity mediate international clean energy technology spillovers and contribute to domestic innovation. The role of environmental policy and similarity in environmental policies between countries for the countries' international collaboration and technology diffusion in green energy technologies was queried by Corrocher and Mancusi (2021) and Verdolini and Bosetti (2017). Their findings reveal that collaboration among countries is hindered by distance in their environmental policy stringency. Although these studies have shown that international collaboration in green technologies is promoted by the availability of domestic technological capabilities, the distance between partnering countries is a significant setback.

Moving ahead to the environmental and emission effects of CT spillovers, prior empirical studies provide some indication of their impacts and related diffusion channels. Costantini et al. (2013) report that technological and geographical proximity-mediated technology spillovers lead to emission reductions among Italian regions. Additionally, using regional data, Ghisetti and Quatraro (2017) show that sectoral input−output relationships facilitate technology spillovers that influence environmental productivity (i.e., economic output per unit of emissions). At provincial- and regional-level, Huang et al. (2018) examine how carbon intensity across the panel of 30 Chinese provinces responds to domestic R&D investment and spillovers arising from FDI and trade over the period of 2000–2014. The results reveal that domestic R&D and technology spillover from overseas contribute to the reduction of carbon intensity across the examined panel of provinces. Wan et al. (2015) show that international trade links facilitate energy productivity convergence among EU countries, thus also highlighting the role of trade connections in energy technology diffusion. Analyzing the GHG emissions of Nordic countries, Alola and Rahko (2024) show that climate change technology spillovers facilitated by geographic proximity contribute to national emission reductions. These results are corroborated by Zhou et al. (2023), who show that spatial proximity mediates technology spillovers that influence regional carbon emissions. While Sun et al. (2021) study the role of geographic proximity for energy intensity convergence in a sample of 24 countries, we lack similar large scale country-level evidence for CO_2 emissions.

Another strand of studies interprets inward and outward foreign direct investments (FDI) as a proxy for technology diffusion and knowledge spillovers. While international trade and FDI facilitate technology diffusion, the literature also argues that they may lead to intensified international specialization and higher pollution or energy intensity in some countries (Copeland and Taylor, 1999, 2004). Thus, this strand of literature may conflate these two effects. These studies, such as Zhou et al. (2019), Pan et al. (2020) and Li and Ouyang (2020), provide indication that international technology diffusion through FDI improves carbon and green productivity in China. In addition, e.g., Wang et al. (2021) and Chen et al. (2023) use spatial Durbin model to analyze the effect of regional CT spillovers on carbon intensity and green total factor productivity; however, their results are mixed. While spatial spillovers in environmental outcomes have been studied in other settings as well, overall, studies focusing on spillovers remain scarce; see, e.g., Hecker et al. (2020). Thus, there is a lack of especially country-level studies analyzing the environmental impacts of CT spillovers.

The above-described literature implies that geographical proximity and trade links transmit technologies across national borders and within countries, but these studies, with the exception of Verdolini and Galeotti (2011), do not show a comparison of the different diffusion channels. Generally, despite the evidence provided by the above studies, there is a lack of deliberation on how the modes of diffusion of CTs influence the trend of emissions. While in country-level studies, the diffusion of CTs and environmental innovations has been mostly illustrated by foreign direct investment (FDI) or by not accounting for the differential effects associated with the different CT diffusion channels, the current study deviates from this traditional approach. Importantly, this study contributes to the body of related knowledge by exploring the factors of distance from the country of origin of climate-friendly technology, trade connections associated with imports and technological similarity.

3. Methods and variable description

3.1. Model specification

We take the STIRPAT model (STochastic Impacts by Regression on Population, Affluence and Technology) as an empirical starting point (Dietz and Rosa, 1997; York et al., 2003). When written in logarithmic form and considering CO_2 emissions as the environmental outcome of interest, we obtain the following equation:

$$\ln (CO_2)_{it} = \beta_0 + \beta_1 \ln POP_{it} + \beta_2 \ln \frac{GDP_{it}}{POP_{it}} + \beta_3 \ln T_{it} + \beta_4 \ln S_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{1}$$

The dependent variable is the environmental impact, i.e., the level of CO_2 emissions, which depends on population (POP), GDP per population and technology. The technology component of the STIRPAT model consists in our case of two explanatory variables: a country's own climate technology innovations (T) and CT spillovers (S) from other countries. Moreover, γ_i is the time invariant country fixed effect of country i, and μ_t is the year fixed effect for year t. These two variables may be interpreted as the time-invariant country-specific technology factor and a general time trend in technological development.[1]

Spillovers (S) may occur along various channels, as summarized in Section 2. Thus, in the present study, we focus on spillovers transmitted through free technology diffusion (unweighted spillovers, S_1), imports (S_2), geographic (S_3) and technological proximity (S_4). We include them one by one in Equation (1). The formation of the spillover and other variables is described in Section 3.3.

3.2. Data

We collect our data from the World Bank database, World Integrated Trade Solution (WITS), which was also developed by the World Bank, the OECD REGPAT patent database and the OECD Environmental Policy Stringency Index. The World Bank is the source of CO_2 emissions, GDP and population data. We use patent data from the OECD REGPAT (Autumn, 2023 release) database to measure CT innovations and CT spillovers. We focus on European countries; thus, we rely on patent applications filed at the European Patent Office (EPO) following prior studies (Costantini et al., 2013; Többelmann and Wendler, 2020). We consider that CT patents represent the technological progress that is relevant for CO_2 emissions. Thus, CT patents are counted as the number of patent applications in technology classes Y02 and Y04 (Angelucci et al., 2018). Technologies captured by classes Y02 and Y04 include, e.g., renewable energy technologies, energy efficient heating and transport technologies, technologies improving the efficiency of industrial processes and climate change technologies related to improved waste management. Patent applicant information is used to allocate patents to countries because we wish to capture the utilization of inventions. If there are multiple applicants, fractional counting is applied to avoid double counting.

The formation of spillover variables requires information about geographic and technological distances and bilateral trade flows between countries. The import data for each country is collected from the WITS. Technological similarity is measured using patent data and is described in detail in the next section. The measure of geographic distance is the distance between capital cities (in kilometers).[2] Finally, our instrumental variable for technology spillovers is based on the technology support policies adopted in foreign countries. The technology support policy data come from the OECD Environmental Policy Stringency Index and its subindex for Technology Support Policies.

3.3. Formation of independent variables

Next, we describe the formation of our main variables of interest, i.e., the technology variables. We expect that new technologies may have an effect over a longer period. Therefore, we construct the accumulated CT stock using annual patent counts and the perpetual inventory method, as

[1] As robustness tests, we also tested country-specific linear time trends as well as year fixed effects that were allowed to vary across the following country groups: Eastern European countries and other countries, EU member states and non-member states, and countries with above-median initial CO2 intensity (CO_2 emissions per GDP in 1990) and countries with below-median CO_2 intensity. Our main results regarding the impacts of domestic CT innovations and CT spillovers remained in line with the results presented in Tables 1 and 3

[2] We used the dataset provided by professor K.S. Gleditsch (http://ksgleditsch.com/data.html).

is common in the literature (Verdolini and Galeotti, 2011; Sun et al., 2021). The CT stocks representing the countries' own climate change innovations are calculated as follows:

$$T_{it} = (1-\delta)T_{it-1} + P_{it} \tag{2}$$

In Equation (2), P represents the number of climate change mitigation patent applications in year t in country i and T is the respective accumulated technology stock. δ is the depreciation rate, which is set to 15%, as is typical in the related literature (Hall et al., 2010). We do not separately estimate the starting values because EPO patent data start from 1978 and our estimation sample starts from 1990.

The national CT stocks are further used to compute the technology spillover variables. The spillover variables are computed as follows:

$$S_{it} = \sum\nolimits_j w_{ijt} T_{jt} \tag{3}$$

where S is the spillovers available for home country i in year t. T_{jt} is the domestic technology stock in foreign country j. w_{ijt} reflects the weights. In the case of free technology diffusion (S_1), w_{ijt} equals 1 for all foreign countries, and the spillover stock is the unweighted global technology stock, excluding the technology stock of the home country. In the case of import weighted spillovers (S_2), w_{ijt} is the share of country i's imports coming from country j in year t based on the WITS data. In the case of distance-weighted spillovers (S_3), we compute m_{ijt} as the 1/km distance between the capital cities. In the case of technological similarity weighted spillovers (S_4), we count the technological similarity of countries following Jaffe (1986):

$$m_{ijt} = \frac{\left(J_i J_j'\right)}{\left(J_i J_i'\right)^{1/2}\left(J_j J_j'\right)^{1/2}} \tag{4}$$

where J_i is a vector $J_i=(J_{i1}, J_{i2}, J_{i3}, \ldots, J_{i52})$, $J_{i\tau}$ is the share of country i's CT patents in CT subcategory τ, and J_j is the technology vector of foreign country j. There are 52 subcategories considering the subclass and group-level classification in Y02 and Y04.[3]

Finally, the geographic and technological proximity weights are scaled to obtain the final weights as follows:

$$w_{ijt} = \frac{m_{ijt}}{\sum_j m_{ijt}} \tag{5}$$

Scaling using Equation (5) is conducted so that the weights, w_{ijt}, sum to one. In the estimation, we control for country fixed effects; hence, scaling does not affect our estimation results. However, scaling is useful because it eases the interpretability and comparison of spillover variables and instrumental variables. The weights based on import shares naturally sum to one.

3.4. Endogeneity issues

Technology spillovers accrue from innovation activities conducted by other countries. Therefore, the concern of endogeneity may be less marked than in the case of one's own technological innovations. Nevertheless, various omitted factors may lead to endogeneity bias, e.g., regional demand shocks may influence not only emissions but also the innovation activities of nearby countries that are import partners as well as geographically close and, hence, important spillover sources. Therefore, we use the instrumental variable method to address this potential bias.

We use an instrument that is based on technology support policies in place in foreign countries, i.e., spillover source countries. Our approach is inspired by the micro-level studies that form instrumental variables based on geographically varying R&D tax credits (Bloom et al., 2013; Tseng, 2022). The environmental technology support policy of a foreign country is argued to influence the incentives for innovation activities and hence the level of CT innovation in the foreign country (Dechezleprêtre and Sato, 2017; Ghisetti and Pontoni, 2015). Thus, the proposed instrument is argued to meet the criterion of relevance.

Second, the instrument needs to meet the exogeneity criterion, i.e., the foreign technology support policy should not have a direct impact on the domestic level of emissions but should only have an indirect effect through foreign technology spillovers after we have included the necessary control variables. It is understood that environmental policies may also have policy spillovers that influence innovation incentives in other countries (Costantini et al., 2017). However, we control this concern because innovation activities in the home country are also included as an independent variable. We also include time controls that capture the general trends in technology support policies, and in robustness tests, we also control for the domestic technology support policy. Thus, we are confident that, conditional on the controls, the foreign technology support policy should not have a direct impact on domestic emissions and should only have an influence through possible technology spillovers. However, we do not believe that this argumentation extends to the use of domestic technology support policy as an instrument for domestic innovation, as domestic policy may have a direct influence on emissions. Thus, we do not have an instrumental variable for T, i.e., domestic CTs, and endogeneity bias remains possible for this variable.

We compute the instrumental variables as follows:

$$Z_{it} = \sum\nolimits_j w_{ijt} PI_{jt} \tag{6}$$

Z_{it} is the instrumental variable; PI is the technology support policy index for country j in year t based on the OECD Environmental Policy Stringency subindex for Technology Support Policy. The weights w_{ijt} are the weights discussed in the previous section, i.e., the weights are based on import shares, geographical distance and technological similarity when forming instruments Z_2, Z_3 and Z_4, respectively. Thus, the instrument is the weighted average of the technology support policy index in the spillover source countries, and we have a separate weighted instrument for each spillover variable. For S_1, the free diffusion of technology, the instrument (Z_1) is simply the average technology support policy index, excluding the policy index in country i. The instrumental variables are country-year specific. First, the weights vary by country. Second, the import and technological similarity-based weights change over the years, whereas the geographic distance-based weights do not change. Finally, the technology support indices also vary over the years.

A limitation of our instrument is that the OECD data do not include the policy indices for all countries. Thus, the instrument is a weighted average technology support policy index in those spillover source countries where the data are available, i.e., the weights w_{ijt} for the instruments are rescaled to sum to one and exclude the countries with missing data. On average, the index is available for 87% of the spillover source countries using import weights, 85% of the source countries using technological similarity weights and 79% of the source countries using geographic distance weights. Implicitly, we also assume that the policy indices for noncovered countries are on average the same as those for the countries for which we do have data, as we do not exclude noncovered countries from our spillover variables (S). If this assumption is inaccurate, the instrumental variable could suffer from measurement error, which could lead to a weak instrument problem. However, the policy index data covers the most important spillover source countries, lending support to the strength of the instrument. Finally, it is worth mentioning that we can only conduct instrumental variable estimation for free technology diffusion, i.e., unweighted spillovers, without year fixed effects because the respective instrument is the average technology

[3] E.g., Y02A10 "Technologies for adaptation to climate change: at coastal zones; at river basins", Y02T10 "Climate change mitigation technologies related to transportation: Road transport of goods or passengers", etc..

support index, which in practice becomes fully absorbed by the year fixed effects once they are included.

3.5. Sample description

Our sample includes European countries and is an unbalanced panel for the period 1990–2020. The countries included are Albania, Andorra, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxemburg, Malta, Moldova, Montenegro, the Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, the Slovak Republic, Slovenia, Spain, Sweden, Switzerland, the United Kingdom and Ukraine. The import data are not available for all the countries at the beginning of our observation period; thus, the number of observations for import-weighted climate change technology spillovers and the related instrumental variable (the import-weighted technology support index in the spillover source countries) are lower. We present the descriptive statistics of the variables in Table A1 in Appendix A.

A critical interest of our study is also to compare the different measures of technology spillovers. Thus, we first investigated the correlations between the different spillover variables. The correlation coefficients are presented in Table A2 in Appendix A. The spillover variables have high but not one-to-one correlations. It appears that the correlation is especially high, on the one hand, between the import-weighted and distance-weighted spillovers and, on the other hand, between aggregate global climate change technology stock and technological similarity-weighted spillover stock. The first finding is intuitive, as geographically proximate countries also trade more frequently. The second finding is also logical, as the last two measures do not consider the geographic location of the innovation, unlike the first two measures.

4. Results

4.1. Main results

We proceed to the empirical estimation of the STIRPAT model. Table 1 presents the panel fixed effect (FE) estimation results. As most of the related literature on technology spillovers has not included year controls (Verdolini and Galeotti, 2011; Wan et al., 2015; Sun et al., 2021) or has relied on cross-sectional data (Ghisetti and Quatraro, 2017; Costantini et al., 2013), we first present the results without year fixed effects and then proceed to estimation that includes year dummies. Tables 2 and 3 present our instrumental variable (IV) estimation results for the 1st and 2nd stage. The IV models include country fixed effects, and like FE estimations, the IV estimations are first performed without year fixed effects and then include them.

The results in Column 1 in Table 1 indicate that increases in population and affluence (GDP per capita) increase CO_2 emissions as expected. However, domestic CT innovations (T) have a negative and significant influence on emissions, which is in line with the findings of prior studies summarized in Section 2. However, when we include the spillovers from CT innovations in other countries, first in the form of unweighted global CT stock (S_1), the domestic innovations are no longer statistically significant.[4] However, the global stock is strongly significant. Notably, the inclusion of the spillover variable substantially increases the R-squared of the model, thus highlighting the importance of foreign technological development for domestic emissions. Turning to the comparison of different spillover mechanisms, we can observe that all our spillover variables produce quite similar results when we do not include year fixed effects. All the spillover variables are significant and indicate that when the foreign climate change patent stock increases by 10%, domestic CO_2 emissions decrease by approximately 1.9–2.6%.

The results change significantly when the year fixed effects are included, i.e., when we decompose the impacts of technological change between domestic CTs, CT spillovers and autonomous technical change captured by the year effects. Now, only the import weighted spillover stock (S_2) remains statistically significant. Its coefficient is −0.230, and it hardly changes after the inclusion of year fixed effects. When calculating the global CT stock and the distance weighted spillovers, the spillover source country weights are time invariant. Thus, given these time invariant weights, the variation in these variables is mostly captured by the overall time trends captured by the year fixed effects. The technological similarity weights change over time; nevertheless, the technological similarity weighted spillovers are not statistically significant in Column 10.

In Table 2, we show the IV estimation 1st stage results. The instrumental variable is the weighted average of the technology support index in the spillover source countries, as discussed in Section 3.4. Our IV equations are exactly identified and, thus, we do not have over-identifying restrictions to test. However, we tested whether our instruments are weak following the suggestions of Andrews et al. (2019). At the bottom of Table 2, the effective F-statistic of Montiel Olea and Pflueger (2013) is reported. Moreover, in Table 3 we report the p-value from the Anderson–Rubin test, which is a weak-instrument-robust test of whether the endogenous variable is statistically significant. Results in Table 2 and the first-stage efficient F-statistics indicate that our instrumental variables meet the criterion of relevance and are not weak. The exception is Model 6, which includes geographical distance weighted spillovers and year controls. Thus, when we control for time effects, the time-invariant geographic weights in combination with country-level changes in the technology support index do not create enough identifying variation, leading to a weak instrument problem.

In Table 3, we report the IV estimation results. We first estimate the regression without year controls and then include them. We do not estimate an equation where the global climate change technology stock is

[4] The domestic CT stock (T) changes quite slowly over time and the largest annual changes happen in countries that have relatively few patents. Thus, the annual changes in CT stock contain some measurement error that can be sizable for these countries. This implies that the fixed effect coefficient estimate for the variable can be biased toward zero. When the estimations were repeated excluding countries with the lowest domestic CT stocks, the coefficient estimate was more strongly negative. At the same time, the role of spillovers was weaker. However, we find it important to include all countries in the sample, because the main interest of the study is the role of spillovers and the international technology spillovers are expected to be central for smaller countries that rely on foreign sources for technological development. In addition to this, we have also estimated the model using all patents, only energy-related CT patents and annual CT patent counts. Our findings did not change. Finally, we have also explored whether the domestic CT stock would have a stronger impact towards the end of our observation period. Indeed, the coefficient of domestic CT stock is more systematically negative in the later years; however, it is not statistically significant unless year fixed effects are dropped.

Table 1
Panel estimation results with country fixed effects.

	1	2	3	4	5	6	7	8	9	10
ln(POP)	0.322	0.749***	0.515*	0.745***	0.572**	0.731**	0.744**	0.422	0.750***	0.727**
	(0.236)	(0.266)	(0.256)	(0.260)	(0.265)	(0.272)	(0.276)	(0.252)	(0.275)	(0.269)
ln(GDP/POP)	0.122	0.404***	0.407***	0.407***	0.248***	0.385***	0.394***	0.352***	0.389***	0.392***
	(0.074)	(0.092)	(0.100)	(0.091)	(0.077)	(0.109)	(0.112)	(0.106)	(0.107)	(0.112)
ln(T)	−0.079***	−0.005	−0.013	0.000	−0.027	0.009	0.012	−0.005	0.008	0.006
	(0.021)	(0.017)	(0.014)	(0.018)	(0.018)	(0.017)	(0.017)	(0.015)	(0.017)	(0.018)
$\ln(S_1)$		−0.211***					1.680			
		(0.045)					(2.070)			
$\ln(S_2)$			−0.265***					−0.230***		
			(0.052)					(0.084)		
$\ln(S_3)$				−0.233***					0.408	
				(0.047)					(0.770)	
$\ln(S_4)$					−0.190***					0.046
					(0.058)					(0.078)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	1131	1131	1038	1131	1131	1131	1131	1038	1131	1131
Adj. R-squared	0.146	0.316	0.328	0.329	0.225	0.436	0.438	0.462	0.438	0.437

Notes. The dependent variable is $\ln(CO_2$ emissions). Standard errors are clustered by country. *, ** and *** denote statistical significance at 10%, 5% and 1% level respectively.

Table 2
Instrumental variable panel estimation 1st stage results with country fixed effects.

	1	2	3	4	5	6	7
ln(POP)	1.262***	0.836**	1.003***	0.910***	−0.379	−0.049	0.106
	(0.401)	(0.416)	(0.361)	(0.284)	(0.353)	(0.040)	(0.118)
ln(GDP/POP)	0.759***	0.791***	0.644***	0.393***	0.099	−0.010	−0.075
	(0.157)	(0.100)	(0.143)	(0.112)	(0.101)	(0.014)	(0.075)
ln(T)	0.160***	0.126***	0.158***	0.156***	−0.030	0.003	0.036*
	(0.038)	(0.033)	(0.035)	(0.029)	(0.020)	(0.003)	(0.020)
$\ln(Z_1)$	0.561***						
	(0.047)						
$\ln(Z_2)$		0.335***			0.193***		
		(0.032)			(0.041)		
$\ln(Z_3)$			0.446***			−0.029*	
			(0.037)			(0.017)	
$\ln(Z_4)$				0.309***			0.981***
				(0.033)			(0.247)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	Yes	Yes	Yes
Observations	1131	1038	1131	1131	1038	1131	1131
1st stage F-statistic	141.543	109.632	146.420	87.415	22.187	2.967	15.809

Notes. IV estimation 1st stage results. The dependent variable is respective endogenous CT spillover variable. The instrumental variable is the weighted average of the technology support index in the spillover source countries. Standard errors are clustered by country. *, ** and *** denote statistical significance at 10%, 5% and 1% level, respectively. 1st stage F-statistic is the effective F-statistic of Montiel Olea and Pflueger (2013).

included with year controls, as the corresponding instrument, global average technology support, is almost fully absorbed by year controls.

The IV results in Table 3 are largely in line with the FE results. In Models 1–4, the empirical evidence indicates that an increase of 10% in foreign technology spillovers leads to a 1.8%–3.6% decrease in domestic CO_2 emissions. Thus, the variation in the estimates is slightly greater. The Anderson–Rubin weak-instrument-robust test indicates that the coefficients are statistically significant even in the presence of a weak instrument. When the year controls are included, only the import weighted spillovers (S_2) remain statistically significant, which is also confirmed by the Anderson–Rubin test. Now, the results indicate a twice as large reduction in emissions, indicating that the FE estimation would have underestimated the impact of import-mediated CT spillovers. The geographical distance weighted spillovers suffer from the weak instrument problem; however, according to Table 2, the instrument for technological similarity weighted spillovers is strong. Nevertheless, its coefficient in Model 7 is statistically insignificant.

Overall, we conclude that foreign CT spillovers appear to have a greater impact on domestic emissions than domestic innovations. This finding is perhaps not surprising since our sample countries are, on average, small countries and the role of foreign technology can be expected to be high. As Probst et al. (2021) report, the top 10 CT innovating countries contribute more than 90% of innovations, which is reflected in our findings that emphasize the role of spillovers. For instance, with its uniformly strict environment-related trade framework within the European Green Deal, the European Union imported twice as much it exported to extra-EU countries in terms of climate-related energy technologies such as liquid biofuels, solar panels, and wind turbines in 2021 (European Commission, 2022). Notably, this further affirms the role of climate-related technology imports even at the regional level. Therefore, it is not unexpected that the environmental benefits associated with the penetration of foreign CT technologies across Europe outweigh domestic climate change-related innovations. Moreover, the evidence from the abovementioned EU scenario is not unrelated to the findings in the current examination, which show that international trade and imports appear to be key channels of foreign technology spillovers.

Table 3
Instrumental variable panel estimation results with country fixed effects.

	1	2	3	4	5	6	7
ln(POP)	0.699***	0.647**	0.686***	0.720**	0.320	0.877***	0.732***
	(0.264)	(0.271)	(0.257)	(0.280)	(0.270)	(0.294)	(0.263)
ln(GDP/POP)	0.371***	0.515***	0.368***	0.323***	0.391***	0.414***	0.384***
	(0.093)	(0.110)	(0.086)	(0.082)	(0.117)	(0.109)	(0.114)
ln(T)	−0.014	0.007	−0.011	0.003	−0.017	−0.000	0.010
	(0.019)	(0.020)	(0.019)	(0.026)	(0.017)	(0.019)	(0.020)
ln(S_1)	−0.186***						
	(0.045)						
ln(S2)		−0.357***			−0.549***		
		(0.069)			(0.195)		
ln(S3)			−0.201***			3.083	
			(0.045)			(1.959)	
ln(S4)				−0.303***			−0.008
				(0.077)			(0.126)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	Yes	Yes	Yes
Observations	1131	1038	1131	1131	1038	1131	1131
Adj. R-squared	0.287	0.276	0.300	0.167	0.377	0.314	0.413
AR test p-value	0.005	0.000	0.002	0.003	0.034	0.130	0.949

Notes. The dependent variable is ln(CO_2 emissions). The instrumental variable is the weighted average of the technology support index in the spillover source countries. Standard errors are clustered by country. *, ** and *** denote statistical significance at 10%, 5% and 1% level, respectively. AR test p-value refers to the Anderson-Rubin weak-instrument-robust test of the coefficients on the endogenous regressors.

4.2. Robustness tests and heterogeneity of results

A concern regarding the validity of our instrument is that foreign policy may create policy spillovers and influence the adoption of domestic policies. Hence, we conduct a robustness test and include the domestic technology support policy index (PI) as a control variable. These results are reported in Table 4. This time we do not report the IV 1st stage results, but only the relevant test statistics at the bottom of the table. As all European countries are not covered by the OECD data, the number of observations is now lower. The countries that do not have technology support indices available are Albania, Andorra, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Latvia, Lithuania, Malta, Moldova, Montenegro, Romania, Serbia and Ukraine. As shown in Table 4, the domestic technology support index does not have a significant direct impact on the level of domestic CO_2 emissions. Neither does its inclusion change our main results regarding the technology spillover variables. Due to the smaller sample size, the standard errors are nevertheless larger; hence, the statistical significance of the results is weaker, even though the magnitude of the coefficients remains similar.

Table 4 also indicates that the results are not sensitive to changes in the group of sample countries. Next, we explore this aspect further. As indicated in the literature, in some countries, domestic innovations may be more important than they are in others. Similarly, foreign technology spillovers may be more important in some countries. Regarding CO_2 emissions and aggregate energy use, it is possible that Western European and Eastern European countries have different economic and energy

Table 4
Instrumental variable panel estimation results including the domestic policy index.

	1	2	3	4	5	6	7
ln(POP)	0.512**	0.972***	0.514**	0.432*	0.680***	0.865**	0.661***
	(0.230)	(0.353)	(0.234)	(0.252)	(0.247)	(0.337)	(0.193)
ln(GDP/POP)	0.360***	0.734***	0.348***	0.346***	0.448**	0.323***	0.230**
	(0.105)	(0.129)	(0.103)	(0.116)	(0.188)	(0.121)	(0.117)
ln(T)	0.007	0.062	0.016	0.020	0.007	0.009	0.021
	(0.037)	(0.052)	(0.038)	(0.050)	(0.032)	(0.036)	(0.034)
PI	0.002	0.033*	0.004	0.002	0.009	0.020	0.000
	(0.014)	(0.017)	(0.014)	(0.014)	(0.014)	(0.022)	(0.013)
ln(S_1)	−0.202***						
	(0.065)						
ln(S_2)		−0.564***			−0.476		
		(0.130)			(0.404)		
ln(S_3)			−0.227***			3.896	
			(0.067)			(3.187)	
ln(S_4)				−0.322***			0.113
				(0.115)			(0.239)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	Yes	Yes	Yes
Observations	766	702	766	766	702	766	766
Adj. R-squared	0.247	0.186	0.267	0.154	0.490	0.349	0.477
1st stage F-statistic	98.558	54.251	109.131	38.874	4.311	2.119	48.794
AR test p-value	0.014	0.003	0.009	0.023	0.199	0.108	0.635

Notes. The dependent variable is ln(CO_2 emissions). The instrumental variable is the weighted average of the technology support index in the spillover source countries. Standard errors are clustered by country. *, ** and *** denote statistical significance at 10%, 5% and 1% level, respectively. 1st stage F-statistic is the effective F-statistic of Montiel Olea and Pflueger (2013). AR test p-value refers to the Anderson-Rubin weak-instrument-robust test of the coefficients on the endogenous regressors.

sector structures, which could imply that CT innovations and technology spillovers have different roles in these countries, as suggested, e.g., by Wan et al. (2015). Hence, we test whether the results are heterogeneous across these country groups[5] by interacting the innovation and spillover variable with the country group indicator variable. As the import weighted spillovers appear to be the most robust spillover measure, we focus on these spillovers in Table 5. Columns 1 and 2 report the panel FE results, and Columns 3 and 4 report the IV estimation results. The instrument for the interaction is the original instrument interacted with the group indicator. The IV estimation test statistics are reported at the bottom of the table.

The results in Table 5 do not reveal that domestic CT innovations would play a different role in these two country groups. The panel fixed effect results indicate that foreign technology spillovers have a greater impact on emission reductions in Eastern European countries. Nevertheless, according to the IV estimations, this difference is statistically insignificant. In summary, there is some indication that technology spillovers may be more important for Eastern European countries, but overall, the effects of innovations and spillovers do not vary greatly across countries in our sample.

Another question of interest is whether CT spillovers mainly originate from other European countries or from outside Europe. Prior literature indicates that CT innovation activities are geographically concentrated, with Japan, the US, South Korea, China and Taiwan ranking among the top inventor countries (Amoroso et al., 2021; Probst et al., 2021). Our baseline measurement of CT spillover variables includes CT patents from all countries. Next, we divide the spillover variable into two parts based on whether the source country is located in Europe or outside Europe. The results are presented in Table 6, with the IV estimation test statistics reported at the bottom of the table. The empirical results in Table 6 suggest that other European countries are more important sources for CT spillovers than countries outside Europe. The coefficient of import-mediated CT spillovers within Europe is strongly negative and significant. However, according to our preferred IV specification (Model 4), CT spillovers from outside Europe also significantly contribute to CO_2 emission reductions indicating that trade connections facilitate technology spillovers across the globe. Yet, the magnitude of their coefficient is about half the size of the coefficient for European spillovers.

Finally, previous studies have often included further explanatory variables such as urbanization, share of renewables in energy production, economic structure and openness to trade or FDI (Balsalobre-Lorente et al., 2022; Du et al., 2019; Többelmann and Wendler, 2020; Yıldırım et al., 2022). Many of these characteristics are controlled by the inclusion of country fixed effects; however, as these characteristics may also change over time, we also confirm the robustness of our results to the inclusion of these control variables. In Table 7, we include openness to international trade, the share of urban population, the service sector's share of GDP, the industrial sector's share of GDP and the share of renewable energy in aggregate energy use.[6]

As evident from Table 7, the share of renewable energy has a strong negative relationship with the level of CO_2 emissions. The other additional control variables are not statistically significant. However, it is notable that our main conclusions do not change with respect to our main variables of interest. Foreign technology spillovers mediated

Table 5
Heterogeneity of results across country groups.

	1	2	3	4
	FE	FE	IV	IV
ln(POP)	0.259	0.335	0.408	0.362
	(0.265)	−0.258	(0.266)	(0.275)
ln(GDP/POP)	0.475***	0.396***	0.547***	0.376***
	(0.099)	(0.107)	(0.110)	(0.134)
ln(T)	−0.018	−0.015	0.021	−0.023
	(0.029)	(0.028)	(0.039)	(0.036)
ln(T)xEast	0.005	0.019	−0.035	0.010
	(0.035)	(0.034)	(0.044)	(0.043)
ln(S_2)	−0.227***	−0.178*	−0.345***	−0.585**
	(0.072)	(0.095)	(0.091)	(0.232)
ln(S_2)xEast	−0.110*	−0.081	−0.021	0.006
	(0.064)	(0.064)	(0.085)	(0.090)
Country FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
Observations	1038	1038	1038	1038
Adj. R-squared	0.341	0.466	0.290	0.363
1st stage F-statistic			72.063	9.878
AR test p-value			0.001	0.054

Notes. The dependent variable is ln(CO_2 emissions). The instrumental variable is the weighted average of the technology support index in the spillover source countries. Standard errors are clustered by country. *, ** and *** denote statistical significance at 10%, 5% and 1% level, respectively. 1st stage F-statistic is the Kleibergen & Paap F-statistic. AR test p-value refers to the Anderson-Rubin weak-instrument-robust test of the coefficients on the endogenous regressors.

Table 6
Heterogeneity of results depending on spillover source countries.

	1	2	3	4
	FE	FE	IV	IV
ln(POP)	0.576**	0.469*	0.441	0.719**
	(0.280)	(0.272)	(0.287)	(0.280)
ln(GDP/POP)	0.415***	0.346***	0.358***	0.528***
	(0.105)	(0.109)	(0.113)	(0.104)
ln(T)	−0.009	0.001	0.001	0.007
	(0.014)	(0.014)	(0.015)	(0.021)
ln(Europe S_2)	−0.214***	−0.284***	−0.582***	−0.247***
	(0.055)	(0.103)	(0.199)	(0.071)
ln(Outside Europe S_2)	−0.063**	−0.018	−0.008	−0.121**
	(0.027)	(0.032)	(0.045)	(0.048)
Country FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
Observations	1038	1038	1038	1038
Adj. R-squared	0.324	0.473	0.402	0.265
1st stage F-statistic			6.980	65.683
AR test p-value			0.100	0.001

Notes. The dependent variable is ln(CO_2 emissions). The instrumental variable is the weighted average of the technology support index in the spillover source countries. Standard errors are clustered by country. *, ** and *** denote statistical significance at 10%, 5% and 1% level, respectively. 1st stage F-statistic is the Kleibergen & Paap F-statistic. AR test p-value refers to the Anderson-Rubin weak-instrument-robust test of the coefficients on the endogenous regressors.

[5] The following countries are included in the Eastern European group: Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Moldova, Montenegro, Northern Macedonia, Poland, Romania, Russia, Serbia, Slovak Republic, Slovenia, Ukraine. Countries included in the Western European group are: Andorra, Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxemburg, Malta, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom.

[6] These variables are obtained from the World Bank data. Openness to trade is measured as the sum of exports and imports of goods and services divided by GDP. The share of urban population is the population living in urban areas divided by total population. The service sector's share of GDP is measured as the GDP produced by ISIC divisions 45–99 divided by GDP. The industrial sector includes manufacturing and construction sectors. The share of renewable energy is the renewable energy consumption divided by total final energy consumption.

Table 7
Panel estimation results including additional control variables.

	1	2	3	4
	FE	FE	IV	IV
ln(POP)	0.648***	0.547***	0.641***	0.541***
	(0.198)	(0.186)	(0.209)	(0.174)
ln(GDP/POP)	0.473***	0.465***	0.466***	0.468***
	(0.080)	(0.089)	(0.098)	(0.085)
Openness to trade	−0.029	−0.040	−0.031	−0.039
	(0.057)	(0.062)	(0.056)	(0.061)
Share of urban population	0.112	0.296	0.093	0.300
	(0.449)	(0.444)	(0.484)	(0.429)
Service sector (% of GDP)	−0.361	−0.626	−0.366	−0.657
	(0.735)	(0.626)	(0.745)	(0.603)
Industrial sector (% of GDP)	−0.537	−0.725	−0.514	−0.764
	(0.885)	(0.743)	(0.850)	(0.730)
Share of renewable energy	−1.700***	−1.495***	−1.710***	−1.499***
	(0.324)	(0.308)	(0.312)	(0.306)
ln(T)	0.008	−0.000	0.008	−0.001
	(0.015)	(0.016)	(0.017)	(0.015)
$\ln(S_2)$	−0.196***	−0.266***	−0.190**	−0.288**
	(0.046)	(0.064)	(0.079)	(0.144)
Country FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
Observations	878	878	878	878
Adj. R-squared	0.611	0.633	0.593	0.616
1st stage F-statistic			55.828	19.247
AR test p-value			0.060	0.095

Notes. The dependent variable is $\ln(CO_2$ emissions). The instrumental variable is the weighted average of the technology support index in the spillover source countries. Standard errors are clustered by country. *, ** and *** denote statistical significance at 10%, 5% and 1% level, respectively. 1st stage F-statistic is the effective F-statistic of Montiel Olea and Pflueger (2013). AR test p-value refers to the Anderson-Rubin weak-instrument-robust test of the coefficients on the endogenous regressors.

through imports have a strong negative effect on emissions, whereas the coefficient of domestic innovations is insignificant. Nevertheless, the effect of spillovers is now somewhat lower, which indicates that part of the effect of technological change is mediated through the change in the energy mix toward renewable energy sources. Given that renewable energy technologies are one main category of climate change technologies in our patent-based measure, this finding is not surprising.

5. Conclusion, policy implications and limitations

The development of climate change mitigation technologies is strongly concentrated in few countries, and despite the vast potential for global technology spillovers, technology diffusion has remained insufficient (Probst et al., 2021). The importance of climate-friendly technologies for CO_2 emission abatement is explored in this investigation by considering the case of European countries. The focus is mainly on the channels through which climate change mitigation technologies diffuse between countries. By covering selected European countries in an unbalanced panel over the period 1990–2020, this investigation quantifies CO_2 emission effects based on the diffusion of climate change-related technologies that are associated with imports, geographical and technological proximity and free technological diffusion, in addition to the domestic development of climate change-related technologies. The empirical section relies on panel fixed-effects estimation and fixed-effects estimation with instrumental variable, where the instrument is based on the technology support policies present in the spillover source countries.

Evidently, the results reveal that CO_2 emissions increase with increasing population and affluence (per capita income) in the examined panel. In contrast, international spillovers of climate-friendly technologies have a negative influence on emissions, thus promoting emission reductions across the European region. We find that international technology spillovers have a larger and more robust impact than domestic innovations have. Furthermore, irrespective of which diffusion channel of climate change-related technologies is examined, there is a decline in CO_2 emissions. Specifically, a 10 percent increase in foreign climate change patent stocks is responsible for a 1.9 to 2.6 percent decline in CO_2 emissions across Europe according to the fixed effect model and even up to a 5.5 percent decline according to the instrumental variable estimation. However, after including year fixed effects to control for autonomous technological trends, only the results for import-mediated spillovers of climate change-related technologies remain robust. This finding also remains clear after additional robustness tests.

Our results highlight trade contacts as a key technology diffusion channel. While we did not explore spillovers through foreign direct investments or export connections, the prior literature (Keller, 2021; Ang and Madsen, 2013) suggests that these trade connections could also matter, and further studies should validate these findings in the context of climate change mitigation technologies. Moreover, the outcome of this study should further inform policymaking on how to prioritize the adoption of climate-friendly technologies, especially in terms of policy around trade. Notable initiatives center around the debate regarding climate clubs (Nordhaus, 2015) and policies such as the Carbon Border Adjustment Mechanism (CBAM), which may help to solve free-riding problems related to climate agreements and carbon leakage in energy intensive industries. However, such policies may also lead to additional trade frictions; hence, they need to be carefully designed to avoid slowing global climate technology diffusion. Overall, the broader literature indicates that climate change technology diffusion remains insufficient, indicating that markets do not provide adequate incentives; thus, further policies are warranted, especially in the trade policy context. Domestic policies also need to contribute to building absorptive capacity that enables countries to absorb technology spillovers. This is especially crucial for small economies, i.e., the vast majority of countries, where foreign sources of technology provide the bulk of technological advances and contain the highest potential for emission abatement. Moreover, the results indicate the role of technological spillovers may be more central for the Eastern European countries, which highlights the importance of trade contacts for this region.

Nevertheless, this investigation is not without identifiable limitations. The restrictions on the coverage of the study with regard to the selected countries and time span, which are due to data availability, can be improved in future investigations. Given that the current investigation lacks information on the specificity of climate change-related technologies, future studies could also focus on differentiating the diffusion of various types of foreign climate change-related technologies and especially across Europe's central, eastern, northern, and southern regions. Moreover, climate change-related technologies could be disaggregated in terms of sectoral use, e.g., energy, transport and others, or other classifications in future investigations. In this case, for future endeavor, attention can be paid to the diffusion of climate change-related technologies from non-European clean technology producing countries such as China and the United States. Additionally, further analysis could better explore the conditions under which countries are best able to benefit from international technology diffusion. Finally, from the perspective of empirical methods, spatial approaches such as spatial correlation and spatial econometrics could be explored in future investigations.

CRediT authorship contribution statement

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

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.

Appendix A

Table A1
Descriptive statistics

	Mean	Median	Std. Dev.	N
CO_2 emissions (CO_2)	161,525.7	50,937.3	306,580.38	1131
Population (POP)	19.742	7.992	29.760	1131
GDP per capita (GDP/POP)	27,339.238	21,117.019	22,215.522	1131
Domestic CT patent stock (T)	628.698	29.053	1822.915	1131
Global CT patent stock (S_1)	54,378.724	47,202.324	32,560.976	1131
CT spillovers, import weighted (S_2)	2948.573	2508.194	1636.088	1038
CT spillovers, distance weighted (S_3)	377.635	313.898	254.06	1131
CT spillovers, tech. similarity weighted (S_4)	611.442	584.983	270.813	1131
Technology support, global (Z_1)	1.419	1.350	0.648	1131
Technology support, import weighted (Z_2)	1.787	1.711	0.666	1038
Technology support, distance weighted (Z_3)	1.698	1.620	0.808	1131
Technology support, tech. similarity weighted (Z_4)	1.520	1.377	0.657	1131
Domestic technology support index (PI)	1.665	1.500	1.329	766

Table A2
Correlations between the spillover variables

	1	2	3	4
1. Global CT patent stock (S_1)	.			
2. CT spillovers, import weighted (S_2)	0.766	.		
3. CT spillovers, distance weighted (S_3)	0.819	0.862	.	
4. CT spillovers, tech. similarity weighted (S_4)	0.867	0.742	0.768	.

Data availability

The used datasets are openly available online.

References

Acemoglu, D., 2012. Introduction to economic growth. J. Econ. Theor. 147 (2), 545–550.
Alcott, B., 2005. Jevons' paradox. Ecol. Econ. 54 (1), 9–21.
Aldieri, L., Bruno, B., Lorente, D.B., Vinci, C.P., 2022. Environmental innovation, climate change and knowledge diffusion process: how can spillovers play a role in the goal of sustainable economic performance? Resour. Pol. 79, 103021.
Alola, A.A., Rahko, J., 2024. The effects of environmental innovations and international technology spillovers on industrial and energy sector emissions – evidence from small open economies. Technol. Forecast. Soc. Change 198, 123024. https://doi.org/10.1016/j.techfore.2023.123024.
Amoroso, S., Aristodemou, L., Criscuolo, C., Dechezleprêtre, A., Dernis, H., Grassano, N., Moussiegt, L., Napolitano, L., Nawa, D., Squicciarini, M., Tübke, A., 2021. World Corporate Top R&D investors: paving the way for climate neutrality. A joint JRC and OECD report JRC126788.. https://doi:10.2760/49552.
Andrews, I., Stock, J.H., Sun, L., 2019. Weak instruments in instrumental variables regression: theory and practice. Annu. Rev. Econ. 11, 727–753.
Ang, J.B., Madsen, J.B., 2013. International R&D spillovers and productivity trends in the Asian miracle economies. Econ. Inq. 51 (2), 1523–1541.
Angelucci, S., Hurtado-Albir, F.J., Volpe, A., 2018. Supporting global initiatives on climate change: the EPO's "Y02-Y04S" tagging scheme. World Pat 54, S85–S92. https://doi.org/10.1016/j.wpi.2017.04.006.
Balsalobre-Lorente, D., Driha, O.M., Halkos, G., Mishra, S., 2022. Influence of growth and urbanization on CO2 emissions: the moderating effect of foreign direct investment on energy use in BRICS. Sustain. Dev. 30 (1), 227–240.
Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica 81 (4), 1347–1393.
Chen, H., Yi, J., Chen, A., Peng, D., Yang, J., 2023. Green technology innovation and CO2 emission in China: evidence from a spatial-temporal analysis and a nonlinear spatial durbin model. Energy Pol. 172, 113338.
Cheng, C., Ren, X., Dong, K., Dong, X., Wang, Z., 2021. How does technological innovation mitigate CO2 emissions in OECD countries? Heterogeneous analysis using panel quantile regression. J. Environ. Manag. 280, 111818.
Copeland, B.R., Taylor, M.S., 1999. Trade, spatial separation, and the environment. J. Int. Econ. 47 (1), 137–168. https://doi.org/10.1016/S0022-1996(98)00020-8.
Copeland, B.R., Taylor, M.S., 2004. Trade, growth, and the environment. J. Econ. Lit. 42 (1), 7–71. https://doi.org/10.1257/002205104773558047.
Corrocher, N., Mancusi, M.L., 2021. International collaborations in green energy technologies: what is the role of distance in environmental policy stringency? Energy Pol. 156, 112470.
Costantini, V., Crespi, F., Marin, G., Paglialunga, E., 2017. Eco-innovation, sustainable supply chains and environmental performance in European industries. J. Clean. Prod. 155, 141–154.
Costantini, V., Mazzanti, M., Montini, A., 2013. Environmental performance, innovation and spillovers. Evidence from a regional NAMEA. Ecol. Econ. 89, 101–114. https://doi.org/10.1016/j.ecolecon.2013.01.026. May 2013.
Dechezleprêtre, A., Glachant, M., Haščič, I., Johnstone, N., Ménière, Y., 2011. Invention and transfer of climate change–mitigation technologies: a global analysis. Rev. Environ. Econ. Pol. 5 (1), 109–130.
Dechezleprêtre, A., Sato, M., 2017. The impacts of environmental regulations on competitiveness. Rev. Environ. Econ. Pol. 11 (2), 183–206.
Dietz, T., Rosa, E.A., 1997. Effects of population and affluence on CO2 emissions. Proc. Nat. Acad. Sci. 94 (1), 175–179.
Du, K., Li, J., 2019. Towards a green world: how do green technology innovations affect total-factor carbon productivity. Energy Pol. 131, 240–250.
Du, K., Li, P., Yan, Z., 2019. Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data. Technol. Forecast. Soc. Change 146, 297–303.
Erdoğan, S., Yıldırım, S., Yıldırım, D.Ç., Gedikli, A., 2020. The effects of innovation on sectoral carbon emissions: evidence from G20 countries. J. Environ. Manag. 267, 110637.
European Commission, 2022. EU green energy product imports: €13.8 billion. https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20221128-1. (Accessed 20 October 2023).
Ferreira, J.J., Fernandes, C., Ratten, V., 2019. The effects of technology transfers and institutional factors on economic growth: evidence from Europe and Oceania. J. Technol. Tran. 44 (5), 1505–1528.

Ghisetti, C., Quatraro, F., 2017. Green technologies and environmental productivity: a cross-sectoral analysis of direct and indirect effects in Italian regions. Ecol. Econ. 132 (February 2017), 1–13. https://doi.org/10.1016/j.ecolecon.2016.10.003.
Ghisetti, C., Pontoni, F., 2015. Investigating policy and R&D effects on environmental innovation: a meta-analysis. Ecol. Econ. 118, 57–66.
Hall, B.H., Mairesse, J., Mohnen, P., 2010. Measuring the returns to R&D. In: Handbook of the Economics of Innovation, vol. 2, pp. 1033–1082. North-Holland.
Hecker, L.P., Wätzold, F., Markwardt, G., 2020. Spotlight on spatial spillovers: an econometric analysis of wastewater treatment in Mexican municipalities. Ecol. Econ. 175, 106693.
Huang, W., Chen, W., Anandarajah, G., 2017. The role of technology diffusion in a decarbonizing world to limit global warming to well below 2 C: an assessment with application of Global TIMES model. Appl. Energy 208, 291–301.
Huang, J., Liu, Q., Cai, X., Hao, Y., Lei, H., 2018. The effect of technological factors on China's carbon intensity: new evidence from a panel threshold model. Energy Pol. 115, 32–42.
Hübler, M., Baumstark, L., Leimbach, M., Edenhofer, O., Bauer, N., 2012. An integrated assessment model with endogenous growth. Ecol. Econ. 83, 118–131.
Jaffe, A., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. Am. Econ. Rev. 76 (5), 984–1001. http://www.jstor.org/stable/1816464.
Jiang, W., Cole, M., Sun, J., Wang, S., 2022. Innovation, carbon emissions and the pollution haven hypothesis: climate capitalism and global re-interpretations. J. Environ. Manag. 307, 114465.
Kassouri, Y., Alola, A.A., 2023. Examining the interaction of technology adoption-diffusion and sectoral emission intensity in developing and emerging countries. J. Clean. Prod. 405, 136920.
Keller, W., 2010. International trade, foreign direct investment, and technology spillovers. In: Handbook of the Economics of Innovation, vol. 2. North-Holland, pp. 793–829.
Keller, W., 2021. Knowledge Spillovers, Trade, and Foreign Direct Investment. National Bureau of Economic Research Working Paper No. w28739. https://doi.org/10.3386/w28739.
Kim, Y.J., Verdolini, E., 2023. International knowledge spillovers in energy technologies. Energy Strat. Rev. 49, 101151.
Li, P., Ouyang, Y., 2020. Technical change and green productivity. Environ. Resour. Econ. 76, 271–298.
Mandel, A., Halleck Vega, S., Wang, D.X., 2020. The contribution of technological diffusion to climate change mitigation: a network-based approach. Clim. Change 160, 609–620.
Milindi, C.B., Inglesi-Lotz, R., 2022. The role of green technology on carbon emissions: does it differ across countries' income levels? Appl. Econ. 54 (29), 3309–3339.
Montiel Olea, J.L., Pflueger, C., 2013. A robust test for weak instruments. J. Bus. Econ. Stat. 31 (3), 358–369.
Nordhaus, W., 2015. Climate clubs: overcoming free-riding in international climate policy. Am. Econ. Rev. 105 (4), 1339–1370.
Pan, X., Li, M., Wang, M., Chu, J., Bo, H., 2020. The effects of outward foreign direct investment and reverse technology spillover on China's carbon productivity. Energy Pol. 145, 111730.
Probst, B., Touboul, S., Glachant, M., Dechezleprêtre, A., 2021. Global trends in the invention and diffusion of climate change mitigation technologies. Nat. Energy 6 (11), 1077–1086.
Sun, H., Edziah, B.K., Kporsu, A.K., Sarkodie, S.A., Taghizadeh-Hesary, F., 2021. Energy efficiency: the role technological innovation and knowledge spillover. Technol. Forecast. Soc. Change 167, 120659.
Töbelmann, D., Wendler, T., 2020. The impact of environmental innovation on carbon dioxide emissions. J. Clean. Prod. 244, 118787.
Touboul, S., Glachant, M., Dechezleprêtre, A., Fankhauser, S., Stoever, J., 2023. Invention and global diffusion of technologies for climate change adaptation: a patent analysis. Rev. Env. Econ. Pol. 17 (2), 316–335.
Tseng, K., 2022. Learning from the Joneses: technology spillover, innovation externality, and stock returns. J. Account. Econ. 73 (2–3), 101478.
UNFCCC, 2020. Innovative approaches to accelerating and scaling up climate technology implementation for mitigation and adaptation. Technology Executive Committee Report. Available at: https://unfccc.int/ttclear/innovativeapproaches. (Accessed 25 October 2023).
Verdolini, E., Bosetti, V., 2017. Environmental policy and the international diffusion of cleaner energy technologies. Environ. Resour. Econ. 66, 497–536. https://doi.org/10.1007/s10640-016-0090-7.
Verdolini, E., Galeotti, M., 2011. At home and abroad: an empirical analysis of innovation and diffusion in energy technologies. J. Environ. Econ. Manag. 61 (2), 119–134.
Wan, J., Baylis, K., Mulder, P., 2015. Trade-facilitated technology spillovers in energy productivity convergence processes across EU countries. Energy Econ. 48, 253–264.
Wang, H., Cui, H., Zhao, Q., 2021. Effect of green technology innovation on green total factor productivity in China: evidence from spatial durbin model analysis. J. Clean. Prod. 288, 125624.
Yıldırım, D.Ç., Esen, Ö., Yıldırım, S., 2022. The nonlinear effects of environmental innovation on energy sector-based carbon dioxide emissions in OECD countries. Technol. Forecast. Soc. Change 182, 121800.
York, R., Rosa, E.A., Dietz, T., 2003. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecol. Econ. 46 (3), 351–365.
Zhou, K., Yang, J., Yang, T., Ding, T., 2023. Spatial and temporal evolution characteristics and spillover effects of China's regional carbon emissions. J. Environ. Manag. 325, 116423.
Zhou, Y., Jiang, J., Ye, B., Hou, B., 2019. Green spillovers of outward foreign direct investment on home countries: evidence from China's province-level data. J. Clean. Prod. 215, 829–844.