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International knowledge spillovers in energy technologies

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ABSTRACT

This study examines the impact of barriers to knowledge diffusion in energy technologies in 29 countries from 1990 to 2015, distinguishing between efficient fossil-based generation and mature renewable options, namely wind and solar. We show that knowledge flows are higher in countries with similar technological profiles, particularly for mature renewables. The study finds that international knowledge spillovers have increased in intensity for wind and solar, while the opposite is true for fossil-based technologies. That means that foreign knowledge has increasingly informed domestic investors and points to the key role that knowledge flows from abroad had in promoting innovation in low-carbon technology options. Integrated assessment models should account for the role international knowledge spillovers play in the generation of new knowledge and in contributing to rapid decrease in costs.

1. Introduction

Knowledge flows play an important role in (low-carbon) innovation. Existing literature shows that innovators build on the knowledge in their own country but also source knowledge from foreign inventor when they push the frontiers of their own knowledge [1]. Innovations in low-carbon technologies benefit from intertemporal knowledge spillovers [2] as well as from international knowledge spillovers [3]. In this paper, we focus on estimating the extent to which inventors in one country rely on foreign knowledge. This is an important research question because to date advanced climate mitigation technologies have been developed only by a handful of countries [4]. These small groups of countries play a big role in inventing and diffusing new and improved low-carbon energy technologies. Yet, to achieve stringent decarbonisation targets, low-carbon energy technologies have to be adapted to local conditions, and further improved [5]. In this context, a better understanding of how knowledge flows across countries is needed.

This paper presents an up-to-date analysis of international knowledge flows and spillovers in two key sets of low-carbon energy technologies: efficient fossil-based and mature renewable energy technologies. These two families of technologies play very different roles in decarbonisation pathways. Efficient fossil-based technologies are those which reduce energy use and carbon emissions by improving energy efficiency of fossil-fuel based power generation technologies [6]. These include, for instance, highly efficient gas-based generation technologies. Mature renewable energy technologies are those which can produce energy with no associated greenhouse gas emissions [7]. In this analysis, we restrict our attention to wind and solar technologies because they are the ones where significant reduction in costs have been achieved thanks to innovation and learning-by-doing dynamics over the last two decades. These technologies are now cost-competitive with fossil-based energy generation technologies [8]. Understanding the knowledge flows dynamics which have accompanied this large decrease in cost, and how they differ from knowledge flows patterns in fossil-based technologies, is an interesting case study which can inform future innovation policies as well as climate mitigation efforts.

Our econometric approach builds on Peri [9] and Verdolini and Galeotti [3]. We postulate that spillovers depend on the ability to overcome key geographical, linguistic, economic, technological and policy-related knowledge diffusion barriers. This is in line with the extant literature, that shows that knowledge flows are reduced due to geographical [10], linguistic barriers [11] and trade barriers [12], while they are higher the more similar the technological expertise of two given countries [13] and the lower the distance in the policy space [14].

We use data for 29 countries, including fast-developing economies, over the years 1990–2015 to estimate the role of different knowledge diffusion barriers in mature renewable technologies as opposed to efficient fossil-based generation. We focus both on the overall sample

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period as well as on two sub-periods (1990–2002 and 2003–2015) to test whether the strength of different diffusion barriers has changed over time. This split is motivated by the fact that in 2003 the EU adopted the European Union (EU) Emissions Trading System (ETS) Directive [15]. We also explore the extent to which changes in spillovers patterns depend on the relative stringency of environmental policies of the source and the receiving country. Our paper differs from existing analysis because it focuses on a large set of countries and compares knowledge flows in two different technological domains. Grafström analyses international knowledge spillover in wind power from 1978 to 2008 using patent data [16]. Peter shows evidence of policy-induced knowledge spillover in solar Photovoltaics (PV) in 15 Organisation for Economic Cooperation and Development (OECD) countries from 1978 to 2005 [17].

Overall, we show that spillovers change over time, and do so differently for mature renewables as opposed to efficient fossil-based technologies. Geographical barriers reduce knowledge flows across both technological domains, but their role changes over time: geographical distance hindered knowledge flows comparatively more in mature renewables as opposed to efficient fossil-based technologies in the period 1990 to 2002, but not afterwards. Mature renewable energy knowledge flows easier across linguistic border than does fossil-based technology knowledge flows. Trade barriers do not hinder knowledge flows in either types of technologies. Technological distance hinders knowledge flows similarly in the period up to 2002 for mature renewables as opposed to fossil-based technologies, but in the following period matters more for wind and solar, suggesting that as technologies mature, it is harder for knowledge to flow to countries which do not have a similar technological profile.

We use our empirical results to build knowledge spillover matrixes that can be fruitfully used by modellers to update the calibration of knowledge production functions in integrated assessment model (IAMs) and more realistically model international knowledge spillovers. From a modelling point of view, overlooking the knowledge spillover effects that occur across countries may lead to an underestimation of the speed at which technology costs may decrease, or, conversely, and overestimation of the costs of compliance with stringent climate policy as we would underestimate the possibility that a given country builds on foreign knowledge to further innovate domestically.

2. Method and data

To examine the role of geographical, linguistic, economic and technological barriers in hindering knowledge flow across countries, we build on Peri [9] and Verdolini and Galeotti [3]. Specifically, as customary in the innovation literature, we use patents as an indicator of an innovation having taken place; citations between patents of different countries are considered a proxy of international knowledge flows [3,9,18–20]. The advantage of using patent and patent citation indicators lies in the richness of information they provide. Patents can be relatively easily classified as belonging to a given technology field and country. Patent citations represent a "trail" of knowledge flows: it is mandatory for inventors to cite "prior art." For these reasons, these data have been widely used, although they still suffer from several shortcomings. These include the fact that patent counts to not reflect commercial value of the innovation and may be the results of strategic patenting behaviors, and the fact that patent citations may be only a partial proxy of knowledge flows [21].

Our baseline econometric model is as follows:

$$c_{i,j} = \exp\left[a_i + a_j + \sum_{n=1}^{7} b_n x_{n(i,j)} + \mu_{i,j}\right] \tag{1}$$

The number of total citations c received from patents in country i from patents in country j within 5 years of the application date of the cited patent is a function of citing country and cited country fixed effects (a_i and a_j) and of a number n of diffusion barriers x. We compute $c_{i,j}$ for both mature renewables and for efficient fossil-based technologies for the full sample period (1900–2015) and for two sub-periods (1990–2002 and 2003–2015).

The citing and cited countries fixed effects a_i and a_j control for the different propensity to patent and to cite across countries. Conversely, the $x_{n(i,j)}$ variables represent time-invariant geographical, linguistic, economic and technological barriers to knowledge flows, and are defined as follows:

$x_{1(i,j)}$ is a dummy variable equal to 1 if the citing and cited countries are different. We expect the coefficient b_1 associated with $x_{1(i,j)}$ to be negative, indicating that any country would cite foreign patents less frequently than domestic patents [22].

$x_{2(i,j)}$ is the geographical distance between citing and cited countries based on the longitude and latitude. The distance data is measured by the shortest geographical distance (most populated cities, km) from GeoDist database [23].[1] We expect the coefficient b_2 associated with $x_{2(i,j)}$ to be negative, implying that an increase in geographical distance further lowers the probability of citation [24].

$x_{3(i,j)}$ is a dummy variable equal to 1 if the citing and cited countries have different official languages, and equal to 0 if they have at least one official language in common. The official language refers to languages spoken by at least 20% of the population of the country. As a country can have several official languages, we compare up to three official languages based on the database [25]. This index captures the presence of linguistic barriers. We expect the coefficient b_3 associated with $x_{3(i,j)}$ to be negative, indicating that knowledge flows are higher between countries which share a common language [11].

$x_{4(i,j)}$ measures trade barriers. The variable is calculated as the share of years in which the citing and cited country are not part of the same Free Trade Agreement (FTA). When this index is equal to one, the two countries are never part of the same FTA for the whole sample period (or analysed subperiods). When it is equal to zero, the two countries are always part of the same FTA. Belonging to the same FTA is based on Mario Larch's Regional Trade Agreements Database [26]. We expect the coefficient b_4 associated with $x_{4(i,j)}$ to be negative as trade borders represent barriers for knowledge flows [27].

$x_{5(i,j)}$ is an index that varies between 0 and 1 and measures technological distance in innovation between the citing and the cited country over the whole sample period (or sub-periods). Or the corresponding sub-period when we estimate equations for different time periods. The index is adapted from Jaffe [28] and calculated as follows:

$$x_{5(i,j)} = 1 - \frac{\left(h_i' h_j\right)}{\left[\sum_s \left(h_{i,s}'\right)^2 \left(h_{j,s}\right)^2\right]^{1/2}} \tag{2}$$

Where h is a share of patents in each technology field s (Appendix Table A1) for the entire period of study. When the index is equal to 1, the countries that have completely different innovation profiles, i.e., their innovation efforts are focused on completely different technologies. Conversely, when the index is equal to 0, the countries are completely similar in their innovation profile. The coefficient b_5 associated with $x_{5(i,j)}$ is expected to be negative. This implies that the more similar the two countries are in technology space, the more likely they are to cite each other [29].

$x_{6(i,j)}$ is an index measures distance in the level of technological development of the citing country i with respect to the cited country j in each technology fields (Appendix Table A1). The index is based on [30] and is calculated as the ratio of the average number of citations received

[1] It is note that we added two missing countries from the database manually (e.g. Liechtenstein (latitude = 47.166 and longitude = 9.5554) and Monaco (latitude = 43.733334 and longitude = 7.416667)).

Table 1
Summary statistics of patents by innovating countries for mature renewable energy (upper panels) and fossil-based (lower panels) technologies, 1990–2002 (left) and 2003–2015 (right).

Citing country	Mature renewable technologies 1990–2002				Mature renewable technologies 2003–2015			
	No. of patents	% over sample	No. of citations	% over sample	No. of patents	% over sample	No. of citations	% over sample
DE	410	23.87	1039	19.98	4169	21.23	20,331	18.02
CH	379	22.06	1032	19.85	2386	12.15	12,387	10.98
US	291	16.96	1146	22.04	3799	19.34	29,837	26.44
JP	207	12.04	692	13.31	1174	5.98	5589	4.95
NL	75	4.35	191	3.67	464	2.36	2269	2.01
DK	60	3.48	113	2.17	1569	7.99	9321	8.26
GB	59	3.41	212	4.08	849	4.32	5018	4.45
FR	45	2.64	117	2.25	941	4.79	3909	3.46
IT	40	2.32	126	2.42	570	2.90	2618	2.32
AU	36	2.10	111	2.14	158	0.80	783	0.69
BE	34	1.95	88	1.69	213	1.08	1276	1.13
SE	22	1.28	118	2.27	165	0.84	691	0.61
AT	21	1.20	75	1.44	189	0.96	1275	1.13
ES	10	0.59	20	0.38	727	3.70	3825	3.39
NO	7	0.38	41	0.79	99	0.50	674	0.60
CA	6	0.36	33	0.63	175	0.89	1320	1.17
IE	5	0.26	16	0.31	29	0.15	180	0.16
FI	3	0.17	6	0.12	92	0.47	390	0.35
KR	3	0.17	7	0.13	1124	5.72	6842	6.06
RU	2	0.09	3	0.06	41	0.21	199	0.18
HU	1	0.08	7	0.13	11	0.05	31	0.03
CN	1	0.06	–	–	463	2.36	2523	2.24
PL	1	0.06	1	0.02	29	0.15	105	0.09
PT	1	0.06	1	0.02	26	0.13	131	0.12
IN	1	0.04	3	0.06	144	0.73	1065	0.94
SI	1	0.03	1	0.02	7	0.04	24	0.02
BR	–	–	–	–	12	0.06	77	0.07
CZ	–	–	–	–	8	0.04	50	0.04
GR	–	–	–	–	11	0.06	88	0.08
Citing country	**Fossil-based technologies 1990–2002**				**Fossil-based technologies 2003–2015**			
	No. of patents	**% over sample**	**No. of citations**	**% over sample**	**No. of patents**	**% over sample**	**No. of citations**	**% over sample**
US	254	30.29	794	35.40	632	29.86	4809	46.85
CH	169	20.11	466	20.78	290	13.71	1220	11.89
DE	162	19.27	337	15.02	423	19.98	1103	10.75
FR	49	5.88	153	6.82	146	6.88	605	5.89
GB	41	4.92	129	5.75	93	4.37	604	5.88
JP	34	4.09	110	4.90	52	2.46	164	1.60
SE	21	2.45	39	1.74	61	2.89	195	1.90
FI	18	2.12	21	0.94	40	1.88	118	1.15
IT	18	2.10	30	1.34	79	3.73	230	2.24
NL	17	2.02	35	1.56	27	1.28	75	0.73
DK	10	1.19	16	0.71	24	1.15	69	0.67
CA	10	1.13	17	0.76	30	1.39	348	3.39
AU	9	1.07	24	1.07	16	0.73	62	0.60
NO	7	0.81	31	1.38	15	0.72	60	0.58
AT	7	0.77	3	0.13	32	1.51	47	0.46
BE	5	0.54	6	0.27	18	0.84	69	0.67
BR	2	0.22	14	0.62	2	0.09	4	0.04
ES	2	0.18	5	0.22	12	0.54	51	0.50
RU	2	0.18	–	–	2	0.09	7	0.07
GR	1	0.12	3	0.13	4	0.19	22	0.21
HU	1	0.12	3	0.13	4	0.19	11	0.11
IN	1	0.12	2	0.09	31	1.48	129	1.26
KR	1	0.12	1	0.04	46	2.18	134	1.31
CN	1	0.06	–	–	20	0.92	83	0.81
PL	1	0.06	2	0.09	10	0.45	19	0.19
SI	1	0.06	2	0.09	2	0.09	4	0.04
CZ	–	–	–	–	6	0.29	14	0.14
PT	–	–	–	–	2	0.07	8	0.08

Notes: self-citations (citations to the same assignee) are excluded. Country names and two-letter codes by Patent Cooperation Treaty (PCT) applicant's guide. A list of countries: AT (Austria), AU (Australia), BE (Belgium), BR (Brazil), CA (Canada), CH (Switzerland), CN (China), CZ (Czech Republic), DE (Germany), DK (Denmark), ES (Spain), FI (Finland), FR (France), GB (United Kingdom), GR (Greece), HU (Hungary), IE (Ireland), IN (India), IT (Italy), JP (Japan), KR (Republic of Korea), NL (Netherlands), NO (Norway), PL (Poland), PT (Portugal), RU (Russia), SE (Sweden), SI (Slovenia), US (United States).

by patents in citing country *i* to the average number of citations received by patents in the cited country *j* within the same technological field *s*, minus one:

$$x_{6(i,j)} = \sum_{s} \left(\frac{f_{i,s}}{f_{j,s}} \right) - 1 \tag{3}$$

Unlike other variables, $x_{6(i,j)}$ can take both positive or negative values. It is less than zero if the low-carbon technologies patents of the citing country give rise to fewer knowledge spillovers (i.e., they are less cited) than those granted to the cited country. Conversely, it is greater than zero if the patents granted to the citing country give rise to more knowledge spillovers (i.e., they are more cited) than those granted to the cited country. An index of 0 indicates that the patents granted in the citing country are on average as cited and important as those by the cited country [9]. We expect the coefficient b_6 associated with $x_{6(i,j)}$ to be negative, implying knowledge flows are from the frontier countries and towards the laggard countries [3].

In addition to the traditional variables measuring geographical, linguistic, trade and technological distance, we also estimate a model which accounts for distance in the space of environmental policies. A few recent analyses have put forward suggestive evidence that distance in the environmental policy space may affect the rate of knowledge flow between two countries. Conti et al. [31], for instance, show that knowledge flows increase as together among those countries of the EU as a consequence of the increase in the stringency in environmental policies. Dechezleprêtre et al. [32] show that the similarity of environmental policy stringency between two countries positively matters for knowledge spillovers. Similarly, Milani [33] argues that market-based environmental policies increase cross-country knowledge collaboration on the ground that innovators innovate to respond to regulation.

The index measuring distance in the policy space is built using data from the OECD Environmental Policy Stringency Index (EPS) database. The EPS provides country-specific measures of the stringency of several environmental policy instruments over the years 1990–2011 [34]. The index is calculated as follows:

$$x_{7(i,j)} = 1 - \frac{\left(k_i^{'} k_j\right)}{\left[\sum_s \left(k_{i,p}^{'}\right)^2 \left(k_{j,p}\right)^2\right]^{1/2}} \tag{4}$$

Where k is the percentage share of the sum of environmental policy stringency across all years (1990–2011) and different types of policy instruments (p). These include R&D subsidies, taxes, trading schemes, feed-in-tariffs, and standards. The index $x_{7(i,j)}$ ranges between 0—indicating countries with completely similar policy profiles—and 1—indicating completely different policy profiles. A negative coefficient b_7 associated with $x_{7(i,j)}$ would imply that the more similar the policy portfolios in the two countries, the higher knowledge flows [33]. We expect the coefficient b_7 to be negative, implying the higher the policy distance hinders the knowledge flows [14].

Using the estimated parameters from equation (1), we then generate diffusion parameters $\widehat{\Phi}_{i,j}$ defined as:

$$\widehat{\Phi}_{i,j} = \exp\left[\sum_{n=1}^{N} \widehat{b}_n x_{n(i,j)}\right] \tag{5}$$

Where $\widehat{\Phi}_{i,j}$ is the estimated probability of knowledge flows from cited country j to citing country i. In practice, $\widehat{\Phi}_{i,j}$ represents the portion of knowledge flows that can be predicted to occur between two countries given their geographical, linguistic, trade and technological distance. In this approach, intertemporal knowledge flows from domestic knowledge $\widehat{\Phi}_{i,i}$ is equal to 1 by construction, as all distance variables between country i and itself would be zero. Conversely, $\widehat{\Phi}_{i,j} < 1$ because only a fraction of the knowledge produced in i will reach j after passing geographical, linguistic, economic and technological barriers. In this context, $\widehat{\Phi}_{i,j}$ represents the probability of citation from patents invented in country i and year t to patents invented in country j between the years t-1 and t-5 relative to the probability that any inventor from country i cites a patent originating from country i over the same time period.

The econometric exercise we carry out is structured as shown in Fig. 1. In first instance, we provide estimates of equation (1) for both mature renewable energy and efficient fossil-based technologies. This is meant to highlight any difference in average knowledge flows for these two very different sets of options over the entire sample period. Second, we split our sample into two periods (1990–2002 and 2003–2015) and repeat the estimation for both technology groups. This allows us to gauge any changes in spillovers intensity over time. Third, we repeat the analysis including an indicator measuring distance in the environmental policy space to test whether this plays a role in the diffusion of knowledge. Equation (1) is estimated using a negative binomial approach to account both for the count data nature of the dependent variable and for the over-dispersion in the data [35,36].

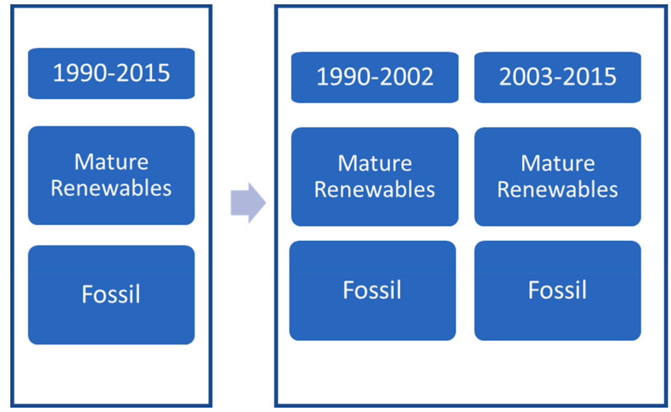


Fig. 1. Flow flowchart.

To identify mature renewable and fossil-based technologies, we follow a tagging system by the European Patent Office (EPO). We categorise the relevant patents by technologies defined by Y02 (climate change mitigation technologies) as of January 2018. Appendix A shows how we define technology fields and merge each table in the EPO's Worldwide Patent Statistical Database (PATSTAT) 2020 Autumn Edition.

We consider citing patents (i.e., mature renewables and efficient fossil-based energy technologies) applied for between 1990 and 2015, and cited patents applied for between 1985 and 2014 (in line with our 5 year-citation lag). The countries in our sample include 29 countries including key developing countries (e.g., China, India, Russia, Brazil). We consider all possible combinations of citing-cited countries, for a total of 29 × 29 = 841 observations. If a given country never cites another given country, we input zero citations.

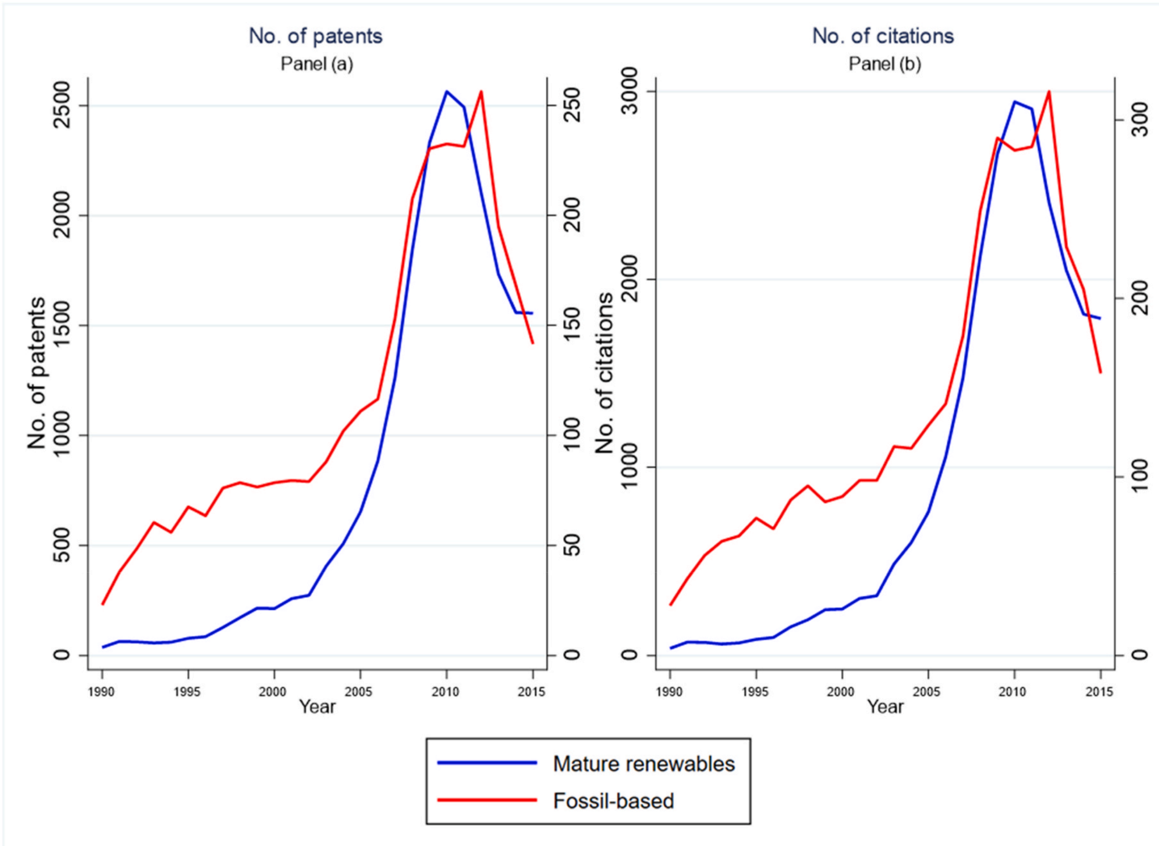
3. Results and discussion

3.1. Descriptive analysis

Fig. 2 shows the number of patents and the number of citations in our sample—Panel (a) and Panel (b), respectively—to examine temporal trends. The number of patents for both technological fields skyrocketed after 2002 and peaked around in 2010, after which they started to decline [37]. Innovation dynamics differ significantly for the two sets of technologies in our analysis: in 2010, the peak year, mature renewable patents were 67-fold higher than in 1990. Conversely, in 2010, fossil-based patents were 10-fold higher than in 1990. Afterwards, the number of patents decreases for both technologies; this is a natural consequence of the truncation of our data, as more recent patents take time to be recorded in the data.

Citation patterns exhibit a similar pattern. Citation dynamics also differ significantly for the two sets of technologies: in 2010, the peak year, mature renewable patent citations were 75-fold higher than in 1990. Conversely, fossil-based patents were 10-fold higher in 1990.

Table 1 shows the number of patents, share of patents over sub-sample, citations and share of patent citations by innovating countries for both sets of technologies and for the two sub-periods. Mature renewables and fossil-based patents represent 88% and 12% of the sample,



Notes: The number of patents in mature renewables and fossil-based technologies in Panel (a) is on the left and right side of the axis, respectively. The number of citations in mature renewables and fossil-based technologies in Panel (b) is on the left and right side of the axis, respectively.

Fig. 2. Number of patents (panel a) and citations (panel b) for mature renewables and fossil-based technologies
Notes: The number of patents in mature renewables and fossil-based technologies in Panel (a) is on the left and right side of the axis, respectively. The number of citations in mature renewables and fossil-based technologies in Panel (b) is on the left and right side of the axis, respectively.

respectively. For both types of technologies, Germany, Switzerland and the US are the top three inventors as well as the countries which receive the most citations. Together, these countries account for 63% (53%) of mature renewable energy patents and for 70% (64%) of fossil-based patents in the first (second) period. The corresponding percentages in terms of citations received are 62% (55%) for mature renewables and 71% (70%) for fossil-based technologies. Different countries follow in the ranking of both patent numbers and citations received.

Table 2
Summary statistics.

Variable [unit]	Observation	Mean	Std. Dev.	Min	Max
No. of citations [#]	841	203	1032	0.00	25,224
Crossing country border [index]	841	0.97	0.18	0.00	1.00
Country distances [1000 km]	841	4.80	4.51	0.00	18.06
Crossing linguistic border [index]	841	0.89	0.31	0.00	1.00
Crossing trade border [index]	841	0.78	0.33	0.00	1.00
Crossing technological distance [index]	841	0.27	0.21	0.00	0.90
Vicinity of citing to the frontier of cited [index]	841	0.09	0.46	−0.74	2.80
Environmental policy stringency distance [index]	841	0.12	0.09	0.00	0.45

Table 2 shows the descriptive statistics of the dependent variable, citations from country j to country i, and of our control variables measuring geographical, linguistic, economic and technological barriers between countries and distance in the policy space. This is balanced panel data with a lot of 0's in the dependent and independent variables. The average number of citations in our sample is 203, with a standard deviation of 1,032, indicating large variations. Within country citations account for 3% of our sample; 89% (78%) of knowledge spillovers cross a linguistic border (trade border). The average distance in technological and policy space are 0.27 and 0.12, respectively; also in this case there is considerable variation in the sample.

Fig. 3 shows the share of citations (i.e., top five citing countries) by technology field and country in the first and second periods. First, the top five patent citing countries in mature renewable technologies include Switzerland, Germany, the US, the UK, and Japan in the early period, but Japan was replaced by Korea in the latter period. Second, the top five patent citing countries in fossil-based has not changed from the early and latter periods of the study.

3.2. Estimation results

Table 3 shows the results of estimation of equation (1) for mature renewable energy and efficient fossil-based technologies over the full sample period (columns 1 and 2) and for the different sub-periods (columns 3 to 6). Compared to the pooled estimation of both

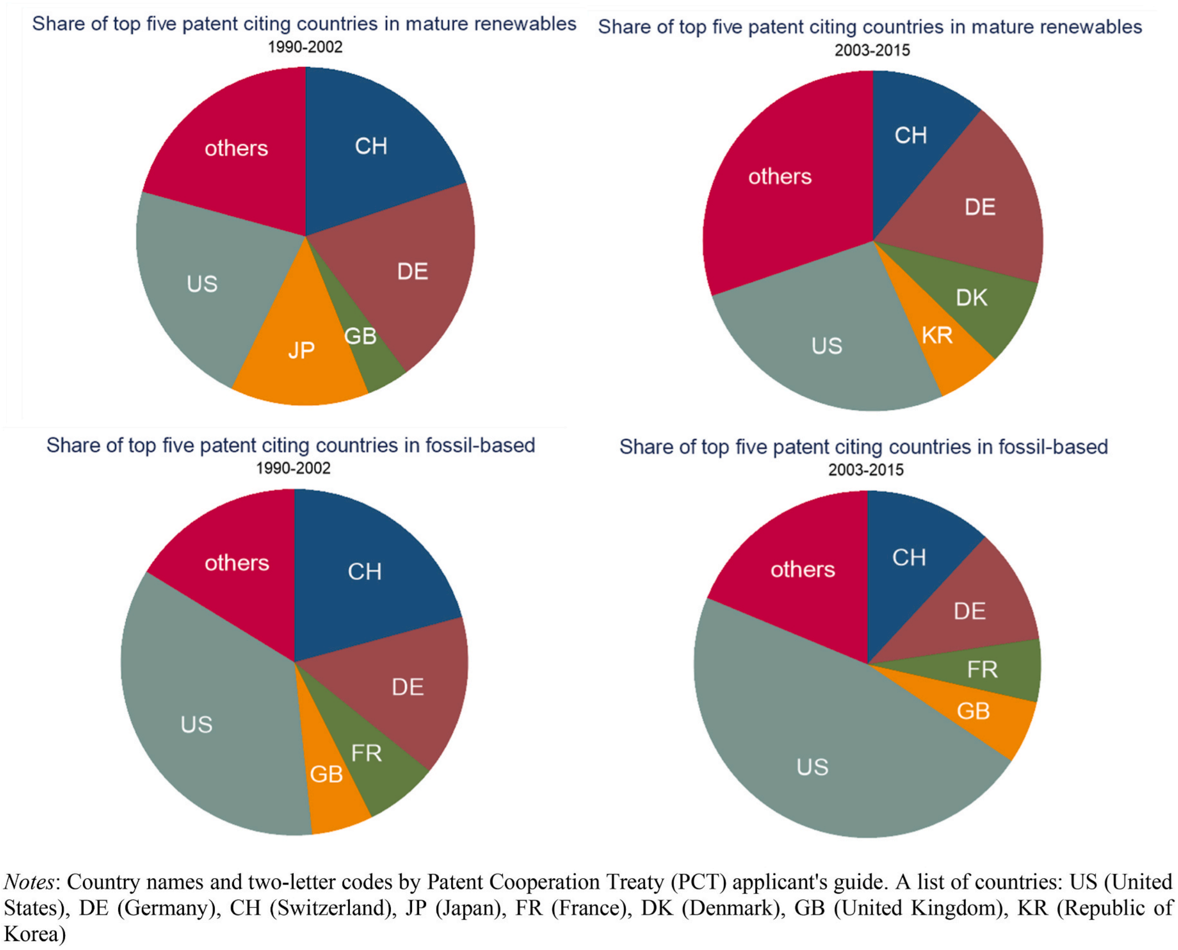


Fig. 3. Share of citations by country for mature renewables (upper panels) and fossil-based (lower panels) technologies, 1990–2002 (left) and 2003–2015 (right) *Notes*: Country names and two-letter codes by Patent Cooperation Treaty (PCT) applicant's guide. A list of countries: US (United States), DE (Germany), CH (Switzerland), JP (Japan), FR (France), DK (Denmark), GB (United Kingdom), KR (Republic of Korea).

Table 3
Barriers to knowledge diffusion in mature renewable technologies and fossil-based technologies, 1990–2015.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Full period		1990–2002		2003–2015	
	Mature renewables	Fossil-based	Mature renewables	Fossil-based	Mature renewables	Fossil-based
Crossing country border						
	−1.238***	−1.186***	−1.488***	−0.697***	−1.185***	−1.165***
Country distance	(0.130)	(0.188)	(0.252)	(0.248)	(0.132)	(0.195)
	−0.014**	−0.031**	−0.033*	−0.028	−0.011	−0.031**
Crossing linguistic border	(0.007)	(0.013)	(0.018)	(0.023)	(0.007)	(0.013)
	−0.086	−0.277***	−0.014	−0.251*	−0.081	−0.280**
Crossing trade border	(0.070)	(0.105)	(0.142)	(0.150)	(0.071)	(0.111)
	0.058	0.005	0.108	0.056	0.017	0.049
Crossing technological distance	(0.047)	(0.146)	(0.097)	(0.198)	(0.045)	(0.144)
	−1.402***	−0.851***	−0.808***	−0.945***	−1.452***	−0.917***
Vicinity of citing to frontier of cited	(0.155)	(0.286)	(0.290)	(0.312)	(0.158)	(0.311)
	−1.454***	0.900	−0.025	0.181	−1.616***	0.609
Constant	(0.288)	(0.695)	(0.085)	(0.144)	(0.312)	(0.834)
	3.621***	0.357	1.605***	−2.975***	3.532***	0.230
Observations	(0.151)	(0.314)	(0.311)	(0.726)	(0.155)	(0.330)
	841	841	841	841	841	841
Citing country FE	YES	YES	YES	YES	YES	YES
Cited country FE	YES	YES	YES	YES	YES	YES

Notes: This table displays the estimation results of barriers to knowledge diffusion in mature renewables and fossil-based technologies, 1990–2015. Dependent variable: all citations within 5-year window from cited country *j* to citing country *i*. We measure the number of patent citations received by patents invented in climate mitigation technology fields (Table A1) from patents invented in mature renewables or fossil-based technologies. We re-constructed three independent variables (crossing trade border, crossing technological distance, and vicinity of citing to frontier of cited) to meet the given time period, respectively. Standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

technologies shown in Table B1 technology-specific patterns emerge.

Crossing a country border is a barrier to knowledge flow for both sets of technologies, albeit with different magnitude. Over the whole sample period, citation between two countries sharing a border is 29% ($e^{-1.238}$) as likely as citation to domestic patents for mature renewable technologies. The corresponding value for fossil-based technologies 31% ($e^{-1.186}$). In our case, the coefficient associated with crossing a country border is smaller than in Ref. [3], potentially indicating that the role of geographical barriers has decreased over time—as is the case for the trade literature [38]. Differently from Ref. [3], additional geographical distance behind the crossing of a country border hinders further knowledge flows: citing a country that is 4800 km away—the average distance in our sample—is 50% as likely as citing a neighboring country.

Linguistic difference is a barrier to knowledge flow only in the case of fossil-based technologies: a citation between two countries which do not have the same official languages is 76% ($e^{-0.277}$) as likely as a citation between countries in the same official languages. Linguistic barriers are not associated with lower citation probabilities in the case of mature renewable technologies.

Trade barriers, on the other hand, are not associated with lower knowledge flows in either technology. This is different from what [3] found in the much earlier period (1975–2000), but in line with evidence of a persistent decline in trade barriers between 2000 and 2014 [38].

Knowledge flows are more likely among countries whose innovation activities are similar, but technological distance represents a higher barrier in the case of mature renewable technologies. Over the sample period, citations between two countries with completely different mature renewable innovation profiles are about 25% ($e^{-1.402}$) as likely as between two countries with the same mature renewable technological profile. The corresponding value for fossil-based technologies is 43% ($e^{-0.851}$). Focusing on the two subperiods, results are generally similar for fossil-based technologies—39% ($e^{-0.945}$) and 40% ($e^{-0.917}$). Conversely, in the case of mature renewable technologies, citations between countries with completely different technological profiles are 23% ($e^{-1.452}$) and 45% ($e^{-0.808}$) as likely as those between two identical countries for the first and second period, respectively. With respect to the variable measuring technological development ($x_{6(i,j)}$), we note that the coefficient is significant, and negative, only in the case of mature renewable technologies for the full-period and the second sub-period.

Table 4 displays the estimation results for mature renewables and fossil-based technologies including environmental policy stringency distance for the full period and the two subperiods. First, the coefficient associated with this variable over the whole sample period is not statistically different from zero for either technology. This implies that distance in the environmental policy space does not hinder the likelihood of citation. However, note that the coefficient associated with this variable in the mature renewables model for the first time period is negative and significant, providing some albeit weak evidence that in the early years' policy distance may have represented a barrier to knowledge diffusion.

3.3. Inter-temporal heat maps

We use the coefficients in Table 3 to generate matrixes of knowledge diffusion parameters for mature renewables and fossil-based technologies over the two periods of time 1990–2002 and 2003–2015 in our sample countries (Equation (5)). These heat maps visually illustrate the results from our empirical estimation. Citing countries, i.e., the countries receiving the knowledge, are listed in the rows, while cited country, i.e., the country source of knowledge, are listed in the columns. Note that the underlying data, i.e., the estimated shares of knowledge flowing between sending and receiving country in the two sample periods, is provided in Table B.2-5 in the Appendix. These can be fruitfully used to calibrate knowledge production functions in a wide range of models for integrated assessment of the energy, the economy and the climate.

These heat maps should be interpreted keeping in mind that the diagonal entry is equal to 1 by construction, as previously explained. That is, the heat maps allow us to compare the intensity of the international knowledge received by the citing country as compared to the own knowledge it produces and builds upon. Also note that by construction, the estimated knowledge diffusion parameters are asymmetric, i.e., the intensity of knowledge flows between two countries differs depending on the direction of knowledge flow.

A few key insights emerge. First, in the earlier period, the intensity of

Table 4
Barriers to knowledge diffusion in mature renewables and fossil-based technologies including environmental policy distance, 1990–2011.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Full period		1990–2000		2001–2011	
	Mature renewables	Fossil-based	Mature renewables	Fossil-based	Mature renewables	Fossil-based
Crossing country border	−1.061***	−1.387***	−0.887***	−0.944***	−1.062***	−1.483***
	(0.133)	(0.219)	(0.281)	(0.344)	(0.132)	(0.231)
Country distance	−0.024***	−0.039***	−0.025	−0.053*	−0.022***	−0.031**
	(0.008)	(0.015)	(0.018)	(0.028)	(0.007)	(0.016)
Crossing linguistic border	−0.028	−0.215*	−0.274*	−0.440**	−0.023	−0.161
	(0.071)	(0.118)	(0.154)	(0.183)	(0.071)	(0.129)
Crossing trade border	0.020	0.204	0.301***	0.311	−0.001	0.200
	(0.048)	(0.166)	(0.111)	(0.249)	(0.047)	(0.174)
Crossing technological distance	−1.687***	−0.820***	−1.932***	−0.295	−1.696***	−0.688**
	(0.164)	(0.306)	(0.328)	(0.364)	(0.165)	(0.339)
Vicinity of citing to frontier of cited	−1.773***	1.114	−0.025	0.001	−1.964***	0.027
	(0.399)	(0.985)	(0.094)	(0.133)	(0.444)	(1.289)
Environmental policy distance	−0.398	0.143	−0.946*	−0.154	−0.374	0.576
	(0.291)	(0.571)	(0.527)	(0.689)	(0.253)	(0.551)
Constant	3.256***	−0.020	0.848**	−1.136**	3.217***	−0.653
	(0.154)	(0.368)	(0.346)	(0.558)	(0.156)	(0.428)
Observations	841	841	841	841	841	841
Citing country FE	YES	YES	YES	YES	YES	YES
Cited country FE	YES	YES	YES	YES	YES	YES

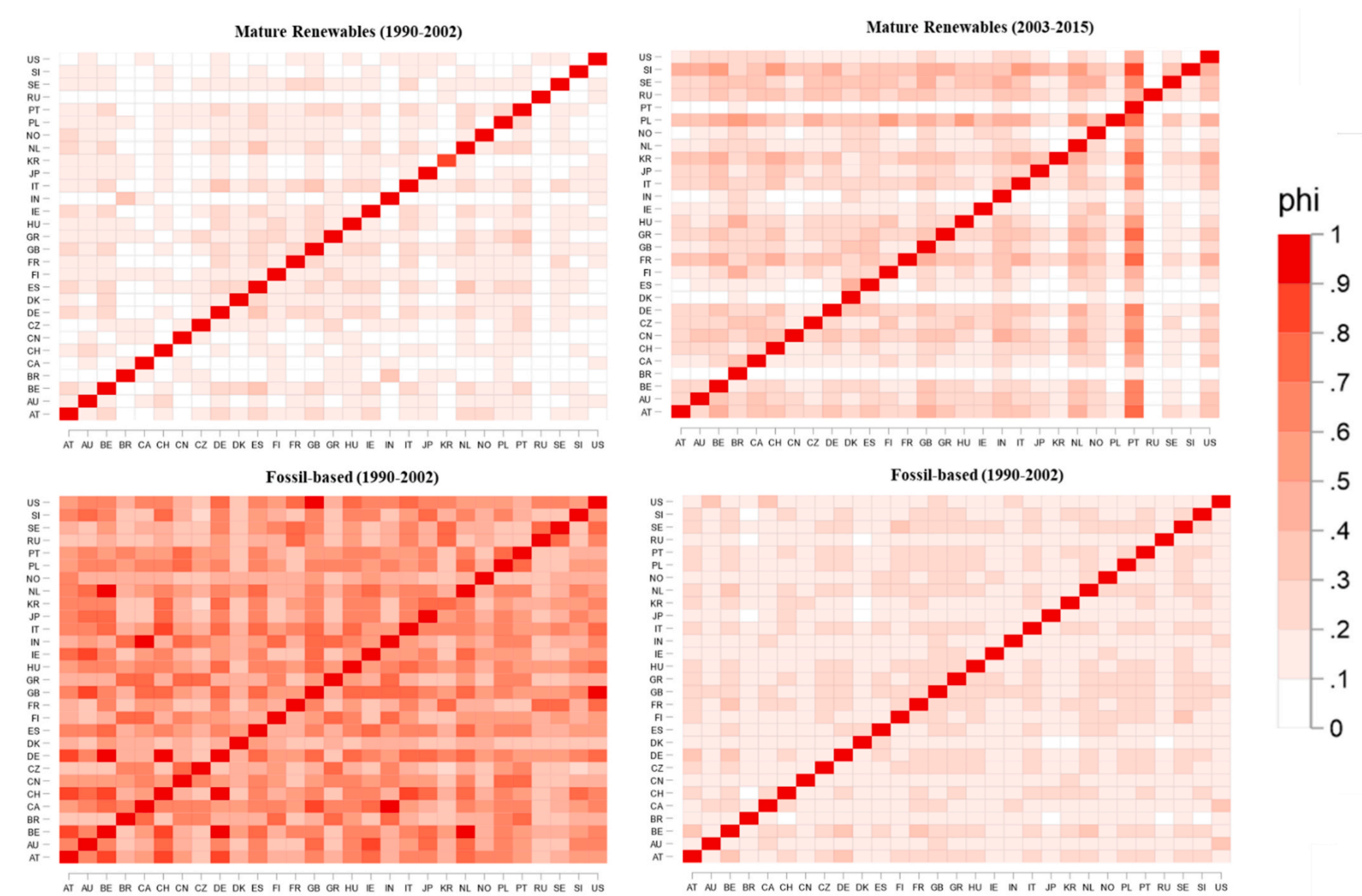
Notes: This table displays the estimation results of barriers to knowledge diffusion in mature renewables and fossil-based technologies, 1990–2011. Dependent variable: all citations within 5-year window from cited country *j* to citing country *i*. We measure the number of patent citations received by patents invented in climate mitigation technology fields (Table A1) from patents invented in mature renewables or fossil-based technologies. We re-constructed four independent variables (crossing trade border, crossing technological distance, vicinity of citing to the frontier of cited, and environmental policy distance) to meet the given time period, respectively. Standard errors in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

international knowledge flows in efficient fossil-based technologies relative to domestic knowledge flows was higher than for mature renewable technologies. For mature renewable technologies, domestic knowledge flows were much more intense (i.e., the cells are of a darker shade) than knowledge flows from abroad (Fig. 4), which were practically inexistent. Second, a very different picture emerges for the second period. On the one hand, the average relative intensity of international knowledge flows relative to that of domestic knowledge flows is higher for mature renewable technologies, including for those countries which did not benefit from knowledge spillovers in the earlier period. On the other hand, the opposite is true for fossil-based technologies: the relative intensity of international knowledge flows decreased as compared to domestic knowledge flows. This indicates that all countries in our sample rely less on international knowledge to foster domestic innovation as compared to the previous period.

4. Conclusion

This paper estimates the role of barriers to knowledge diffusion in mature renewables and fossil-based technologies in a sample of 29 countries—including fast-growing economies—over the period 1990–2015. Our results provide a more nuanced picture than previous analyses. First, we show that geographical barriers hinder knowledge diffusion in both mature renewable and fossil-based technologies, but their role increases over time for former and not for the latter. Second, language is a barrier for knowledge flows only in the case of fossil-based technologies. Third, trade barriers do not appear to hinder knowledge flows in our sample. We show that knowledge flows are higher in countries with similar technological profiles. This is particularly true for mature renewable technologies. Our analysis does not support the conjecture that distance in policy space reduces the probability of knowledge flows.

We use our empirical results to generate knowledge spillover parameters across countries for 1990–2002 and 2003–2015. These parameters further illustrate that international knowledge spillovers increased in intensity as compared to domestic spillovers for mature renewable technologies in the second half of the sample period. This is true in most countries in our sample, including those which showed no



Notes: Raw data is provided in Table B.2-5 in the appendix. Self-citations (citations to the same assignee) are excluded. Country names and two-letter codes by Patent Cooperation Treaty (PCT) applicant's guide. A list of countries: AT (Austria), AU (Australia), BE (Belgium), BR (Brazil), CA (Canada), CH (Switzerland), CN (China), CZ (Czech Republic), DE (Germany), DK (Denmark), ES (Spain), FI (Finland), FR (France), GB (United Kingdom), GR (Greece), HU (Hungary), IE (Ireland), IN (India), IT (Italy), JP (Japan), KR (Republic of Korea), NL (Netherlands), NO (Norway), PL (Poland), PT (Portugal), RU (Russia), SE (Sweden), SI (Slovenia), US (United States)

Fig. 4. Estimated diffusion parameters for mature renewables (upper panels) and fossil-based (lower panel) technologies, 1990–2002 (left) and 2003–2015 (right)
Notes: Raw data is provided in Table B.2-5 in the appendix. Self-citations (citations to the same assignee) are excluded. Country names and two-letter codes by Patent Cooperation Treaty (PCT) applicant's guide. A list of countries: AT (Austria), AU (Australia), BE (Belgium), BR (Brazil), CA (Canada), CH (Switzerland), CN (China), CZ (Czech Republic), DE (Germany), DK (Denmark), ES (Spain), FI (Finland), FR (France), GB (United Kingdom), GR (Greece), HU (Hungary), IE (Ireland), IN (India), IT (Italy), JP (Japan), KR (Republic of Korea), NL (Netherlands), NO (Norway), PL (Poland), PT (Portugal), RU (Russia), SE (Sweden), SI (Slovenia), US (United States).

benefits from international knowledge flows in the first half of the sample. The opposite is true for fossil-based technologies.

Our findings confirm that knowledge spillovers have technology-specific dynamics, and that they are not static over time. Note that the estimated diffusion parameters for foreign knowledge to any country in our sample increased over time, particularly over the last decades in mature renewable technologies. Overall, this is consistent with the hypothesis that domestic knowledge contributes to generating further knowledge also in foreign countries, ultimately increasing our decarbonisation options and lowering the costs associated with mitigation. Ignoring this fact in the generation of mitigation scenarios would lead to an underestimation of the benefits associated with innovation as well as to an overestimation of the costs associated with mitigating climate change. Conversely, low-decarbonisation pathways should account for these specificities. A fruitful avenue of further research lies in the use of our estimated diffusion parameters for the calibration of integrated assessment knowledge with endogenous, country- or region-specific knowledge production functions.

Our paper also points to other interesting future research avenues. These include the need to further explore distance in the policy space as a potential factor hindering knowledge flows, as well as the careful estimation of cross-technology knowledge flows. This latter part is particularly important with respect to cross-technology spillover effect in the learning process of a country might hinder cross-country knowledge spillovers. Cross-technology knowledge flows are also important with respect to digital technologies, and the role they are bound to play in the further development of energy technologies for effective mitigation. Furthermore, the future research avenue also includes the link between knowledge spillovers and cost reductions in low-carbon technologies.

As any study, our paper has a few caveats. First, our set up ignores cross-country collaborations as an important avenue of knowledge spillovers, as we rely on citation counts but do not explore patents which are jointly filed by inventors in different countries. We leave this for further future analyses. Second, environmental policy distance is a newly proposed index in this paper, but there is room for improvement. Third, we consider only two sets of technology fields to compare which warrants the necessity of the more granular level of analysis including the rest of the distinct technology field (e.g., nuclear).

Credit author statement

Yeong Jae Kim: Conceptualization, Methodology, Software, Data curation, Investigation, Visualization, Writing – original draft, Writing-Reviewing and Editing, Elena Verdolini: Conceptualization, Methodology, Investigation, Writing – original draft, Writing- Reviewing and Editing

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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