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ARTICLE

The emergence of renewable energy technologies at country level: relatedness, international knowledge spillovers and domestic energy markets

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ABSTRACT

Global sustainable development critically depends on a fundamental transformation of our current energy systems. This paper looks at how countries develop different types of renewable energy technology to achieve this transformation. We highlight the place-dependence in the global innovation systems of renewable energy technologies by focusing on how countries benefit from local and global knowledge. We show that both the relatedness of a country's knowledge base, and international knowledge spillovers contribute to the development of renewable energy technologies. For low- and middle- income countries, domestic markets for renewables play a crucial role in absorbing and utilising these international knowledge spillovers. The results provide a better understanding of how countries can acquire new knowledge in renewable energy technologies.

KEYWORDS

Renewable energy technologies; technological relatedness; international knowledge spillovers; energy transition; catch-up

1. Introduction

Global sustainable development critically depends on a fundamental transformation of the current energy systems (IEA 2015). This low-carbon transition requires worldwide innovation efforts to develop and deploy renewable energy technologies (Wilson and Grubler 2011), although the energy transition pathways in individual countries may differ (Geels et al. 2016; Cherp et al. 2017).

Of all the elements that shape energy transition pathways, knowledge is the most fundamental and powerful driver of innovation for climate change mitigation (Gallagher et al. 2012; Negro, Alkemade, and Hekkert 2012). Although the knowledge base of renewable energy technologies is increasingly global (Bettencourt, Trancik, and Kaur 2013; Noailly and Ryfisch 2015), the development of new knowledge is unevenly distributed (Dechezleprêtre et al. 2011), and individual countries contribute markedly different knowledge to the global knowledge stock of renewable energy technologies (Sbardella et al. 2018). This paper analyses these differences in how countries benefit from local and global knowledge in developing renewable energy technologies.

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Several bodies of literature provide relevant insights. First, evolutionary perspectives consider knowledge production as a path- and place-dependent process (Dosi 1982; Nelson and Winter 1982; Boschma et al. 2017), where countries tend to develop new knowledge that is related to their existing knowledge bases (Boschma 2017; Hidalgo et al. 2018). Second, the sustainability transitions literature highlights the multi-scalar knowledge dynamics in the global innovation systems of sustainable technologies (Binz and Truffer 2017). On the one hand, this literature suggests that the place-dependence of sustainable innovations results from the idiosyncratic social-technical configuration processes at the local level (Hansen and Coenen 2015). More specifically, innovation activities in renewable energy technologies are heavily influenced by the energy and environmental policies at the national level (Johnstone, Haščič, and Popp 2010; Nicolli and Vona 2016). On the other hand, this literature suggests a role for international knowledge spillovers, especially when a country lacks capabilities in developing renewable energy technologies (Gosens, Lu, and Coenen 2015; Binz and Anadon 2018). But countries benefit differently from these international knowledge spillovers due to different levels of absorptive capacities (Cohen and Levinthal 1990; Mancusi 2008; Verdolini and Galeotti 2011). Both effects may thus be location-specific.

In order to systematically analyse the place-dependent impacts of relatedness and international knowledge spillovers, we study renewable energy patents for the post-Kyoto period between 1998 and 2012. We use transnational priority patents of inventors from 64 countries in the Worldwide Patent Statistical Database (PATSTAT, October 2015 version) maintained and distributed by the European Patent Office (EPO). We identify patents protecting inventions related to renewable energy technologies using the Y02 class in the Cooperative Patent Classification (Veefkind et al. 2012). For our econometric analysis, we investigate whether the technological relatedness of a country's existing knowledge base to renewables and international knowledge spillovers help it develop renewable energy technologies. We further test whether their effects are location-specific by including the effects of domestic markets for renewables in our analyses.

Our contribution is twofold. First, we operationalise the global innovation systems concept proposed by Binz and Truffer (2017) by taking both the local knowledge base and international knowledge spillovers into consideration in explaining why countries differ markedly in their contributions to the global knowledge stock. Second, we highlight the place-dependent development trajectories of renewable energy technologies by focusing on the heterogenous impacts of relatedness and international knowledge spillovers across countries following the call for more place-based evidences in related diversification research (Boschma 2017).

The remaining sections are organised as follows: Section 2 summarises the theoretical debates and describes the conceptual framework for the empirical analysis. Section 3 describes the data, methodology and variables. Section 4 contains the results of our descriptive and econometric analyses. We discuss these results and conclude in Section 5.

2. Conceptual framework

In evolutionary thinking, technological change is considered a path-dependent process (Dosi 1982; Nelson and Winter 1982). As a consequence, not every country has the same opportunities to develop new knowledge in energy technologies. Inventors and firms in a country tend to search locally, because they are able to understand, absorb and utilise external knowledge close to their own knowledge bases (Cohen and Levinthal 1990; March 1991; Kauffman 1993). Thus, the existing knowledge base is a relevant determinant of the direction and rate of technological change (Malerba 2002; Breschi, Lissoni, and Malerba 2003).

The path-dependence of technological change thus leads to the place-dependence, in that a country's existing knowledge base creates opportunities, and sets constraints for future knowledge production within that country (Heimeriks and Boschma 2014; Boschma et al. 2017). Knowledge is localised in tacit learning processes, is specific to the context in which it is created, and consequently costly to use elsewhere (Antonelli 1999). Moreover, most of the channels for transferring tacit knowledge are geographically bounded, such as spin-off processes, inventor collaborations and labour flows (Klepper 2007; Breschi and Lissoni 2009; Eriksson 2011). Knowledge production is also strongly affected by national institutions (Malerba and Orsenigo 1996; Antonelli 1999; Boschma and Capone 2015).

Technological relatedness plays an important role in technological diversification by facilitating the learning process, and creating opportunities for combining related technologies (Breschi, Lissoni, and Malerba 2003; Boschma 2017; Hidalgo et al. 2018). Knowledge spillovers from related technologies reduce the uncertainty in developing new technologies (Mowery and Rosenberg 1998). Given the fact that renewable energy technologies draw knowledge heavily from related technologies (Nemet 2012; van den Berge, Weterings, and Alkemade 2019), their presence will help a country develop new knowledge in such technology. In addition, the presence of related technologies provides opportunities for successful and less risky recombinant innovation (Fleming 2001; Fleming and Sorenson 2001). This is especially important for renewable energy technologies that can be considered as radical innovations resulting from the combination of existing technologies in novel ways (Markard and Truffer 2006; Alkemade et al. 2009; Barbieri, Marzucchi, and Rizzo 2020). We thus expect a positive effect of relatedness on developing renewable energy technologies.

The effect of relatedness may differ across countries (Boschma and Capone 2015; Petralia, Balland, and Morrison 2017; Montresor and Quatraro 2017). The geography of sustainability transitions literature highlights that the place-dependence of sustainable innovations results from the unique social-technical configuration process at different locations (Hansen and Coenen 2015). The development of renewable energy technologies is strongly affected by environmental and energy policies, and market liberalisation processes at the national level (Johnstone, Haščič, and Popp 2010; Nesta, Vona, and Nicolli 2014; Nicolli and Vona 2016; Veugelers 2012). Market formation and development have been identified as important for the development of technological innovation systems in renewable energy technologies (Hekkert et al. 2007; Negro, Alkemade, and Hekkert 2012). Growing markets have formed a vital complement to public R&D in driving innovation activities through various channels, including learning by doing, economies of scale, and private R&D investments (Bettencourt, Trancik, and Kaur 2013; Trancik et al. 2015). However, these market stimulating policies are also found to mostly introduce incremental innovations in renewable energy technologies (Nemet 2009; Hoppmann et al. 2013; Schmidt et al. 2016; Trancik et al. 2015). Thus, we expect that the presence of a domestic market for renewables will strengthen the path-dependent process towards related renewable energy technologies.

With increasing globalisation, international knowledge spillovers have become an important input for the inventive processes, either embodied in traded goods or services, or in various disembodied forms through cross-border flows of people, ideas and face-to-face contacts (Keller 2004). Many studies have shown how geographical proximity facilitates the flow of knowledge (Jaffe, Trajtenberg, and Henderson 1993). More recently, the role of social proximity through inventor collaborations has also been studied (Breschi and Lissoni 2001). Inventor collaborations can accelerate the knowledge spillover process, especially for complex knowledge (Singh 2005; Sorenson, Rivkin, and Fleming 2006). Thus, social proximity can compensate for the lack of cognitive proximity in the innovation process (Boschma 2005; Breschi and Lissoni 2009).

Countries benefit from these international knowledge spillovers when developing new technologies (Mancusi 2008; Malerba, Mancusi, and Montobbio 2013). International knowledge spillovers are especially important for producing knowledge in renewable energy technologies (Verdolini and Galeotti 2011; Garrone, Piscitello, and Wang 2014; Wu and Mathews 2012; Conti et al. 2018). Countries can utilise international knowledge to reduce their energy R&D investments (Bosetti et al. 2008). This is vital in preventing underinvestment in R&D for renewable energy technologies due to the 'double externality problem' – the unappropriated social benefits from both the positive knowledge spillovers during the R&D process, as well as the reduced greenhouse gas emissions during the deployment of renewable energy technologies (Rennings 2000; Jaffe, Newell, and Stavins 2002). In addition, the exchange of external knowledge is essential for reducing uncertainty in the inventive process and for introducing successful innovations (Antonelli 1999; Singh and Fleming 2010; Giuliani, Martinelli, and Rabellotti 2016). This is especially important as renewable energy technologies are often characterised by high uncertainty (Negro, Alkemade, and Hekkert 2012). Thus, we expect a positive effect of international spillovers on developing renewable energy technologies.

Countries may benefit differently from international knowledge spillovers due to different levels of absorptive capacity (Cohen and Levinthal 1990; Mancusi 2008; Verdolini and Galeotti 2011). Cohen and Levinthal (1990) suggested that R&D has two faces: innovation and learning. Knowledge accumulated in previous R&D helps absorbing and utilising external knowledge. Furthermore, learning during the adoption and diffusion of new technologies can also increase the absorptive capacity of a country (Hekkert et al. 2007; Carlsson and Stankiewicz 1991). In addition, we thus expect that countries with larger domestic markets for renewables can benefit more from international knowledge spillovers from renewable energy technologies.

3. Data, methods and variables

3.1. Patent data

Patent data is widely used to study knowledge generation and diffusion (Jaffe and Trajtenberg 2002). Although patents do not capture the overall innovative output (Pavitt 1985; Griliches 1990), they provide one of the most comprehensive and systematic overviews of knowledge production. Technology classifications of patents are widely used to study technological change (Fleming 2001; Fleming and Sorenson 2001) and to characterise firms and countries' knowledge bases (Nesta and Saviotti 2005; Antonelli, Krafft, and Quatraro 2010). Inventor information enables studies on the evolution of inventor collaborations and the ensuing knowledge spillovers (Singh 2005; Breschi and Lissoni 2009). Integrating these earlier methods, we use the filing date of patent applications, the inventor's address, and technology classifications from the Worldwide Patent Statistical Database (PATSTAT, 2015 October edition, maintained and distributed by European Patent Office, EPO) to empirically test how countries' knowledge bases and international knowledge spillovers shape the technological changes in renewable energy technology.

We use transnational priority patents (i.e. with subsequent filings protecting the same invention abroad) filed between 1998 and 2012, at whichever patent office. This methodology gives us a global perspective of technological development and a comprehensive assessment of countries' inventive performance suitable for international comparison (Alkemade et al. 2015; Haščič, Silva, and Johnstone 2015). We assign patents based on the inventor's country of residence, following de Rassenfosse et al. (2013), who employed a systematic approach to retrieve missing information on inventors in the PATSTAT database by examining subsequent filings of the same invention that may include this information. The inventor's country of residence better reflects the geographical origin of the inventive activity, as counting patents based on the applicant country tends to underestimate a country's inventive output when there are a large number of foreign-owned R&D laboratories located in the country (Alkemade et al. 2015; Guellec and de la Potterie 2001). We fractionally split patents with multiple inventors across countries based on the proportion of inventors located in each country. For example, if a patent document lists three inventors, two living in country A and one in country B, two-thirds of that patent is allocated to country A and one-third to country B.

To identify patents relating to renewable energy technologies, we use the Y02 class taken from the Cooperative Patent Classification (CPC) table in the PATSTAT database. The Y02 class identifies patents relating to inventions or technologies for mitigation or adaptation against global climate change. EPO experts developed this class by combining existing International and European Patent Classifications with a lexical analysis of abstracts or claims (Veefkind et al. 2012), and this has been widely adopted by researchers (Fankhauser et al. 2013; Bointner 2014; Haščič and Migotto 2015; Laurens et al. 2017; Choi 2018).

To measure the knowledge bases of renewable energy technologies at the country level, we use an extended version of the IPC-based WIPO technology classification developed by Alkemade et al. (2015), which identifies 401 technologies. We fractionally split patents across technologies based on the share of IPC codes in each technology. For example, if the patent lists three different IPC codes, two in *Semiconductor Devices* and one in *Data Processing Systems*, two thirds of the patent are allocated to *Semiconductor Devices* and one third to *Data Processing Systems*. Furthermore, we assume that all inventors contribute the same technological information to the patent.

Of the total sample of 3,960,563 transnational priority patents, 40,264 are inventions in renewable energy technologies. Figure 1 shows the number of patents for different types of renewable energy technology in the post-Kyoto period between 1998 and 2012. Solar photovoltaics and wind (left-axis) have the highest number of patents, followed by solar thermal, biofuel and waste (right axis). Patenting in all types of renewable energy technology, except geothermal, has increased rapidly since 2000. The number of

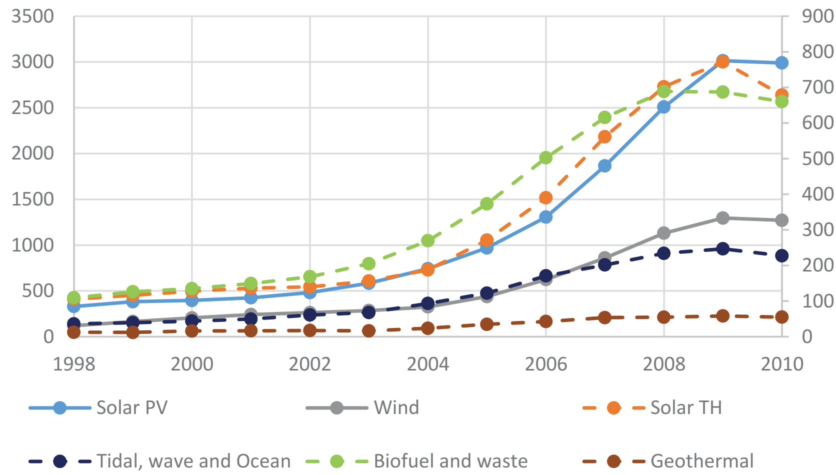

Figure 1. Number of patents by type of renewable energy technology (3-year moving average). Solar thermal, tidal, wave and ocean, biofuel and waste and geothermal are shown on the right axis.

transnational priority patents in recent years on the right of Figure 1 is potentially underestimated, due to censoring issues and incomplete data. The time needed for filing a subsequent application varies between international patenting strategies, from one year under the Paris Convention to 30 months under the Patent Cooperation Treaty (Dechezleprêtre, Ménière, and Mohnen 2017).

3.2. Variables

3.2.1. Measuring specialisation patterns of countries

We use the revealed symmetric technological advantage (*RSTA*) index proposed by Laursen (2015) to indicate a country's specialisation in different renewable energy technologies. This index captures a country's share of technological knowledge produced in a given technology relative to the world average:

$$RSTA_{c,\ i,\ t} = \frac{\left(RTA_{c,i,t} - 1\right)}{\left(RTA_{c,i,t} + 1\right)} \tag{1}$$

with:

$$RTA_{c,i,t} = \frac{P_{c,i,t} / \sum_i P_{c,i,t}}{\sum_c P_{c,i,t} / \sum_i \sum_c P_{c,i,t}} \tag{2}$$

where $P_{c,i,t}$ denotes the number of patents in a given technology i in country c at time t. The value of $RSTA_{c,i,t}$ equals −1 if country c holds no patent in technology i, is equal to 0 if country c's share in technology i equals its share in all technologies (no specialisation) and is greater than 0 if a specialisation is observed. The *RSTA* index corrects for the differences in patenting propensity across technologies and countries (Soete and Wyatt 1983).

3.2.2. Characterising a country's knowledge base

We characterise a country's knowledge base by mapping the technological knowledge production in the country on the global technology space. Inspired by the 'product space' framework (Hidalgo et al. 2007), the global technology space is a network representation of technological knowledge production, where nodes represent technological fields and ties indicate their degree of proximity. Related technologies are close together on the global technology space. We quantify the proximity between each pair of technologies by counting their co-occurrences at the patent level. The proximity between technology i and j at time t is measured as follows:

$$\Phi_{i,j,t} = \frac{P_{i,j,t}}{\sqrt{P_{i,t} * P_{j,t}}} \tag{3}$$

where $P_{i,j,t}$ is the number of patents which list both technology i and j in the patent document at time t. $P_{i,t}$ and $P_{j,t}$ are the numbers of patents in technology i and j at time t.

The density index (Hidalgo et al. 2007) captures the relatedness of a given technology to the knowledge base of a given country by measuring the extent to which new technology produced in a given country tends to cluster around existing technologies within that country. To calculate the relatedness of renewable energy technologies to a country's knowledge base requires a number of steps. First, $Density_{c,i,t}$ is defined as the degree to which technology i is related to all other technologies j that country c specialises in at time t, divided by the total relatedness of technology i to all other technologies in the global technology space at time t:

$$Density_{c,i,t} = \frac{\sum_{j \neq i} \Phi_{i,j,t} * \chi_{c,j,t}}{\sum_{j \neq i} \Phi_{i,j,t}} \tag{4}$$

where $\chi_{c,j,t}$ is a binary variable, indicating whether country c specialises in technology j $\left(\chi_{c,j,t} = 1\right)$, or not $\left(\chi_{c,j,t} = 0\right)$.

Finally, the relatedness of the country c's knowledge base to renewable energy technology r at time t is defined as the weighted average of the $Density_{c,i,t}$ measure:

$$Relatedness_{c,r,t} = \sum_i Density_{c,i,t} * \chi_{c,i,t} * \frac{P_{i,r,t}}{P_{r,t}} \tag{5}$$

where $\chi_{c,i,t}$ denotes whether country c specialises in technology i $\left(\chi_{c,i,t} = 1\right)$, or not $\left(\chi_{c,i,t} = 0\right)$. $P_{i,r,t}$ denotes the number of patents in renewable energy technology r which lists technology i in the patent document. $P_{r,t}$ denotes the number of patents in renewable energy technology r at time t. A higher value of $Relatedness_{c,r,t}$ indicates that renewable energy technology r is more related to the knowledge base of country c at time t.

3.2.3. International knowledge spillovers

$Co\_inv_{c,r,t}$ captures international knowledge spillovers measured as the number of co-invented patents between country c and countries which specialised in renewable energy technology r at time t (Rigby, 2015). We only include the top 10 co-inventing countries for each renewable energy technology, focussing on knowledge spillovers from the global technological frontier. These countries account for 70–90% of all patents in the different renewable energy technologies.

3.2.4. The domestic market for renewables

We calculated the share of electricity generated from non-hydro renewable sources in country c at time t, $Renewables_{c,t}$,to capture the development of the domestic market for renewables following Schmidt and Sewerin (2018). Electricity production data is extracted from the World Energy Balances (International Energy Agency, 2014 edition).

3.2.5. Level of economic development

We control for the level of economic development of countries using the constant (based on 2005) and PPP adjusted GDP per capita (Petralia, Balland, and Morrison 2017). The data on PPP adjusted GDP and population of countries are extracted from the World Bank's Open Data Catalogue. We thereby distinguish high-, and or low- and middle-income countries using the World Bank income classifications.

3.3. Econometric specification

To empirically test our research questions, we estimate the following econometric equation:

$$\begin{aligned}\chi_{c,r,t} = \beta_0 + \beta_1\chi_{c,r,t-1} + \beta_2 Relatedness_{c,r,t-1} + \beta_3 Co\_inv_{c,r,t-1} + \beta_4 Relatedness_{c,r,t-1} \\ * Renewables_{c,t-1} + \beta_5 Co\_inv_{c,r,t-1} * Renewables_{c,t-1} + \beta_6 Relatedness_{c,r,t-1} \\ * GDP_{c,t-1} + \beta_7 Co\_inv_{c,r,t-1} * GDP_{c,t-1} + \emptyset_{c,t} + \varphi_{r,t} + {}_{c,r,t}\end{aligned} \quad (6)$$

where $\chi_{c,r,t}$ is a binary variable, indicating whether country c has a specialisation in renewable energy technology r ($\chi_{c,r,t} = 1$), or not ($\chi_{c,r,t} = 0$). β_1 captures the correlation between specialisation at time *t-1* with specialisation at time *t*. β_2 and β_3 capture the correlation between relatedness and international knowledge spillovers with specialisation. β_4 and β_5 capture whether the correlations between relatedness and international knowledge spillovers with specialisation differ among countries with different domestic market for renewables. β_6 and β_7 capture whether the correlations between relatedness and international knowledge spillovers with specialisation differ among countries with different levels of economic development. All the independent variables are lagged for one period to avoid potential endogeneity issues.

We also include fixed effects in the econometric equation, $\emptyset_{c,t}$ for the time-varying characteristics of a country c and $\varphi_{i,t}$ for those of a renewable energy technology i. The time-varying country fixed effects and time-varying technology fixed effects are included in the model using dummy variables for each country-time pair and each technology-time pair. $\epsilon_{c,r,t}$ denotes the regression residue.

In the econometric analysis, we estimate Equation (6) using a linear probability ordinary least square regression through which we can estimate the probability of observing 0 (no specialisation) or 1 (with specialisation). Scholars usually use logit or probit models if the dependent variable is binary because the linear probability model suffers from drawbacks; it usually generates biased and inconsistent estimates (Horrace and Oaxaca 2006), and it does not deal with measurement error in the dependent variable (Hausman, Abrevaya, and Scott-Morton 1998). However, fixed effects logit or probit models with a large number of dummy variables may lead to biased and inconsistent coefficients due to incidental parameter problems when the number of time periods is limited (Greene 2011). The linear probability model does not suffer from this problem. Moreover, the average effects obtained from the linear probability model are quite similar to marginal effects from non-linear models (Riedl and Geishecker 2014). Thus, the linear probability model is widely used in diversification literature (Petralia, Balland, and Morrison 2017; Colombelli, Krafft, and Quatraro 2014; Montresor and Quatraro 2017). Our use of the *RSTA* index as a robustness check thereby addresses the measurement error.

We include the lagged dependent variable to capture the persistence of knowledge production in renewable energy technologies at the country level. The time-varying country fixed effects in our model exploit variation within technologies, and the technology-time fixed effects exploit variation of countries, thus not correlating with time shocks in the error term, which is the usual bias in a fixed effects panel with lagged dependent variable (Arellano and Bond 1991; Boschma and Capone 2015). Furthermore, we use the system-GMM technique to estimate dynamic panel data models as a robustness check to ensure consistent estimates and address potential endogeneity problems (Blundell and Bond 1998). All independent variables and the lagged dependent variable are treated endogenous, and all possible lags are used as instruments.

We divide the period 1998–2012 into five non-overlapping intervals of 3 years: 1998–2000, 2001–2003, 2004–2006, 2007–2009, and 2010–2012 following existing empirical studies in the regional diversification literature to avoid the impact of volatility in patent statistics on the calculation of our dependent variable (Petralia, Balland, and Morrison 2017; Montresor and Quatraro 2017). We include those countries with more than 10 patents in all five intervals resulting in 1920 observations; 64 countries, 6 renewable energy technologies and 5 time periods (see Table A1). Table A2 shows the correlation statistics of the independent variables. The correlations between independent variables are not high.

4. Empirical results

4.1. Descriptive analysis

Table 1 shows the main specialisations in renewable energy technology of the top 10 patenting countries in renewable energy over time. Countries differ greatly in their contribution to the global knowledge stock. For most countries, the most specialised renewable energy technologies remain stable over time. Emerging economies like Korea, China and Taiwan contributed intensively in recent periods.

Summary statistics in Table 2 show that the knowledge production of renewable energy technologies is persistent over time. 23.8% of the observations are countries maintaining their specialisations, whereas only 14.3% of the observations represent the development of new specialisations.[1]

[1]The tetrachoric correlation between dependent variable and lagged dependent variable is 0.67, also indicating the path-dependence and place-dependence of knowledge production in renewable energy technologies.

Table 1. Top 10 patenting countries in renewable energy and their main technological specialisations.

1998–2000		2004–2006		2010–2012	
Japan	Solar PV, Biofuel	**United States**	Biofuel, Solar PV	**Japan**	Solar PV, Wind
Germany	Wind, Solar TH	**Japan**	Solar PV, Biofuel	**United States**	Biofuel, Geo TH
United States	Geo TH, Biofuel	**Germany**	Geo TH, Solar TH	**Germany**	Solar TH, Wind
Netherlands	Ocean, Solar TH	**United Kingdom**	Ocean, Wind	**Korea**	Solar PV, Ocean
United Kingdom	Ocean, Solar TH	**Korea**	Solar PV, Geo TH	**Taiwan**	Solar PV, Geo TH
France	Biofuel, Solar TH	**France**	Solar TH, Geo TH	**Denmark**	Wind, Biofuel
Denmark	Wind, Ocean	**Spain**	Wind, Solar TH	**France**	Ocean, Solar TH
Switzerland	Geo TH, Solar TH	**Denmark**	Wind, Biofuel	**China**	Solar TH, Wind
Sweden	Geo TH, Wind	**Canada**	Geo TH, Ocean	**United Kingdom**	Ocean, Wind
Australia	Solar TH, Ocean	**Italy**	Geo TH, Solar TH	**Italy**	Solar TH, Geo TH

Table 2. Summary statistics of knowledge production in renewable energy technologies.

Independent Variables	Observations	Mean	SD	Min	Max
$X_{c,r,t-1}$	1,920	0.345	0.475	0	1
$X_{c,r,t-1} = 0$	51.3%			14.3%	
$X_{c,r,t-1} = 1$	10.7%			23.8%	
$Relatedness_{c,r,t-1}$	1,920	0.168	0.169	0	0.810
$Co\_inv_{c,r,t-1}$	1,920	0.235	0.626	0	4.317
Country level independent variables					
$Renewables_{r,c,t-1}$	1,920	0.03	0.049	0	0.276
$GDP_{c,t-1}$	1,920	9.715	0.748	7.617	11.498

Top 10 countries in $Renewables_{r,c,t}$: Philippines, Iceland, Denmark, Finland, New Zealand, Portugal, Spain, Germany, Luxembourg, Austria.

We further show the top 10 countries in the share of electricity generated from renewables. These are mostly European countries that have been promoting renewables to diversify energy supply and decrease their dependence on fossil fuel imports.

4.2. Model outcomes

Table 3 shows the estimation results of Equation (6). A specialisation at time *t-1* is significantly correlated with a specialisation at time *t*, supporting the path-dependence of knowledge production in renewable energy technologies at the country level. As expected, the coefficient of $Relatedness_{r,c,t-1}$ is significantly positive in all columns of Table 3, confirming a correlation between specialisation and a country's knowledge base in related technologies. The results suggest that for renewable energy technologies which are considered more radical and complex, relatedness is still an important driver of knowledge production (Boschma 2017; Hidalgo et al. 2018).

Regarding the interaction terms, the coefficients of $Relatedness_{r,c,t-1} * Renewables_{c,r,t-1}$ are significantly positive in both columns (4) and (5), suggesting that specialisation is more likely to be observed in countries with both higher relatedness and a larger domestic market for renewables. Thus, domestic markets for renewables are likely to strengthen the path-dependence towards related technologies given the positive correlation between relatedness and specialisation.

The coefficients of $Relatedness_{r,c,t} * GDP_{c,t-1}$ are negative in column (2) and (6). The results imply that specialisation is less likely to be observed in countries that have higher relatedness and at the same time higher levels of economic development. However, the

Table 3. Model outcomes (1998–2012).

	Dependent variable: $\chi_{c,r,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\chi_{c,r,t-1}$	0.252***	0.252***	0.287***	0.287***	0.246***	0.245***
	(0.039)	(0.038)	(0.039)	(0.039)	(0.038)	(0.038)
$Relatedness_{c,r,t-1}$	0.656***	0.681***			0.648***	0.676***
	(0.101)	(0.196)			(0.098)	(0.196)
$Co\_inv_{c,r,t-1}$			0.048*	0.041	0.038*	0.018
			(0.024)	(0.075)	(0.021)	(0.069)
$Relatedness_{c,r,t-1} * Renewables_{c,r,t-1}$		3.737**				3.848**
		(1.652)				(1.709)
$Relatedness_{c,r,t-1} * GDP_{c,t-1}$		−0.006				−0.006
		(0.007)				(0.007)
$Co\_inv_{c,r,t-1} * Renewables_{c,r,t-1}$				−0.036		0.191
				(0.434)		(0.337)
$Co\_inv_{c,r,t-1} * GDP_{c,t-1}$				0.0003		0.0004
				(0.002)		(0.002)
Constant	0.169***	0.187***	0.125***	0.125***	0.170***	0.189***
	(0.033)	(0.037)	(0.035)	(0.035)	(0.034)	(0.038)
Observations	1,920	1,920	1,920	1,920	1,920	1,920
R^2	0.466	0.467	0.450	0.450	0.467	0.468

Country-clustered standard errors are in parentheses. Country + time and technology + time dummy variables are included in the linear probability model; ***, **, * statistically significant at .01 percent, .05 percent and .1 percent, respectively.

interaction term is not significant. A possible explanation could be that although higher income countries tend to have more capabilities, like larger public R&D investment in renewable energy technologies, to support the development of less related technologies (Hidalgo and Hausmann 2009; Bointner 2014), they also tend to have larger domestic markets for renewables favouring more related technologies. As shown in Table 2, of the top 10 countries with the largest share of electricity generated from renewable sources 9 are high-income countries. These two effects offset each other.

When we consider the effects of international knowledge spillovers, the coefficients of $Co\_inv_{r,c,t-1}$ are significantly positive in columns (3) and (5), indicating that specialisation are correlated with international knowledge spillovers. Binz and Truffer (2017) argue that the knowledge dynamics of the global innovation systems consist the generation of knowledge in locational subsystems, and the structural coupling among them. Our findings that both relatedness at the national level, and international knowledge spillovers are important for the development of renewable energy technologies provide a first empirical support of these multi-scalar dynamics.

The coefficients of $Co\_inv_{r,c,t-1} * Renewables_{c,r,t-1}$ and $Co\_inv_{r,c,t-1} * GDP_{c,t-1}$ are both positive, suggesting that specialisation is more likely to be observed in countries with more collaborations with countries that are on the technological frontier, and at the same time have larger domestic markets for renewables or higher level of economic development. Interestingly, these two interaction terms are not significant. This result is not in line with our expectations.

In Table 4 we further investigate this by looking at the subsamples of high-, of low- and middle-income countries. The coefficients of $Relatedness_{r,c,t-1}$ are significantly positive in both subsamples, confirming path-dependence. However, the coefficient of $Co\_inv_{r,c,t-1}$ is only significantly positive independently in the subsample of high-income countries. High-income countries tend to have larger absorptive capacities for utilising

Table 4. Model outcomes (1998–2012): Income level.

	(1)	(2)	(3)	(4)
Model	Linear Probability			
Dependent variable	$X_{c,r,t}$			
Subsamples	High-income		Low- and Middle- income	
$X_{c,r,t-1}$	0.268***	0.269***	0.203***	0.178***
	(0.054)	(0.053)	(0.053)	(0.051)
$Relatedness_{c,r,t-1}$	0.680***	0.558***	0.598***	0.429**
	(0.117)	(0.146)	(0.183)	(0.194)
$Co\_inv_{c,r,t-1}$	0.048*	0.051	0.034	−0.094**
	(0.028)	(0.037)	(0.066)	(0.046)
$Relatedness_{c,r,t-1} * Renewables_{c,r,t-1}$		2.714		12.278***
		(1.744)		(4.677)
$Co_{inv\,c,r,t-1} * Renewables_{c,r,t-1}$		−0.051		5.412***
		(0.389)		(0.616)
Constant	0.181***	0.181***	0.237***	0.240***
	(0.058)	(0.059)	(0.037)	(0.038)
Observations	960	960	960	960
R^2	0.461	0.462	0.430	0.446

Country-clustered standard errors are in parentheses. Country + time and technology + time dummy variables are included in the linear probability model; ***, **, * are statistically significant at .01 percent, .05 percent and .1 percent, respectively.

international knowledge spillovers resulting from previous public R&D (Mancusi 2008; Bointner 2014).

An important exception here are low- and middle-income countries with large domestic markets for renewables. Although the coefficient of $Co\_inv_{r,c,t-1}$ is significantly negative, the coefficient of $Co\_inv_{r,c,t-1} * Renewables_{c,t-1}$ is significantly positive in column (4). The results suggest an important role for domestic markets for renewables in low- and middle-income countries in utilising international knowledge spillovers. Although low- and middle-income countries can succeed in developing renewable energy technologies without the development of domestic markets, this type of exporting-oriented development is vulnerable to external shocks. An example is the Chinese solar PV industry which rapidly increased manufacturing output for international markets (Binz and Anadon 2018; Quitzow 2015; Luo, Lovely, and Popp 2017; de la Tour, Glachant, and Ménière 2011). The innovation output of the Chinese solar PV industry lagged behind the manufacturing output and the industry experienced a great shake-out during the trade conflicts with EU and US (Binz, Tang, and Huenteler 2017; Binz and Anadon 2018).

The coefficient of $Relatedness_{r,c,t-1} * Renewables_{c,t-1}$ is only significantly positive in the subsample of low- and middle-income countries, suggesting that the role of domestic market for renewables in strengthening the path-dependent process towards related renewable energy technology is more prominent in low- and middle-income countries. High-income countries tend to have more capabilities for developing less related technologies (Petralia, Balland, and Morrison 2017; Hidalgo and Hausmann 2009).

4.3. Robustness check

We run two additional analyses to check the robustness of our results. First, we re-estimate Equation (6) using the *RSTA* index directly as our dependent variable. Second, we apply the system-GMM techniques. The results are shown in Tables 5 and 6. The

Table 5. Robustness check (1998–2012).

	(1)	(2)	(3)	(4)
Model	OLS		System GMM	
Dependent variable	$RSTA_{c,r,t}$		$X_{c,r,t}$	
$RSTA_{c,r,t-1}$	0.227***	0.223***		
	(0.041)	(0.039)		
$X_{c,r,t-1}$			0.257***	0.257***
			(0.047)	(0.047)
$Relatedness_{c,r,t-1}$	0.606***	0.796***	1.074***	0.995***
	(0.114)	(0.272)	(0.127)	(0.224)
$Co\_inv_{c,r,t-1}$	0.048*	0.076	0.066**	0.011
	(0.028)	(0.089)	(0.027)	(0.066)
$Relatedness_{c,r,t-1} * Renewables_{c,r,t-1}$		4.721**		1.123
		(2.235)		(1.582)
$Relatedness_{c,r,t-1} * GDP_{c,t-1}$		−0.013		0.008
		(0.009)		(0.008)
$Co\_inv_{c,r,t-1} * Renewables_{c,r,t-1}$		0.936**		−0.245
		(0.421)		(0.341)
$Co\_inv_{c,r,t-1} * GDP_{c,t-1}$		−0.003		0.001
		(0.003)		(0.002)
Constant	−0.337***	−0.299***		
	(0.049)	(0.056)		
R^2	0.496	0.499		
Sargan test *p* value			0.017	0.112
AR test (1) in first difference *p* value			0.000	0.000
AR test (2) in first difference *p* value			0.132	0.106
Observations	1,920	1,920	1920	1920

In the linear probability model, country-clustered standard errors are in parentheses. In system-GMM model, robust standard errors are in parentheses. Country + time and technology + time dummy variables are included in the linear probability model; ***, **, * are statistically significant at .01 percent, .05 percent and .1 percent, respectively.

Sargan test tests whether the model is weakened by overidentifying restrictions. Only model column (3) in Table 5 suffers from this issue with a Sargen test *p* value smaller than 0.05. All *p* values from Autoregressive test (1) are smaller than 0.05 and all *p* values from Autoregressive test (2) are larger than 0.05, indicating that all system-GMM estimations are valid. The coefficients of the lagged dependent variable, $Relatedness_{c,r,t-1}$ and $Co\_inv_{c,r,t-1}$ are consistent with our estimations in Tables 3 and 4.

The coefficients of $Relatedness_{r,c,t-1} * Renewables_{c,r,t-1}$ are significantly positive in column (2) in Table 5 and column (3) in Table 6 under a linear model setting using the *RSTA* index as dependent variable, so also consistent with the results in Tables 3 and 4. However, this interaction term is not significant under system-GMM setting. We interpret this result as the presence of reverse causality as past successes in renewable energy innovations may facilitate the legitimation and implementation of market stimulating policies for renewables (Popp, Hascic, and Medhi 2011). For example, maintaining industry leadership is an explicit goal of German energy policy in addition to conventional goals like reducing environmental burden, reducing energy cost, and securing energy supply (Schmidt, Schmid, and Sewerin 2019; Cherp et al. 2017). The effect of the domestic market for renewables is biased upwardly when endogeneity is not properly controlled for; it disappears under the system-GMM setting. This result is in line with recent papers of Popp, Hascic, and Medhi (2011) and Nesta, Vona, and Nicolli (2014).

The coefficient of $Co\_inv_{r,c,t-1}$ is significantly positive in column (2) in Table 6, indicating that high-income countries can benefit from international knowledge

Table 6. Robustness check (1998–2012): Income level.

	(1)	(2)	(3)	(4)
Subsamples	High income		Low- and Middle- income	
Model	OLS	System-GMM	OLS	System-GMM
Dependent variable	$RSTA_{c,r,t}$	$X_{c,r,t}$	$RSTA_{c,r,t}$	$X_{c,r,t}$
$RSTA_{c,r,t-1}$	0.283***		0.134**	
	(0.043)		(0.056)	
$X_{c,r,t-1}$		0.279***		0.209***
		(0.062)		(0.078)
$Relatedness_{c,r,t-1}$	0.438***	1.148***	0.393	1.165***
	(0.152)	(0.181)	(0.293)	(0.187)
$Co\_inv_{c,r,t-1}$	0.008	0.060*	−0.066	−0.018
	(0.031)	(0.037)	(0.061)	(0.049)
$Relatedness_{c,r,t-1} * Renewables_{c,r,t-1}$	2.923	1.363	25.646***	3.947
	(1.995)	(1.395)	(6.988)	(6.982)
$Co\_inv_{c,r,t-1} * Renewables_{c,r,t-1}$	0.643***	−0.345	8.013***	3.378***
	(0.242)	(0.332)	(1.055)	(1.202)
Constant	−0.279***		−0.379***	
	(0.080)		(0.082)	
R^2	0.504		0.451	
Sargan *j* test *p* value		0.208		0.855
AR test (1) in first difference *p* value		0.000		0.000
AR test (2) in first difference *p* value		0.094		0.700
Observations	960	960	960	960

In linear probability model, country-clustered standard errors are in parentheses. In system-GMM model, robust standard errors are in parentheses. Country + time and technology + time dummy variables are included in the linear probability model; ***, **, * are statistically significant at .01 percent, .05 percent and .1 percent, respectively.

spillovers. This is consistent with the findings in column (1) in Table 5. The coefficients of $Relatedness_{r,c,t-1} * Renewables_{c,r,t-1}$ and $Co_{invr,c,t-1} * Renewables_{c,t-1}$ remain significantly positive in the system-GMM model for low- and middle- income countries, further confirming the importance of domestic markets for renewables in low- and middle-income countries for utilising both domestic knowledge base in related technologies and international knowledge spillovers.

5. Conclusion and implications

This paper systematically studies the development of knowledge for renewable energy technologies at the country level during the post-Kyoto period from 1998 to 2012. Building on evolutionary economics and the sustainability transitions literature, we empirically test the impacts of relatedness and international knowledge spillovers. Overall our study confirms the path- and place-dependencies of renewable energy technology development: countries tend to produce more knowledge in renewable energy technologies related to their existing knowledge base.

Furthermore, our results confirm our expectations based on the sustainability transitions literature that the development of emerging sustainable technologies requires both local and global knowledge inputs. The paper thereby provides a first empirical operationalisation of global innovation systems framework proposed by Binz and Truffer (2017). More specifically, we find that international knowledge spillovers help countries to develop new renewable energy technologies. Additionally, in our sample for low- and middle- income countries, we found an important role for domestic market development in utilising these international knowledge spillovers. This provides implications for the catching-up strategy of latecomer countries. Sustainability transitions open new opportunities for latecomer countries to catch up by engaging with the global innovation systems of clean energy technologies (Mathews 2013; Perez 2016; Meckling and Hughes 2018) and the creation of domestic markets can help latecomer countries to seize these opportunities (Yap and Truffer 2019; Binz et al. 2017).

In this paper we highlighted the place-dependence in the global innovation systems of renewable energy technologies. A better understanding of how knowledge and other resources are articulated and combined in the global innovation systems requires further study to also investigate (1) what type of policy can facilitate more radical and unrelated innovations in sustainable technologies to avoid technological lock-in caused by the focus on related technology (Janssen and Frenken 2019; Zeppini and van den Bergh 2011; Safarzyńska and van den Bergh 2013); (2) whether countries also benefit from international knowledge spillovers from other technologies in developing renewable energy technologies (Nemet 2012), and through which channels international knowledge can be better transferred across countries (Popp 2011).

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Appendices

Table A1. Countries included in the econometric analyses and the number of transnational priority patents in each country between 1998 and 2012.

Country	ISO country code	Number of patents
Argentina	AR	1571
Australia	AU	28591
Austria	AT	27787
Belarus	BY	297
Belgium	BE	20879
Brazil	BR	5396
Bulgaria	BG	428
Canada	CA	60748
Chile	CL	698
China (PR of China and Hong Kong)	CN	89355
Chinese Taipei	TW	116691
Colombia	CO	448
Croatia	HR	621
Cuba	CU	205
Cyprus	CY	155
Czech Republic	CZ	3092
Denmark	DK	17215
Egypt	EG	249
Estonia	EE	418
Finland	FI	26124
France	FR	136374
Germany	DE	426272
Greece	GR	1419
Hungary	HU	3089
Iceland	IS	480
India	IN	13387
Indonesia	ID	222
Ireland	IE	5680
Israel	IL	25916
Italy	IT	73456
Japan	JP	910112
Kazakhstan	KZ	110
Korea	KR	236260
Latvia	LV	279
Lithuania	LT	242
Luxembourg	LU	1209
Malaysia	MY	2117
Mexico	MX	2401
Morocco	MA	102
Netherlands	NL	46995
New Zealand	NZ	5519
Norway	NO	9578
Philippines	PH	400
Poland	PL	3309
Portugal	PT	1349
Romania	RO	518
Russian Federation	RU	9459
Saudi Arabia	SA	706
Serbia	RS	256
Singapore	SG	8873
Slovakia	SK	700
Slovenia	SI	1615
South Africa	ZA	4492
Spain	ES	20003
Sweden	SE	42634
Switzerland	CH	42564

(*Continued*)

Table A1. (Continued).

Country	ISO country code	Number of patents
Thailand	TH	659
Turkey	TR	3226
Ukraine	UA	2063
United Arab Emirates	AE	245
United Kingdom	GB	120499
United States	US	732948
Uruguay	UY	161
Venezuela	VE	177

Table A2. Correlation Statistics.

	$X_{c,r,t}$	$Relatedness_{c,r,t}$	$Co\_inv_{c,r,t}$	$Renewables_{c,t}$	$GDP_{c,t}$
$X_{c,r,t}$	1.000	0.461	0.237	0.130	0.153
$Relatedness_{c,r,t}$	0.461	1.000	0.172	0.121	0.127
$Co\_inv_{c,r,t}$	0.237	0.172	1.000	0.168	0.231
$Renewables_{c,t}$	0.130	0.121	0.168	1.000	0.128
$GDP_{c,t}$	0.153	0.127	0.231	0.128	1.000