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Knowledge flows in global renewable energy innovation systems: the role of technological and geographical distance

Deyu Li a,b, Gaston Heimeriks b and Floor Alkemade c

aDepartment of Land Economy, Centre for Environment, Energy and Natural Resource Governance, University of Cambridge, Cambridge, UK; bCopernicus Institute of Sustainable Development, Utrecht University, Utrecht, The Netherlands; cSchool of Innovation Sciences, Eindhoven University of Technology, Eindhoven, The Netherlands

ABSTRACT
Understanding the global knowledge dynamics of renewable energy technologies requires consideration of both technological and geographical dimensions. This paper assesses the relative importance of technological and geographical distant knowledge in the future knowledge development of technological innovation systems (TIS) of renewables. Using global renewable energy patents, we quantify the absorptive capacity of countries as the degree of knowledge accumulation in the knowledge diffusion between domestic actors in a TIS. Our results show that international knowledge flows within a renewable energy TIS are more important for countries with smaller absorptive capacity, whereas countries with larger absorptive capacity benefit more from domestic knowledge originating in other TISs. Consequently, each country faces unique opportunities and constraints with respect to global technological developments when developing renewable energy technologies. These findings lead to policy implications that are specific to developing renewable energy technologies in different countries.

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Global innovation systems; knowledge flows; technological distance; renewable energy technologies

1. Introduction
The development and deployment of renewable energy technologies play a key role in the global energy transitions (Gallagher et al. 2012). Technological change is considered a cumulative process in which new technologies result from the recombination of existing technologies in novel ways (Arthur 2007). This process requires interactions between actors with different backgrounds for knowledge development and diffusion, which is a key mechanism highlighted in the innovation system approaches (Carlsson et al. 2002).

Among the different innovation system approaches, the technological innovation system (TIS) concept contributed significantly to the understanding of the emergence of renewable energy technologies (Bergek et al. 2015; Markard, Hekkert, and Jacobsson 2015). A renewable energy TIS evolves in interactions between actors embedded in various national innovation systems (NIS) and in various existing TISs (Bergek et al. 2008; Carlsson and Stankiewicz 1991; Hekkert et al. 2007). More specifically, knowledge from both actors in other TISs (Andersen and Markard 2020; Malhotra, Schmidt,
and Huenteler 2019) and actors in other NISs (Binz, Truffer, and Coenen 2014) are found to be important for the knowledge development of renewable energy TISs.

However, these exogenous factors have been under-conceptualised in current TIS literature (Bergek et al. 2015). First, knowledge from other TISs may originate in different countries resulting from their distinct knowledge development trajectories (Boschma 2017; Hidalgo et al. 2018; Li, Heimeriks, and Alkemade 2020; Petralia, Balland, and Morrison 2017; Sbardella et al. 2018). Second, most of the early empirical TIS applications were carried out within national boundaries (Coenen, Benneworth, and Truffer 2012). Although the recent global innovation systems concept acknowledges these multi-scalar knowledge dynamics between different TISs and NISs (Binz and Truffer 2017), there is a lack of systematic evidence on how different knowledge flows influence future knowledge development in global renewable energy innovation systems.

In order to address this gap, we investigate the relative importance of different knowledge flows along both technological and geographical dimensions in countries of different levels of absorptive capacity. We base our analysis on patents, and their backward and forward citations. We proxy the absorptive capacity of a country with the degree of knowledge accumulation in the knowledge diffusion between domestic actors in a focal renewable energy TIS. Insights of our analyses help to identify the opportunities and constraints for the development of successful renewable energy technologies at different locations.

The paper is structured as follows. In Section 2, we review the literature and establish our conceptual framework. In Section 3, we describe the data, variables and specifications of econometric models. In Section 4, we present the results of econometric analyses. We conclude with our findings in Section 5.

2. Theoretical background

The production of economically useful new knowledge is considered to result from the collective actions of different actors embedded in an innovation system connected by linkages ranging from informal to formalised network relationships (Lundvall 1992). Based on different delineations of system boundaries, several innovation system approaches have emerged over the years. National innovation systems (Lundvall 1992; Nelson 1993) set system boundaries along the geographical borders of countries. In other cases, system boundaries are set along a technology (Carlsson and Stankiewicz 1991) or a sector (Malerba 2002).

In recent years, the technological innovation systems (TISs) concept help understand how renewable energy technologies have emerged from interaction with firms and knowledge institutions (Bergek et al. 2008; Hekkert et al. 2007; Hekkert and Negro 2009). Initially, emerging technologies have to rely on the available knowledge and institutions of existing technologies (Arthur 2007). Gradually, they develop their own technological trajectories and supporting institutions, thereby reducing their reliance on other technologies over time (Cohen and Levinthal 1990; Dosi 1982). However, the interaction between a focal TIS and other TISs is less studied but equally important (Bergek et al. 2015).

Knowledge flows between TISs are therefore considered important, as they often underlie successful new knowledge recombination (Mowery and Rosenberg 1998; Scherer 1982). Several studies have aimed at identifying their impacts on subsequent technology development in renewable energy TISs. Both Nemet (2012) and Battke et al. (2016) found that knowledge from actors in other TISs are more likely to increase the impacts of renewable energy technologies innovations.

2.1. The geographical dimension of TIS

The TIS approach was originally formulated as a critique of national innovation system approach by explicitly claiming that new technologies may emerge in fluid global networks with actors simultaneously operating at multiple geographical scales (Carlsson 2006). However, most earlier empirical
applications of the TIS concept were carried out within national boundaries (Coenen, Benneworth, and Truffer 2012). Recent systematic empirical evidence shows that countries contribute markedly different new knowledge to the global knowledge base of renewable energy technologies (Li, Heimeriks, and Alkemade 2020; Perruchas, Consoli, and Barbieri 2020; Sbardella et al. 2018), suggesting that countries differ in their capabilities for identifying and exploiting global technological opportunities.

Rooted in evolutionary economics, the recent evolutionary economic geography literature highlights the path- and place-dependence of knowledge production (Boschma et al. 2017). The unique knowledge base of countries and regions constrains, as well as opens up, opportunities for the development of new technologies (Boschma, Heimeriks, and Balland 2014; Heimeriks and Boschma 2014). Countries and regions are more likely to develop new technologies that are related to their existing knowledge bases (Boschma 2017; Hidalgo et al. 2007; Petralia, Balland, and Morrison 2017). This related diversification process is also observed in the development of renewable energy technologies (Li, Heimeriks, and Alkemade 2020; Perruchas, Consoli, and Barbieri 2020).

The place-dependence matters for the knowledge development of renewable energy TISs in two ways. First, although the renewable energy technologies are often considered radical and disruptive (Markard and Truffer 2006), the skills and competences required may still emerge from the existing technologies in the country (Geels 2018; Hansen and Coenen 2015). Van den Berge, Weterings, and Alkemade (2020) found that some clean energy technologies may even partly have developed out of fossil fuel knowledge. The recent case study of the Norwegian oil and gas industries and their roles in the development of offshore wind technology also supports this argument (Mäkitie 2020; van der Loos, Negro, and Hekkert 2020).

Second, the uneven distribution of knowledge across countries also points to the importance of global knowledge networks in tapping into knowledge developed elsewhere (Coenen, Benneworth, and Truffer 2012; Hansen and Coenen 2015; Meckling and Hughes 2018). For example, Binz, Truffer, and Coenen (2014) analysed how actors in the TIS of membrane bioreactor technology are connected through knowledge networks at the global scale. Furthermore, the international linkages are particularly important for the formation of renewable energy TISs in emerging economies (Bento and Fontes 2015; Binz and Anadon 2018; Gosens, Lu, and Coenen 2015; Quitzow 2015).

### 2.2. Multi-scalar knowledge dynamics and absorptive capacity

The recent theoretical and empirical attempts in bringing a geographical dimension into the TIS literature cumulated into the formation of the global innovation systems concept (Binz and Truffer 2017). Global innovation systems can be understood as resulting from two dynamics, the generation of resources in different locational subsystems, and the structural coupling among them (Bergek et al. 2015; Binz and Truffer 2017).

The multi-scalar dynamics are important for analysing the knowledge development processes of emerging TISs. Along the technological dimension, innovations vary in the extent to which they build knowledge along a technology’s own trajectory (within a TIS) or other technologies (between TISs). Along the geographical dimensions, innovations vary in the extent to which they build on domestic sources of knowledge (within a NIS) and international sources of knowledge (between NISs).

Knowledge development processes in renewable energy TISs often need to bridge technological and/or geographical distance to bring together knowledge developed by actors embedded in different TISs and NISs (Andersen and Markard 2020; Binz, Truffer, and Coenen 2014). First, renewable energy technologies are considered as complex technologies which require knowledge input from various technologies (Barbieri, Marzucchi, and Rizzo 2020; Malhotra, Schmidt, and Huenteler 2019; Nemet 2012); Second, knowledge in renewable energy technologies is unevenly distributed across countries (Sbardella et al. 2018), suggesting the importance of international knowledge flows (Li, Heimeriks, and Alkemade 2020; Verdolini and Galeotti 2011). Thus, a proper analysis of the knowledge development of global renewable energy innovation systems has to take into account both technological and geographical dimensions.
Although the novelty associated with external knowledge tends to increase with the technological or geographical distance (Boschma 2005), the difficulties in absorbing and integrating external knowledge also increases (Cohen and Levinthal 1990; Nooteboom 2000). The impacts of technologically or geographically distant knowledge thus depend on the absorptive capacity of countries (Guan and Yan 2016; Mancusi 2008; Phene, Fladmoe-Lindquist, and Marsh 2006).

The original concept of absorptive capacity introduced by Cohen and Levinthal (1990) focused on the learning and innovation of firms. Mancusi (2008) aggregated the knowledge accumulation of firms to proxy the absorptive capacity of countries in different industries. However, Criscuolo and Narula (2008) argued that the aggregation of absorptive capacity from firm level to national level should also consider institutional factors. The innovation system approaches are therefore helpful for delineating the absorptive capacity of countries (Carlsson et al. 2002). The knowledge interactions between actors in an innovation system can create positive feedback loops that are important for knowledge accumulation (Hillman et al. 2008). In other words, countries will have larger absorptive capacity if the knowledge diffusion between domestic actors are more prominent. Consequently, we expect the impacts of technologically or geographically distant knowledge on future technology development to differ for countries with different levels of absorptive capacity.

3. Data and methods

3.1. Patent data

The data used in this paper are patent applications filed at the European patent office (EPO), the United States Patent and Trademark Office (USPTO) and through the Patent Cooperation Treaty (PCT-route) from 1980 to 2015. Patent applications are extracted from the European Patent Office Worldwide Patent Statistics Database PATSTAT 2018 Autumn Version. Since multiple equivalent patent applications can be filed at different patent offices to protect the intellectual property rights of the same invention, we use the simple patent family in the PATSTAT as the unit of analysis in this paper. A simple patent family is a collection of patent documents that share identical technical content and are considered to cover a single invention (Martínez 2011). Using patents from different patent offices and patent family as a unit of analysis can also reduce the home country bias in the citation practice of individual patent office (Bacchiocchi and Montobbio 2010).

The year of a simple patent family is based on the application year of the earliest patent in the family. In the following, one ‘patent’ represents one ‘simple patent family’, and citations between patents represent citations between patent families. Moreover, we only focus on patents assigned to companies and institutions following Mancusi (2008) that individual applicants often apply patents for low quality inventions. The type of applicant is identified using the PATSTAT Standardized Name Table developed by ECOOM in KU Leuven (Du Plessis et al. 2009; Magerman et al. 2009).

Patents relating to different types of renewable energy technology are identified using the Y02 class in the newly launched Cooperative Patent Classification (CPC). The Y02 class is developed by EPO experts by combining existing International Patent Classifications (IPC) and European Patent Classifications with a lexical analysis of abstracts or claims (Veefkind et al. 2012), and has been widely adopted by researchers to study climate change mitigation and adaptation technologies (Haščić and Migotto 2015; Sbardella et al. 2018).

3.2. Dependent variable: technological impact within TIS

We aim to assess the impacts of technologically or geographically distant knowledge on subsequent knowledge development in renewable energy TISs. Counts of forward citations received by patents have been widely used as a proxy for the technological impact of inventions (for a review, see Jaffe and de Rassenfosse (2017)). Following Nemet (2012) and Battke et al. (2016), we count the number of forward citations a patent received from patents in the same type of renewable energy technology.
as its impact on future knowledge development of the focal TIS. The Y02 class helps identify the boundary of each type of renewable energy technology to evaluate the technological impacts within each renewable energy TIS. We count the number of forward citations within the 5-year citation buffer window. As a result, we include patents applied until 2010 in the analyses. In the robustness check, we also use a 10-year citation buffer window.

3.3. Independent variables

3.3.1. Technological and geographical distance

Backward citations of patents are frequently used as an indicator of the extent to which an invention relies on previous technology (Jaffe and de Rassenfosse 2017). We identify a backward citation as a knowledge flow between TISs (i.e. an innovation building on technologically distant knowledge) when the cited patent is not labelled as the same type of renewable energy technology as the citing patent following Battke et al. (2016). Since our sample started from 1980, we only consider patents applied after 1990 to ensure that each patent has a minimum of ten years of patent history from which it can cite prior art following Nemet (2012).

Backward citations are also frequently used to trace knowledge flows across geographical boundaries (Jaffe, Trajtenberg, and Henderson 1993). The inventor’s address can better identify where the R&D was performed given the significant presence of multinational corporations (Alkemade et al. 2015; de Rassenfosse and Seliger 2020). We assign each patent to the country of residence of the first named inventor in the patent document which can be the best proxy of the location where innovation activities take place following Mancusi (2008). A backward citation is considered as an international knowledge flow (i.e. an innovation building on geographically distant knowledge) when the focal patent cited a foreign patent.

We then classify each of the backward citations into four mutually exclusive categories along both geographical and technological dimensions: Domestic Proximate (domestic knowledge flows within the focal TIS), Domestic Distant (domestic knowledge flows between TISs), International Proximate (international knowledge flows within the focal TIS), and International Distant (international knowledge flows between TISs). We count the numbers of backward citations of a focal patent in all four categories and include them in the regression as independent variables. To avoid strategic citations to prior art, self-citations are excluded by removing backward citations to patents assigned to the same applicant as the citing patent (Hall, Jaffe, and Trajtenberg 2005).

Of the independent variables representing the different types of knowledge, renewable energy innovations typically relied extensively on technologically distant knowledge and/or geographically distant knowledge. On average, one renewable energy patent cites 1.93 Domestic Proximate patents, 3.17 Domestic Distant patents, 3.10 International Proximate patents, and 4.70 International Distant patents. This is in line with the existing literature suggesting that renewable energy technologies are more reliant on technological distant knowledge than technological proximate knowledge (Barbieri, Marzucchi, and Rizzo 2020).

3.3.2. Absorptive capacity of countries

We proxy the Absorptive Capacity of a country in a specific type of renewable energy technology with the average number of backward citations to domestic patents in this technology per patent. We calculate this variable using patents applied in the five years prior to the application year of the focal renewable energy patent. This variable is adapted from the absorptive capacity variable used in Mancusi (2008) who counted the average number of self-citations per patent in a country in an industry and argued that self-citations indicate knowledge accumulation internal to the firm, and thus are a good proxy for absorptive capacity resulting from internal R&D.

Similarly, we use the domestic knowledge flows within the focal TIS per patent to capture the domestic knowledge accumulation within the focal TIS. Lee and Yoon (2010) argued that the degree of domestic knowledge flows represents the degree of internalisation of innovation
capability of countries, in other words, absorptive capacity. Wu and Mathews (2012) applied the
domestic knowledge flows to capture the absorptive capacity of countries in solar photovoltaic tech-
nology. Since self-citations are excluded in the calculation, this variable captures the positive feed-
back loops resulting from the knowledge diffusions between domestic actors in an innovation
system (Hillman et al. 2008). This variable thus captures both the size of the knowledge stock of a
focal renewable energy TIS in a country, and how strongly the actors in a country build upon knowl-
edge created by other domestic actors in the focal TIS. Thus, countries will have larger value of
Absorptive Capacity if the knowledge diffusion between domestic actors is more prominent.

3.3.3. Control variables
Following earlier work on knowledge flows and forward citations (Battke et al. 2016; Nemet 2012;
Stephan et al. 2019), we included five control variables. First, we control for the size of the patent
family (Family size). Since filing patent applications at different patent offices is costly, companies
will only do so for their important innovations. A positive effect of Family size is therefore expected.
Second, we control for the size of the team by including the number of inventors (Team size). A posi-
tive effect of Team size is expected since larger teams tend to have a more diverse knowledge pool to
tap from previous inventions, and larger teams also tend to have larger collaboration network which
increases the likelihood of the invention being used by other inventors in the future (Singh and
Fleming 2010). Third, we include the dummy variable Public to indicate whether a patent is assigned
to universities or public research institutes. Nemet (2012) found that patent assigned to companies
are more likely to receive more citations. Fourth, the existing literature shows that patents incorpor-
ating scientific knowledge are more likely to receive more forward citations (Sorenson and Fleming
2004). We control for this influence by including the number of citations to the non-patent literature
by the focal patent (Non-Patent Literature). Finally, following Nemet (2012), we control for the
average backward citation lag. A negative effect of Citation lag is expected since the value of the
cited patent decreases with its age (Criscuolo and Verspagen 2008). For patents without any back-
ward citation, we use zero for citation lag, following Battke et al. (2016). In the robustness check, we
exclude the patents without backward citations. The results are consistent.

3.4. Empirical strategy
Since our dependent variable, the number of forward citations, is a count variable, we use the negative
binomial regression model to test our hypotheses. We included the country, technology, and time
dummies to control for unobserved heterogeneities. Since the distribution of our four main indepen-
dent variables capturing knowledge flows and the number of non-patent literature citations are highly
skewed, we include the log transformed value of them in the model. Summary statistics for variables
used in the regression are presented in Table 1. The independent variables are not highly correlated.

4. Results
4.1. Econometric results
Table 2 presents the results of the econometric analyses. Domestic_Proximate and International-
_Proximate are positively associated with the technological impacts of renewable energy inventions
in both columns, suggesting the cumulative knowledge development within a TIS (Hillman et al.
2008). The coefficient of International_Proximate is larger than the coefficient of Domestic_Proximate
in column (1), suggesting a more important role of international knowledge. Domestic_Distant and
International_Distant are negatively correlated with the technology impacts of renewable energy
technology inventions. Absorptive_Capacity is positively correlated with the technological impacts
of renewable energy inventions in both columns, indicating that countries with larger absorptive
capacity are more likely to introduce high impact renewable energy inventions. This is in line with
Table 1. Mean, standard deviation and correlation of variables.

<table>
<thead>
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<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
<th>(11)</th>
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<td>0.166</td>
<td>0.307</td>
<td>0.096</td>
<td>0.171</td>
<td>0.151</td>
<td>0.034</td>
<td>−0.046</td>
<td>0.158</td>
<td>0.034</td>
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<td>1.000</td>
<td>0.464</td>
<td>0.347</td>
<td>0.113</td>
<td>0.548</td>
<td>0.058</td>
<td>0.000</td>
<td>−0.089</td>
<td>0.252</td>
<td>0.099</td>
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<tr>
<td>3. Domestic_Distant</td>
<td>0.166</td>
<td>0.464</td>
<td>1.000</td>
<td>0.034</td>
<td>0.449</td>
<td>0.554</td>
<td>0.114</td>
<td>0.041</td>
<td>−0.067</td>
<td>0.359</td>
<td>0.128</td>
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<td>4. International_Proximate</td>
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<td>0.034</td>
<td>1.000</td>
<td>0.186</td>
<td>0.029</td>
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<td>0.018</td>
<td>−0.040</td>
<td>0.174</td>
<td>0.097</td>
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<td>5. International_Distant</td>
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<td>0.113</td>
<td>0.449</td>
<td>0.186</td>
<td>1.000</td>
<td>0.061</td>
<td>0.281</td>
<td>0.070</td>
<td>−0.041</td>
<td>0.348</td>
<td>0.140</td>
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<td>6. Absorptive capacity</td>
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<td>0.548</td>
<td>0.554</td>
<td>0.029</td>
<td>0.061</td>
<td>1.000</td>
<td>−0.066</td>
<td>0.008</td>
<td>−0.067</td>
<td>0.178</td>
<td>0.079</td>
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<td>7. Family size</td>
<td>0.151</td>
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<td>0.173</td>
<td>0.281</td>
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<td>−0.053</td>
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<td>8. Team size</td>
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<td>0.177</td>
<td>0.157</td>
<td>1.000</td>
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<td>0.140</td>
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<td>0.712</td>
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<td>0.974</td>
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<td>2.262</td>
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<td>1</td>
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<td>Max</td>
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existing literature that most high impacts renewable energy inventions are still introduced by countries with well-functioning TIS (Dechezleprêtre et al. 2011).

The interaction term \( \text{International}_\text{Proximate} \times \text{Absorptive}_\text{Capacity} \) is significantly negative, suggesting a more important role of international proximate knowledge in latecomer countries. In contrast to previous findings that latecomer countries are mostly recipients of international knowledge (Mancusi 2008), our results suggest that the knowledge development of a focal TIS in latecomer countries can generate significantly new insights for global technology development. Latecomer countries like China and India have unique social-technical systems which can help to further improve the existing technological trajectories of renewable energy technologies (Hansen and Coenen 2015).

The interaction term \( \text{Domestic}_\text{Distant} \times \text{Absorptive}_\text{Capacity} \) is significantly positive. This result first points out the importance of the geographical origin of knowledge flows from other TISs, which is understudied in previous studies focusing on the technologically distant knowledge in TIS research (Battke et al. 2016; Malhotra, Schmidt, and Huenteler 2019). Given the disruptive role of renewable energy technologies in the energy sector, bringing together technologically distant technologies within an economy will face less pressure from existing institutions (Frenken 2017;
Janssen and Frenken (2019). Furthermore, the result suggests that sufficient absorptive capacity of a country is required for identifying and utilising technological opportunities outside the focal TIS (Carlsson et al. 2002; Cohen and Levinthal 1990). Since actors may be active in multiple TISs at the same time, the knowledge diffusion between domestic actors in a TIS can facilitate the learning between different TISs to generate the positive feedback loops which are important for system functioning and growth (Hillman et al. 2008; Malhotra, Schmidt, and Huenteler 2019). The interaction

Figure 1. Interaction plots.
term International_Distant*Absorptive_Capacity is significantly negative, indicating that integrating knowledge of both geographically and technologically distance are less likely to be successful.

Figure 1 shows the interaction effects between absorptive capacity of countries with Domestic Distant knowledge and International Proximate knowledge. We plotted the predicted counts of forward citations for absorptive capacity of countries at the one standard deviation below mean value, mean value and one standard above mean value. The results show that the marginal effects of Absorptive_Capacity are substantial as the number of Domestic_Distant knowledge or International_Proximate knowledge increases. Moreover, the contribution of international proximate knowledge is much larger than domestic distant knowledge.

Of the controls, Family size and Team size are positively correlated with the technological impact of renewable energy innovations, as expected. Citation Lag is negatively correlated with the technological impact, also as expected. Non-Patent Literature is positively correlated with the technological impact, probably indicating the role of science as an especially relevant source for invention. The coefficient of Public is, however, significantly negative. This indicates that universities or public research institutes have a relatively minor role in generating high-impact inventions compared to businesses.

### Table 3. Robustness check.

<table>
<thead>
<tr>
<th>Model</th>
<th>Dependent variable</th>
<th>Time period</th>
<th>(1) Negative binomial</th>
<th>(2) Negative binomial</th>
<th>(3) Logit</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>10-year citation</td>
<td>5-year citation</td>
<td>Patent with at least one backward citation</td>
<td>Highly-cited</td>
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<tr>
<td>Domestic_Proximate</td>
<td>0.281***</td>
<td>0.309***</td>
<td>0.463***</td>
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</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.020)</td>
<td>(0.077)</td>
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<td></td>
</tr>
<tr>
<td>Domestic_Distant</td>
<td>−0.133***</td>
<td>−0.115***</td>
<td>−0.226***</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.020)</td>
<td>(0.082)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intentional_Proximate</td>
<td>0.617***</td>
<td>0.529***</td>
<td>0.826***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.013)</td>
<td>(0.062)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>International_Distant</td>
<td>−0.020</td>
<td>−0.015</td>
<td>0.021</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.012)</td>
<td>(0.058)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Domestic_Proximate*Absorptive_Capacity</td>
<td>0.061***</td>
<td>0.001</td>
<td>0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.005)</td>
<td>(0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Domestic_Distant*Absorptive_Capacity</td>
<td>0.001</td>
<td>0.018***</td>
<td>0.033*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.005)</td>
<td>(0.018)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intentional_Proximate*Absorptive_Capacity</td>
<td>−0.092***</td>
<td>−0.061***</td>
<td>−0.085***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.004)</td>
<td>(0.015)</td>
<td></td>
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<tr>
<td>International_Distant*Absorptive_Capacity</td>
<td>−0.038***</td>
<td>−0.019***</td>
<td>−0.025*</td>
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</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.004)</td>
<td>(0.015)</td>
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</tr>
<tr>
<td>Absorptive_Capacity</td>
<td>0.058**</td>
<td>0.074***</td>
<td>0.089**</td>
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<tr>
<td></td>
<td>(0.027)</td>
<td>(0.010)</td>
<td>(0.041)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Family size</td>
<td>0.033***</td>
<td>0.031***</td>
<td>0.050***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Team size</td>
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<td>0.033***</td>
<td>0.084***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.004)</td>
<td>(0.015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Public</td>
<td>−0.130***</td>
<td>−0.136***</td>
<td>−0.167*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.022)</td>
<td>(0.095)</td>
<td></td>
<td></td>
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<tr>
<td>Non-patent literature</td>
<td>0.102***</td>
<td>0.054***</td>
<td>0.087***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.008)</td>
<td>(0.027)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citation lag</td>
<td>−0.007**</td>
<td>−0.011***</td>
<td>−0.029***</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
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<td>−1.056***</td>
<td>−4.827***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.166)</td>
<td>(0.136)</td>
<td>(0.539)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Country dummy</td>
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<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time dummy</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
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<tr>
<td>Observations</td>
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<td>29,383</td>
<td>30,720</td>
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<td>Log likelihood</td>
<td>−27,696.630</td>
<td>−67,110.490</td>
<td>−4,875.862</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: *Significant at 0.1, **significant at 0.05 and ***significant at 0.01
4.2. Robustness check

Several complementary analyses were performed in order to check the robustness of our findings. Table 3 presents the results. First, we use a ten-year citation buffer window. Consequently, we limit the period to 1990–2005. Second, we exclude patents without any backward citation following Battke et al. (2016) to test the robustness of using zero for citation lag in patents without any backward citation. Third, we change the estimation strategy and employ a logit regression model to explore the correlation between different types of knowledge flows of a patent with the likelihood of being highly-cited. Following Arts and Veugelers (2015), we consider a patent as highly-cited if the number of its forward citations is larger than the mean plus two standard deviations of the number of forward citations in the cohort of the same type of renewable energy technology patents applied in the same year. The results of these robustness checks in Table 3 show that our findings considering the heterogenous impacts of different types of knowledge flows on the technological impact of renewable energy innovations are highly robust.

5. Conclusion

Both geographical and technological dimensions which are considered important in understanding the impacts of external knowledge on future knowledge development in renewable energy TISs (Andersen and Markard 2020; Bergek et al. 2015; Binz, Truffer, and Coenen 2014; Köhler et al. 2019). This paper provides a systematic empirical analysis of the multi-scalar knowledge dynamics in the global renewable energy innovation systems proposed by Binz and Truffer (2017).

Most importantly, our results show the relative importance of different external knowledge critically depends on the absorptive capacity of countries, which represents knowledge accumulation results from the knowledge diffusion between domestic actors in a TIS. Countries with larger absorptive capacity benefit more from domestic knowledge from other TISs, whereas international knowledge flows within a TIS are more important for countries with smaller absorptive capacity.

Since many countries intend to build innovation systems to better deploy renewable energy technologies at home, understanding this place-specifi city in the global renewable energy innovation systems is crucial for formulating country-specific transition pathways and facilitating future technology development. The focus of latecomer countries should be on how to facilitate the knowledge diffusion between both domestic and international actors within the renewable energy TISs since they can contribute to the global technology development by utilising international knowledge. However, for countries with well-functioning renewable energy TISs (i.e. advanced countries like United States, Germany and Japan), the focus should be shifted to bringing in knowledge, skills and experiences from domestic actors in other TISs to facilitate further knowledge development.

Our study is not without limitations. Several studies have found that the knowledge dynamics of renewable energy technologies are also affected by technology-specific characteristics (Binz and Truffer 2017; Schmidt and Huenteler 2016). It might be more difficult for latecomer countries to develop more complex renewable energy technologies by utilising international knowledge since the spatial diffusions of complex knowledge is difficult (Balland and Rigby 2017; Sorenson, Rivkin, and Fleming 2006). The increasing globalisation of supply chains of renewable energy technologies offers opportunities for latecomer countries to move from less complex components to more complex components of renewable energy technologies through learning-by-doing (Malhotra, Schmidt, and Huenteler 2019; Meckling and Hughes 2018). Future research therefore should take into account knowledge flows between different components of renewable energy TISs.

Note

1. We focus on six types of non-hydro renewable energy technology: solar photovoltaic (Y02E10/5), solar thermal (Y02E10/4), wind (Y02E10/7), Ocean (Y02E10/3), biofuel (Y02E50/1) and geothermal (Y02E10/1).
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Disclosure statement

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Note on contributors

Deyu Li is a postdoctoral research associate in energy technology innovation and policy in the Centre for Environment, Energy and Natural Resource Governance, University of Cambridge. He holds a PhD in Innovation Studies from Utrecht University. His research focuses on the understanding of the interactions between actors, technologies and policies in the global clean energy sectors.

Gaston Heimeriks is Assistant Professor in Innovation Studies at the Copernicus Institute of Sustainable Development at Utrecht University, and a senior researcher at the Centre for Science and Technology Studies (CWTS) in Leiden University. He holds a PhD in Communication Science from University of Amsterdam. His research focuses on improving our understanding of the world’s complexity arising from the co-evolutionary development of knowledge, economy and institutions.

Floor Alkemade is Professor and Chair of Economics and Governance of Technological Innovation at the School of Innovation Science at Eindhoven University of Technology. She holds a PhD in Agent Based Evolutionary Economics from Eindhoven University of Technology. Her PhD work was done at the Dutch National Centre for Mathematics and Computer Science (CWI). Her research goal is to identify the general and the location-specific mechanisms that lead to successful innovations for sustainability.

ORCID

Deyu Li http://orcid.org/0000-0002-9154-6302
Gaston Heimeriks http://orcid.org/0000-0002-0577-6938
Floor Alkemade http://orcid.org/0000-0002-2231-1913

References


