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Published in:
Journal of Regional Science

DOI:
[10.1111/jors.12340](https://doi.org/10.1111/jors.12340)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2018

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Noseleit, F. (2018). Renewable energy innovations and sustainability transition: How relevant are spatial spillovers? *Journal of Regional Science*, 58(1), 259-275. <https://doi.org/10.1111/jors.12340>

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ORIGINAL ARTICLE

Renewable energy innovations and sustainability transition: How relevant are spatial spillovers?

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Abstract

In the societal challenge to switch to renewable energy, innovation has become an ever-increasing critical determinant. However, while sustainability transition is a global challenge, diffusion and adoption of innovation tends to be uneven in space and unequal access may cause substantial heterogeneity in energy transition. This research analyzes how domestic and foreign innovation activities in the renewable energy sector influence energy transition over time. Empirical testing shows that a country's domestic innovation activity impacts renewable electricity generation capacity sooner than foreign technological innovations. I document that there are substantial barriers to substitute foreign technologies for domestic innovation efforts in the short run but also observe that foreign technologies have a stronger impact after some years. These findings have implications for cross-border coordination of governmental innovation support and complementary policy instruments that aim at increasing adoption speed across borders.

KEYWORDS

diffusion, geography, innovation, sustainability, transition

1 | INTRODUCTION

Technological advancements in the renewable energy sector are argued to play a major supporting role in the transition toward renewable energy (cf. Veugelers, 2012). Although this transition is a global challenge, we have little knowledge about the spatiality of the impact of innovations. It is therefore increasingly important for scholars and policymakers to understand how innovations influence interrelated locations at a supra-national level. Since adoption of innovation is more likely when in spatial proximity to the location of the invention, heterogeneity in technological innovations can be expected to cause transition heterogeneity. Slow flows of technology to more distant places can cause substantial time lags between invention and usage of that technology. Consequently, countries that lack domestic innovation activities may experience substantial delay in adopting technological solutions to deal with global challenges like the transition to renewable energy.

While previous work has analyzed the spatiality of knowledge creation in the renewable energy sector (Verdolini & Galeotti, 2011), little is known about how innovation activity influences the actual transition process in space. This

will be the main concern of this work. Few studies have had an explicit spatial perspective on sustainability transitions (Coenen, Benneworth, & Tuffer, 2012). This is especially surprising since “the very notion of a sustainability transition, with its concern for humankind and the planet, reflects a process of globalization or interconnectedness [...]” (Kates & Parris, 2003, p. 8064). Questioning the assumption of a “global technological opportunity set” (Carlsson, 1997; Carlsson, 2006) to which actors have equal access, Binz, Truffer, and Coenen (2014, p. 138) claim that “the broader (global) context of the system under study is often conceptualized as representing a ubiquitous ‘global technological opportunity set’, to which all actors have indiscriminate access.”

This work deviates from earlier contributions by explicitly focusing on the spatial–temporal dimension of renewable energy transition. Next to the direct effect of technological innovation on renewable energy supply, I investigate the spillover effect to assess how much innovations from outside countries’ borders benefit the challenge to increase energy generation based on renewables. This paper uses data on innovations in the renewable energy sector and renewable electricity generation capacity for 15 European countries over a 16-year period. I focus on the country as the unit of analysis since energy supply is commonly a concern of larger spatial entities. Considering a model that allows for spatial lags of the dependent variable and spatial lags of the independent variables, I present estimates for the direct and indirect impact of technological innovations on renewable energy production. This model contrasts with estimations of spatially blind models (those that only consider domestic innovations) and models that assume indiscriminate access to foreign technological innovations (considering all foreign innovations as being equally important to domestic transition). I show that technological innovation benefits sustainability transition in the home country of the innovation. This finding provides empirical evidence that—along with other rationales like the desire to build up and support a “national” industry—national efforts to support innovation in the renewable energy sector can benefit the local transition to renewable energy production. Next, substantial spillover effects can be observed, suggesting that innovations in other countries can substitute for innovations invented in the country itself. However, substituting domestic innovation efforts with foreign technologies is limited by substantial time lags. It is shown that similarities in local conditions, approximated by the similarity of the renewable energy mix, provide a good reflection of how technological innovations influence sustainability transition across space. This suggests that other forms of congruence besides pure geographic proximity matter to how technological innovations influence sustainability transition across borders.

This work is relevant in multiple respects. First, it suggests that literature studying the impact of innovations can benefit from overcoming an implicit “indiscriminate access” assumption and instead build upon a more explicit consideration of spatial–temporal influence. The empirical exercise also documents that analyzing spatial mechanisms is sometimes only rewarding when using an explicit time dimension: local and spatially lagged dynamics can be considerably different over time. The direct and indirect effects of technological innovation is an important informant for policymakers about the overall impact and effectiveness of stimulating R&D in the renewable energy sector to support energy transition. In this respect, this study helps to assess the possible impact of stimulating R&D when prospects for global agreements are fragile and pressure for unilateral policies increases (cf. Böhringer, Fischer, & Rosendahl, 2013). It also adds to our understanding of why sustainability transitions can occur slowly even when political consensus is strong (e.g., Hess, 2014) and how technological environmental innovations can effectively diffuse (Huber, 2008).

Moreover, this work yields important implications about the design of support mechanisms. Knowing about the relative importance of domestic and foreign technological innovation for energy transition helps to inform policymakers about the right policy instruments to support timely transition. Since the results indicate that cross-border effects of technological innovation are well reflected by similarities of local conditions existing policy measures may benefit from cross-country coordination of R&D support and additional measures to allow timely transfer of knowledge and/or adoption of new technologies. My findings provide also indirect evidence for a trade-off faced by policymakers concerning the large-scale deployment of new technologies across borders and nurturing and protecting domestic firms and markets (cf. Kirkegaard, Hanemann, Weischer, & Miller, 2010). Based on these findings it is argued that the design of policy instruments should explicitly consider technology diffusion mechanisms to benefit the effectiveness of supporting policies for energy transition. Close alignment of innovation and cross-border

diffusion instruments can also be considered a good strategy to influence sustainability transition beyond the borders of a country in situations when pressure for unilateral policies increases. When domestic technological innovation is difficult to substitute in the short run by new technologies from other countries, policies that either benefit the development of domestic technologies and/or policies that spur international technology diffusion may be especially beneficial.

This paper is structured as follows. First, I briefly review arguments in favor of adapting a spatial perspective when studying the role of technological innovations for energy transition. Sections 3 and 4 describe the data collection and discuss the methodology. Section 5 presents the results for the estimates of the direct and indirect effects of technological innovation on energy transition. I conclude by discussing the implications of the spatial-temporal influence of innovations in the renewable energy sector for policymaking and future research.

2 | TECHNOLOGICAL INNOVATION AND SUPPLY IN SPACE AND TIME

Shifts in the supply curve are commonly assumed to come from—among other things—changes in prices, firm dynamics (such as number of firms), and technological innovations. This work is especially concerned with the latter one. The main objective of this section is to sketch a model describing the impact of technological innovation in space and time on local renewable energy generation capacity. To better understand how innovation influences local renewable energy generation in space I adopt a proximity perspective that goes beyond geographic proximity and also considers other forms of proximity. While previous literature deepens our understanding of the role of spillovers in the knowledge creation process, this study aims to analyze how innovation activities in space influence local energy generation capacity. As such I focus on a direct indicator of sustainability transition. For example, design innovations in the wind turbine industry, like slow-moving and large rotor blades and monitoring systems that adjust angle and direction of blades, decreased the cost of producing wind energy. This shifted the supply curve downward and made wind power more competitive with conventional power sources in many countries. For such an analysis, larger geographical entities are often useful starting points to gain deeper insights. In fact, a few countries are responsible for most new technologies. For most, at least 90 percent of domestic productivity growth is due to foreign technologies (Keller, 2004). However, especially during early phases, market formation exhibits a strong localized component. Binz et al. (2014) emphasized the relevance of colocation between users and producers—quoting Kemp, Schot, and Hoogma (1998), they highlighted the relevance of “learning spaces” in the broader innovation process, which have been prominently studied in the renewable energy sector elsewhere (e.g., Garud & Karnoe, 2003). Interviews accompanying this study pointed to a similar case in which a joint venture between a provider of innovative technology and a local energy supplier were key to pronounced transition efforts. I argue that interrelations in space and the location where technological innovations occur is crucial to understand how innovation affects transition between production technologies.

Spatial diffusion is commonly understood as a process in which an event spreads from one or a few points of origin within a given area through time (Brown, 1968). Figure 1 shows expansion-type diffusion.

As mentioned above, many studies have noted the importance of geography for knowledge spillovers in the innovation process (e.g., Jaffe, 1989; Agrawal, 2002; Jaffe & Trajtenberg, 2002). Moreover, Verdolini and Galeotti (2011) documented that proximity is also relevant with respect to international knowledge spillovers in energy technologies. While this does not necessarily imply that geography equally shapes all outcomes of this knowledge production, it does suggest that similar mechanisms may hold for technology-driven interregional supply shifts as well. Keller (2004) states that “there is no indication that a global pool of knowledge yet exists,” highlighting the necessity of “domestic technology investments.” In fact, there is some evidence that this may especially hold for technological developments in the renewable energy sector. For example, hoping to increase renewable energy production substantially, the British government is heavily supporting R&D to cut costs, particularly in offshore wind. An illustrative case is the development of a floating tension leg wind turbine, combining knowledge on existing off shore wind systems and oil and gas production platform technology (FS-UNEP, 2014). This example highlights the fact that local knowledge may be more likely to influence new locally generated technologies than more distant knowledge.

FIGURE 1 Expansion-type diffusion (adapted from Brown, 1968)

Also when new technologies cross space via trade, the well-known observation that trade decreases with geographic distance implies that proximity to the origins of these technologies increases the speed of adoption. This suggests that domestic technologies are more likely to be used at home first. Recent empirical work has documented that technology adoption tends to be slower to places that are farther away from adoption leaders (Comin, Dmitriev, & Rossi-Hansberg, 2012). Comin et al. (2012) provided robust empirical evidence on the importance of space to understand the speed of technology diffusion—while the effect of space tends to be rather strong at the beginning, it decays over time and may disappear completely.

All other things equal, technological disparities in space may therefore be responsible for country differences in the speed of energy transition toward renewable energy production. Because the location of an invention is also more likely to be the location of initial innovation adoption (cf. Kemp et al., 1998), the origin of new technologies are likely to shape the process of energy transition. Consequently, countries with higher levels of technological innovations are expected to benefit sooner from these innovations. Furthermore, countries proximate to the origins of innovations are likely to experience faster transition because proximity is expected to ease technology diffusion. This does not need to be geographic proximity. In fact an increasing body of literature acknowledges different forms of proximity. For example, Agrawal, Kapur, and McHale (2008) differentiated between social and geographic proximity in the context of knowledge generation at the inventor level. From an evolutionary economic geography perspective, Boschma (2005) and Boschma and Frenken (2010) theoretically distinguished five forms of proximity in the context of innovation (geographic, cognitive, organizational, social, and institutional). Also for innovation-driven sustainability transition, there is no reason that geographic proximity may be more important than other types of proximity.

For the specific case of sustainability transition, the simultaneous rise of various alternative technologies introduces an additional complexity. In fact, the association between renewable energy innovations and transition to energy sustainability is likely to be more complex than unidirectional “flows” and relationships of one single technology. In fact, a variety of technological solutions are taking hold at different locations suitable to support sustainable transition. This implies that different technologies compete in space, resulting in more complex spatial patterns of transition. It is likely that different technological paths do not occur randomly but are, for example, influenced by local conditions that allow efficient application of these technologies. Similarities of such local conditions may influence adoption patterns in space. Again, the British case of combining knowledge of existing offshore wind systems and oil and gas production platform technology is a good illustration, given the distinctive location. Consequently, it is likely that such technologies diffuse more easily to regions with similar implementation conditions.

Next, spatial feedback effects may occur. For example, a new technology developed in the focal country and later adopted in neighboring countries to produce renewable energy, which is exported back to the focal country influences its outcome variable indirectly. Figure 2 visualized such a pattern of complex spatial relationships. In this figure a high proximity in implementation conditions is indicated by contrasting two different “local conditions,” indicated by areas

FIGURE 2 Diffusion with multiple technologies, different types of proximity, and feedback effects

A and B. For example, these conditions may reflect that in one group of regions wind turbines can be more effectively employed while in the other group of regions this would be solar technologies.

Notwithstanding, new technologies may also have a locally restricted impact after all. For example, a technological solution successful in one location may not be very feasible in other locations (hydroelectric power may be very efficiently used in Sweden but not in other countries). The consequence can be that new technologies occur locally and are only used in a specific context (such as because of diverging natural conditions, different support systems, or institutional settings). In this context, a certain similarity to the concept of stimulus diffusion (Kroeber, 1940) becomes noticeable in which a specific technology used in one location is rejected in another one (wind turbines may be rejected because of low social acceptance), but the underlying idea (such as energy transition) is accepted.¹ In any case, one would observe a positive relationship between technological innovation and renewable energy transition only locally. The implications for policy are straightforward. If innovation affects transition mainly locally, it is predominantly local actors' responsibility to find innovative solutions for sustainability transition. When substitutability of domestic and foreign innovations is high, coordination of efforts and timely transfer of new problem solutions becomes key.

The following section briefly introduces the data. After that I discuss the empirical strategy to consider the spatial relationships as outlined in Figure 2.

3 | DATA

The empirical analysis is carried out at the country level, in line with the perspective that the nation-state represents one of the dominant regime actors when it comes to energy transition (c.f. Sagar & van der Zwaan, 2006; Verbong & Geels, 2006). Meadowcroft (2009) highlights two features of sustainability transition that are likely to be best reflected at the country level, namely the notion of societal steering originating from limited individual "capacities to anticipate or to determine the future" and interactivity in the sense of a "collective discovery of preferred social development pathways" (p. 323). Finally, an analysis at the country level allows for several relevant insights, for example, about the rationales for domestic R&D support, the possible existence and extent of vertical complementarities of policy instruments, or externalities of national efforts to global sustainability transition. Using country-level data has limitations. First, country data hardly allows investigating dynamics at the micro level. Second, some of the spatial heterogeneity is lost. For example, some countries may exhibit substantial within-country variation. It is likely that spatial heterogeneity at the subnational level is more pronounced in relatively larger countries with subnational entities that have more pronounced possibilities to influence sustainability transition (e.g., less centralized countries) and countries that exhibit more variations in local conditions. I focus on a sample of 15 European countries because of a high level of institutional proximity, joint goal formulation, and low barriers due to membership in the European Union. At the same

¹ This can be observed, for example, in the current dispute over high-voltage power lines planned to carry renewable energy from northern Germany to the industrial south (cf. "Der Wink mit dem Strommast," *Frankfurter Allgemeine Zeitung*, 17.05.2015). In the Netherlands, one can observe a high acceptance of energy transition and strong local resistance against wind turbines (cf. "Daar gaat de laatste vrije horizon" *Brief van de dag*, *Volkskrant*, 3.07.2015).

time, these countries differ considerably in their innovation activities in the renewable energy sector, their progress on energy transition, and their local conditions concerning the application-specific technologies. These countries in the sample are Austria, Belgium, Germany, Denmark, Spain, Finland, France, the U.K., Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Sweden. The dependent variable is the generation capacity of renewable electricity in million kilowatts. This data comes from the OECD. Installed renewable energy capacity describes maximum capacity under optimal conditions. Energy generation and capacity measure are hardly comparable to other production output measures and investments in renewable energy reflect a mix of market, policy, and societal influences. Hence, common production functions are difficult to apply since energy production—especially renewable energy—is embedded in the context of a variety of political, economic and social aspects. Consequently, the data collected for this study aims to represent such diverse factors. Data on patents in the renewable energy sector—the main variable of interest—comes from the OECD Patent Statistics. I consider all international applications filed under the Patent Cooperation Treaty (PCT) in technology domains related to renewable energy production. These domains include wind energy, solar thermal energy, solar photovoltaic energy, solar thermal-photovoltaic hybrids, geothermal energy, marine energy, and hydroenergy. The patents are distributed across countries based on the country of residence of the inventor.

Additional data to control for prices, policies, market size and economic and innovation-adoption conditions was collected, since these characteristics may influence sustainability transition as well. To account for differences in the absorptive capacity, I use cumulative patenting activity in “electrical machinery, apparatus, energy,” “optics,” “basic materials chemistry,” “materials, metallurgy,” “mechanical elements,” and “civil engineering.” This variable aims to account for differences in the ability to adopt new technologies. The data comes from the World Intellectual Property Organization (WIPO). To proxy a potential demand-pull effect, I collected data on energy prices using Eurostat data on consumer energy prices.² Data on environmentally related taxes can proxy environmental policy instruments (tax revenues in million U.S.\$). This data comes from the OECD Environment Statistics (2014). In addition, GDP per capita is used to control for changing economic conditions of a country. To control for country size differences and changes in the size of the market, I include population. Data on GDP and population comes from Eurostat. In addition, I introduce a set of dummy variables that reflect the adoption of specific policy instruments—these variables take on a value of unity if a country makes use of specific policy in a specific year and zero otherwise. The policy instruments are “feed-in-tariffs,” “quota/TGC,” “tender,” and “tax incentives.”

The panel data set covers the time period from 1995 to 2012 and is mainly restricted by information on energy prices and policies, for which I do not have data before 1995. Because the dependent variable enters the empirical model with one year forward lag, I have 16-year observations for each country, resulting in an overall sample of 240 country-year observations. Patent data is available for much longer periods of time, which allows considering rather long time lags between innovative activities and energy transition. Summary statistics are documented in Tables A1 and A11.

4 | METHOD

I start with a simple, spatially blind, fixed effects model predicting domestic energy transition, and estimate

$$\ln Y_{i,t+1} = \alpha_i + X_{it} \beta + t\lambda + \varepsilon_{it}, \quad (1)$$

where renewable energy production $\ln Y$ proxies energy transition in country i at time $t + 1$, α is a country-specific fixed effect, X represents a vector of time variant explanatory variables, and λ indicates a time trend. Since the dependent variable is log-transformed, a time trend accounts for exponential growth. All explanatory variables reflect domestic conditions, such as domestic innovations. The spatially blind approach does not explicitly consider space—every country has only access to technologies developed domestically. Next, I extend Equation (1) to include not only domestic patents but also those of all the other countries in the sample. This implies departing from a *spatially blind*

² For Austria the energy price for the year 1995 was imputed and for Sweden the prices for 1995 and 1996 were imputed because this data was not available.

explanation of how technological innovations affect sustainability transition and allow for an *indiscriminate-access* explanation, which assumes a (foreign) technology pool accessible without restrictions. In this model, I do not differentiate between foreign technologies that are in some way more proximate or distant. Still, this model discriminates between domestic and foreign innovations.

Next to the spatially blind model and its indiscriminate-access counterpart, I test for the possibility that foreign technologies impact energy transition dependent on the proximity to the origin of the technologies by means of a spatial Durbin model. A spatial Durbin model allows considering spatial lags of the dependent variable and spatial lags of the explanatory variables, which otherwise would be unobserved determinants of renewable energy production (Elhorst, 2013).³ Spatial processes concerning the impact of innovation across different countries can be different than those initiated by feedback effects. Central to this analysis is the spatial lag of the explanatory variables because it allows revealing patterns of substitution or complementarity via the spatial lag coefficient (Blonigen, Davies, Waddell, & Naughton, 2007). Seeking to answer the question to which degree innovation activities in the renewable energy sector within the country and in other countries affect the transition toward renewable energy, the following equation will be estimated:

$$\ln Y_{i,t+1} = \rho \sum_{j=1}^N V_{ij} Y_{jt} + \alpha_i + X_{it}\beta + \sum_{j=1}^N W_{ij} X_{jt}\theta + t\lambda + \mu_{it}, \quad (2)$$

where a country's renewable energy production is considered to depend also on the weighted average of renewable energy production in neighboring countries based on the matrix product VY and the explanatory variables from other regions based on matrix product WX . When considering spatial lags of the dependent variable, one cannot interpret coefficients as marginal effects, because they include feedback effects and spatial spillovers (LeSage & Pace, 2009). Instead the model allows deriving three types of marginal effects—direct, indirect, and total. The direct effect represents the effect of changes in the independent variable in the focal country on its own renewable energy production, plus the feedback effect. This feedback effect is the effect that the focal country-independent variables (technological innovations, in this case) have on renewable energy production in neighboring countries, which, in turn, may affect the transition process in the focal country itself. For example, a technology developed in one country may be adopted in a neighboring country and used to produce renewable energy, which is then exported back to the first country. The indirect effect—often referred to as a spatial spillover effect—measures the impact of innovations (and other independent variables) in other countries on renewable energy production in the focal country. The total effect is simply the sum of the direct and the indirect effects. It can be interpreted, for example, as the average total impact of a unit increase in the explanatory variable of one particular region on renewable energy production across all countries. For example, the coefficient for renewable energy patents would indicate the average impact over all regions' renewable energy production for a unit change in the number of patents in one country.

A considerable time lag between filing a patent and some outcome variable Y is likely—especially if innovation activity is linked to some kind of physical output. In this case, one can expect lag-heterogeneity as well, that is, in the presence of delayed spatial adoption of innovations, the lag is expected to be longer for the indirect effect compared to the direct effect. To reflect this, I apply different time lags for the innovation variable, ranging from $t - 1$ to $t - 10$, and include these lagged variables one after the other to avoid problems due to multicollinearity since the patent count variable is highly correlated with lagged patent count. I expect to find longer time lags to be especially relevant for the indirect effect. As such, the spatial mechanism at hand is expected to be closely intertwined with a temporal dimension.

A central weakness of spatial models is that identification is often a central issue. Generally, for the data used in this work, time lags and controls for confounding factors are crucial for identification. I forward-lagged the dependent variable to reduce potential endogeneity issues. Country-specific fixed effects are included in all estimations to deal with unobserved heterogeneity across countries. Here, country-specific fixed but unobserved preferences and abilities related to finding and utilizing technological solutions and managing sustainability transition timely are considered

³ Further information on estimating Spatial Durbin Models using panel data is provided by Belotti, Hughes, and Mortari (2013) for STATA and Elhorst (2014) for Matlab.

to be of importance. These fixed effects are supposed to control for time-invariant country characteristics, including innate historical factors, the time-invariant component of expectations of the development of renewables in a country, persistent institutional differences, and time-invariant differences in domestic conditions to employ-specific technologies. However, time lags and fixed effects may not be sufficient to deal with endogeneity. For example, it might be that innovations are a result of expected future growth of renewable energies domestically or abroad. In my selection of control variables, I aimed to cover country characteristics that correlate with such expectations (e.g., policies related to renewables and GDP growth), but the nature of the empirical approach does not allow me to make final causal claims. In addition, as noted by Gibbons and Overman (2012), inherent identification issues remain as the spatial weight matrices are unknown and accordingly some remarks on the assumed processes regarding the underlying spatial relationships can be helpful.

4.1 | Choice of spatial weight matrices

I expect feedback loops and technology adoption processes to be structurally different—therefore requiring two different spatial weight matrices. The spatial weight matrix V in Equation (2) reflects how renewable energy production in other countries influences a country's own renewable production capacity. In the specific context of renewable energy generation capacity, I argue that border-sharing outperforms other distance-based weight matrices, including geographic distance and technological congruence. The economic rationale for this is that the electricity grid is most relevant when it comes to exporting energy across borders and the existing links of the grid are often well reflected by shared borders. Accordingly, I adjust the binary border-sharing matrix and corrected for some grid-linkages not sufficiently reflected by (land) borders (such as Italy to Greece). Next, I also weight borders with border length to proxy the relative importance of such links. In the context of renewable energy generation this V -matrix turns out to be well suited to reflect dependencies on the spatial autoregressive term.

The spatial weight matrix W in Equation (2) aims to capture the influence of new renewable energy technologies on renewable energy transition in space. In informal interviews with renewable energy experts, it was suggested that it is not necessarily geographic weights that matter most. In fact, it was highlighted that similarities of local conditions and (policy) preferences regarding the type of technologies are more decisive than, for example, geographic distance. However, I tested different weights because the nature of diffusion of new technologies in space is *a priori* unclear. For example, in the presence of hierarchical expansion diffusion, new technologies may leapfrog from one “big” country to another “big” one due to its market size or implementation of generous support programs, bypassing other, less relevant countries. If shared borders are more relevant, for example, because of higher similarities in natural conditions or the nature of market internationalization, contagious expansion diffusion may be more likely and new technologies may affect direct neighbors first. The best fit of the model was obtained with a similarity measure based on the relative importance of photovoltaic, hydro, wind, and maritime energy that aims to reflect differences in domestic conditions and usage of different technologies. The spatially lagged impact of innovation activities may imply that the technological congruence and similarity of domestic conditions is most relevant. To calculate the similarity measure, I first generated a dyadic dataset of all country combinations and then calculated the similarity of the renewable energy mix between two countries. To do so, averaged primary production data on renewables from Eurostat is used. I calculate similarity using the angular separation similarity measure, the cosine of the angle between the energy-mix vectors of two countries.

5 | RESULTS

In Table I, I report the results from the spatial Durbin models; in Table II, I report a summary of estimation results of a spatially blind model and a model allowing for indiscriminate access to foreign technologies. I report different time lags for renewable energy innovation activities. This is not only because innovation measured as patenting activity is expected to impact transition to renewable energy production with some time lag, but especially because I expect that foreign innovations impact transition with a time lag. This means that technological innovation in the renewable

TABLE I Spatial Durbin model with fixed effects (marginal effects)

Dependent Variable: Renewable Electricity Installed Capacity (ln)		Model 1	Model 2	Model 3	Model 4
Direct	Renewable energy patents, $t - 1$	0.00185***			
		(0.000268)			
	Renewable energy patents, $t - 4$		0.00330***		
			(0.000433)		
	Renewable energy patents, $t - 7$			0.00955***	
				(0.00101)	
	Renewable energy patents, $t - 10$				0.0139***
					(0.00133)
	Absorptive capacity (ln), $t - 1$	0.445***	0.458***	0.461***	0.470***
		(0.172)	(0.170)	(0.163)	(0.161)
	Energy prices (ln), $t - 1$	0.107	0.0969	0.0629	0.0720
		(0.0865)	(0.0833)	(0.0802)	(0.0801)
	Tax revenues (ln), $t - 1$	0.268***	0.309***	0.208**	0.233**
		(0.101)	(0.0994)	(0.0965)	(0.0933)
	GDP per capita (ln), $t - 1$	2.164***	1.847**	1.989***	2.562***
		(0.727)	(0.731)	(0.703)	(0.697)
	Population (ln), $t - 1$	-0.274	0.0699	0.123	0.00190
		(0.303)	(0.348)	(0.295)	(0.309)
	Feed-in-tariff	-0.0792	-0.0621	-0.0505	-0.0232
		(0.0686)	(0.0680)	(0.0644)	(0.0637)
	Quota/TGC	0.161*	0.187**	0.182**	0.235***
		(0.0854)	(0.0847)	(0.0806)	(0.0797)
	Tender	-0.0289	-0.0369	-0.0269	-0.00934
		(0.0709)	(0.0695)	(0.0665)	(0.0654)
	Tax incentives	0.327**	0.361***	0.323**	0.409***
		(0.141)	(0.139)	(0.132)	(0.129)
	Year	0.0153	-0.00172	-0.0245	-0.00893
		(0.0175)	(0.0195)	(0.0180)	(0.0178)
Indirect	Renewable energy patents, $t - 1$	0.00113			
		(0.00130)			
	Renewable energy patents, $t - 4$		0.00253		
			(0.00180)		
	Renewable energy patents, $t - 7$			0.0219***	
				(0.00662)	
	Renewable energy patents, $t - 10$				0.0167**
					(0.00813)
	Absorptive capacity (ln), $t - 1$	0.116*	0.115*	0.110*	0.114*
		(0.0651)	(0.0634)	(0.0598)	(0.0600)
	Energy prices (ln), $t - 1$	0.0270	0.0236	0.0146	0.0171
		(0.0248)	(0.0229)	(0.0207)	(0.0211)

(Continued)

TABLE I (Continued)

Dependent Variable: Renewable Electricity Installed Capacity (ln)				
	Model 1	Model 2	Model 3	Model 4
Tax revenues (ln), $t - 1$	0.0670** (0.0329)	0.0746** (0.0335)	0.0476* (0.0273)	0.0544** (0.0278)
GDP per capita (ln), $t - 1$	0.534** (0.222)	0.438** (0.203)	0.452** (0.197)	0.595*** (0.220)
Population (ln), $t - 1$	-0.0656 (0.0789)	0.0198 (0.0883)	0.0317 (0.0740)	0.00302 (0.0760)
Feed-in-tariff	-0.0194 (0.0186)	-0.0145 (0.0176)	-0.0112 (0.0159)	-0.00496 (0.0158)
Quota/TGC	0.0432 (0.0317)	0.0481 (0.0320)	0.0446 (0.0294)	0.0577* (0.0323)
Tender	-0.00615 (0.0186)	-0.00788 (0.0176)	-0.00517 (0.0162)	-0.00117 (0.0164)
Tax incentives	0.0831* (0.0484)	0.0885* (0.0481)	0.0755* (0.0429)	0.0972** (0.0468)
Year	0.00331 (0.00439)	-0.000913 (0.00511)	-0.00616 (0.00543)	-0.00255 (0.00477)
Total				
Renewable energy patents, $t - 1$	0.00299** (0.00137)			
Renewable energy patents, $t - 4$		0.00582*** (0.00187)		
Renewable energy patents, $t - 7$			0.0314*** (0.00698)	
Renewable energy patents, $t - 10$				0.0306*** (0.00850)
Absorptive capacity (ln), $t - 1$	0.561** (0.230)	0.573** (0.226)	0.571*** (0.215)	0.584*** (0.213)
Energy prices (ln), $t - 1$	0.134 (0.109)	0.121 (0.105)	0.0776 (0.0997)	0.0891 (0.1000)
Tax revenues (ln), $t - 1$	0.335*** (0.128)	0.384*** (0.126)	0.255** (0.120)	0.288** (0.116)
GDP per capita (ln), $t - 1$	2.698*** (0.904)	2.286** (0.900)	2.441*** (0.861)	3.157*** (0.857)
Population (ln), $t - 1$	-0.339 (0.379)	0.0897 (0.435)	0.155 (0.367)	0.00492 (0.384)
Feed-in-tariff	-0.0986 (0.0859)	-0.0766 (0.0846)	-0.0618 (0.0795)	-0.0281 (0.0790)
Quota/TGC	0.204* (0.115)	0.235** (0.114)	0.226** (0.107)	0.292*** (0.109)
Tender	-0.0351 (0.0889)	-0.0448 (0.0864)	-0.0320 (0.0822)	-0.0105 (0.0812)

(Continued)

TABLE I (Continued)

Dependent Variable: Renewable Electricity Installed Capacity (ln)				
	Model 1	Model 2	Model 3	Model 4
Tax incentives	0.410** (0.182)	0.450** (0.179)	0.398** (0.167)	0.507*** (0.165)
Year	0.0186 (0.0217)	−0.00263 (0.0244)	−0.0307 (0.0230)	−0.0115 (0.0224)
Spatial rho	0.235*** (0.0511)	0.228*** (0.0507)	0.218*** (0.0494)	0.222*** (0.0487)
R ² (within)	0.78	0.79	0.81	0.81

Note: Standard errors in parentheses. Significant at *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. The number of observations is 240 (15 countries, 16 years). The weight matrix for spatially lagged innovation activities is based on the similarity of the renewable energy mix of a country-pair. For the spatial-autoregressive term, a border-length contiguity weight is used.

energy sector is expected to increase renewable energy generation more quickly in the country of invention, while spatial spillover effects are expected to occur only after some years. I estimated the effects of technological innovation in the renewable energy sector for time lags up to ten years. For brevity, Tables I and II report only estimation results for a time lag of one, four, seven, and ten years.

The upper part of Table I reports the direct effect of the independent variables on renewable energy generation capacity. Regarding the central variable of interest, this table reports the impact of a country's patent activities in renewables on its own domestic renewable energy production plus the feedback effect. The second part, the indirect effects, reports the spatial spillover effects. For the central variable of interest, this spillover measures the impact of innovations in other countries on the focal countries' renewable energy production. The last part of this table reports the total effect, which is the sum of the direct and indirect effects. The estimated direct, indirect, and total effect of patenting on renewable electricity generation for all time lags that I considered is displayed in Figure 3.

In the first part of Table II (columns 1–4), I document an excerpt of the spatially blind models, where I regress domestic innovation activities and some additional control variables, on renewable energy generation capacity. Next, in columns 5–8 of Table II, I include the innovation activities of the other countries as an additional independent variable—thus allowing for unweighted, international spillover effects (indiscriminate access). Consequently, the models reported in columns 5–8 treat innovations from all other countries as equally important as an input to sustainability transition.

I find that absorptive capacity, energy tax revenues, and GDP per capita have positive direct effects on the control variables reported in Table I. Concerning the policy instruments, I find some evidence for a positive effect of "quota/TGC" and "tax incentive" policies. "Feed-in-tariffs," arguably among the most successful policy instruments, turn out to be insignificant. This could be because variations over time are rather limited for this policy instrument. These results are similar for the control variables in the spatially blind and the indiscriminate-access models, which are not reported for brevity. Regarding the indirect effect of the spatial Durbin model, I observe that tax revenues and GDP per capita are significant.

The central variable of interest, innovation activities in the renewable energy sector, is positively related to sustainability transition (see upper part of Table I). There is a positive and significant association with renewable energy generation capacity for all time lags that were analyzed. However, while I find a statistically significant association already in early years this effect is rather weak in the beginning but becomes more pronounced after some time. This direct effect in the spatial Durbin model is rather similar to the impact of domestic patents in the spatially blind model (Table II, columns 1–4)—similarly, I also observe a positive and significant impact of domestic patents when controlling for innovation activities in the other countries (Table II, columns 5–8). Based on the results reported in Table I, I find that in $t - 1$, an additional patent in the renewable energy sector would be associated with additional

TABLE II Spatially blind versus indiscriminate access regressions

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Renewable energy patents, $t - 1$	0.00178*** (0.000531)	-	-	-	0.00189** (0.006498)	-	-	-
Renewable energy patents, $t - 4$	-	0.00316*** (0.000988)	-	-	-	0.00371*** (0.000927)	-	-
Renewable energy patents, $t - 7$	-	-	0.00768** (0.00233)	-	-	-	0.0105*** (0.00130)	-
Renewable energy patents, $t - 10$	-	-	-	0.0113*** (0.00201)	-	-	-	0.0159*** (0.00185)
Renewable energy patents other countries, $t - 1$	-	-	-	-	-0.000192 (0.000151)	-	-	-
Renewable energy patents other countries, $t - 4$	-	-	-	-	-	-0.000229 (0.000279)	-	-
Renewable energy patents other countries, $t - 7$	-	-	-	-	-	-	0.00282** (0.00074)	-
Renewable energy patents other countries, $t - 10$	-	-	-	-	-	-	-	0.00467*** (0.00106)
R ²	0.74	0.75	0.76	0.77	0.74	0.75	0.77	0.78

Note: Standard errors in parentheses. Significant at *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. The number of observations is 240 (15 countries, 16 years). All estimations include absorptive capacity, energy prices, tax revenues, population, GDP per capita, and a time trend as additional covariates. Additionally, a set of dummy variables controls for presence of policy instruments.

FIGURE 3 Direct and indirect effects of innovations in the renewable energy sector on renewable electricity generation over time

growth of renewable energy generation capacity of less than 0.2 percent and in $t - 5$, the impact would be around 0.5 percent (for comparison purposes: Denmark had 3 patents in 1996 and 68 patents in 2006).

Interestingly, in the spatial Durbin model, I do not find indication for an indirect effect in the early years after the innovation occurs. Similarly, in the indiscriminate-access models, there is no significant association between foreign technological innovations and renewable energy generation capacity for time lags up to $t - 6$ (Table II, columns 5–7).

However, from $t - 6$ onward, I find strong evidence for spatial spillover effects of innovation activities. In the spatial Durbin model, I find evidence for a pronounced multiplier effect of innovation activities on sustainability transition—statistically and economically significant—suggesting an important temporal-spatial lag. The direct and indirect impact of innovation activity is not significantly different in $t - 6$. From $t - 7$ to $t - 9$, the indirect effect exceeds the direct effect, and in $t - 10$, direct and indirect effect are again not significantly different from each other. Since econometric routines for cross-model testing in the Spatial Durbin fixed effects model are nonexistent, I am hesitant to interpret the differences in the direct and indirect effects of innovation activities across models. The indiscriminate access models also show that foreign patents are significantly associated with domestic generation capacity for larger time lags, but in contrast to the spatial Durbin models, this relationship is not very pronounced. Attributing different weights to innovations from different countries thus leads to a more pronounced relationship between foreign innovation activities and sustainability transition. Still, my findings suggest that a considerable amount of time is needed: the cumulative relevance of the impact of foreign innovations in neighboring countries on domestic renewable electricity production exceeds the domestic innovation effect only after eight years. This indicates a rather strong increase of domestic renewable electricity supply induced by foreign innovations—although only after a long delay.

I observe that the spatial Durbin models outperform their alternatives, especially when considering time lags larger than $t - 5$. This suggests that the spatiality of the proposed processes depends on the time that innovations need to influence renewable energy transition in other countries. More specifically, the autoregressive part is significant throughout all model specifications, but the spatially lagged term matters mostly as a temporal-spatial lag.

My results support the idea that evaluating the impact of innovations in the renewable energy sector on energy transition requires accounting for sufficiently large temporal lags as well as interdependencies between countries. This documents that considering a spatial dimension when studying sustainability transition is a valuable addition to the literature (Coenen et al., 2012). The observed positive relation between domestic innovations and energy transition is only a part of the story—probably even not the most important one. However, due to the well-known identification issues in spatial regression models, further research is required. In addition, the temporal dynamics of the relative importance of domestic and foreign innovations is crucial. My results suggest that it is rather the interplay of the local innovation test bed, with perhaps a high relevance of learning spaces and colocation between users and producers (e.g., Binz et al., 2014; Kemp et al., 1998), and the large-scale adoption of technologies (cf. Keller, 2004) that are jointly needed to manage transition successfully. While domestic innovations influence energy transition faster than foreign

innovations the relation between foreign innovations and energy transition tends to be more pronounced after some time. This indicates that slow cross-border adoption of new technologies can be a substantial obstacle to timely large-scale use.

I have carried out a variety of additional analyses. First, I used a variety of different weights for both the autoregressive term and the spatially lagged innovation activity. For example, I used population weighted distance measures and spatial contiguity weights. Concerning the autoregressive term, I observe that border length and a simple spatial contiguity weight provide a rather good approximation to model spatial dependencies. Using border length results in somewhat better results. For the spatially lagged innovation activity, a weight matrix based on the similarity of the employed renewable energy technologies outperforms spatial contiguity and distance based weights, that is, nongeographic weights provide a better fit than commonly used geographic weights. I also tried to estimate models that include several time-lagged variables simultaneously, which resulted only in model misspecification since the time-lagged patents are highly correlated, which causes severe multicollinearity. I also used renewable energy generation and consumption as alternative dependent variables and find results that imply rather similar insights to those documented here. In addition, I carried out two “placebo” tests to check if the results may be the outcome of a spurious correlation. First, I used all patents that are not directly related to the renewable energy sector as an indicator for innovation activities and did not find a robust relationship of time and spatially lagged innovation activities with sustainability transition. Alternatively, I restricted the sample to innovations related to Solar-PV energy and isolated a component in PV-energy generation caused by variations in yearly hours of sunshine, which I used as a dependent variable. As expected, no robust relationship was found. Finally, I tested models excluding policy related variables and find similar results as reported above.

6 | DISCUSSION AND CONCLUSIONS

It has often been argued that innovation is a central factor in dealing with many of the challenges in the journey toward sustainable economies. This paper provides an empirical assessment of the relevance of technological innovation for this process, while paying special attention to potential difficulties caused by country borders as spatial barriers that can hamper energy transition.

This tension causes a dilemma for policymakers when assessing whether they should support costly domestic R&D efforts or rely on foreign innovations. The question to which degree foreign innovations can substitute domestic efforts is an empirical one and has not been investigated before. I find that domestic innovations have a timelier and initially more pronounced impact compared to innovations originating from other countries. In this respect, I provide some evidence that the location of the invention is also more likely the location of initial innovation adoption (cf. Kemp et al., 1998) for the specific case of renewable energy. However, after some time, innovation activity in others countries is more relevant to energy transition than domestic innovation activities.

The findings also suggest that substitution of new technologies is especially likely among countries with a similar composition of renewable energy mix, implying that technological congruence and domestic conditions matter. While there have been many advancements in our understanding of the geographic concentration of innovations or knowledge diffusion in space, we have limited insights into the consequences of the spatial-temporal adoption process of new technologies. For example, little is known about the similarities and differences in spatial patterns of knowledge generation and use. In this respect the benefits of “learning spaces” during the innovation process highlighted by some scholars (e.g., Binz et al., 2014), can later restrict (global) diffusion. In a more general sense, the role of geography for adoption of innovation is much less researched as compared to the underlying knowledge production itself (cf. Comin et al., 2012). The findings of this work suggest that literature, studying the impact of innovations, may strongly benefit from overcoming an implicit “indiscriminate access” assumption and instead build upon a more explicit consideration of spatial-temporal influence. In this respect, the empirical exercise in this paper documents that analyzing spatial mechanisms is sometimes only productive with an explicit time dimension, such as when local and spatially lagged dynamics are considerably different.

Some implications for policy can be derived. In a nutshell, my findings suggest that a global challenge can be more effectively tackled by joint innovation efforts, exchange of problem solutions, and increasing the speed of adoption across country borders. For example, when agreeing on joint goals for energy transition across a group of countries, like in the European Union (or more specifically, the 20–20–20 targets, European Commission, 2008), the coordination of R&D activities, subsequent knowledge transfer, and spatial diffusion and adoption of new technologies can be key to achieve mutual goals. I provide preliminary evidence suggesting that joint solutions are working best in a subset of countries—transition clubs—which share, for example, similar conditions to employ new technologies. Coordination of R&D activities across countries may benefit from the implementation of complementary policies instruments aiming at subsequent diffusion. The findings of this study also have implications for the optimal level of cross-country coordination. If domestic conditions and technological congruence matter for spatial–temporal transition processes, coordination comprising too many diverse countries may be less effective. Jointly, this may imply, for example, that the European Union could employ more effective policies when allowing R&D coordination to take place within a subset of its member states, while national R&D efforts of a single member state may benefit from joint coordination with other countries.

This paper also points to a technology-driven challenge in countries for which it may be difficult to build up an innovative domestic industry. A lack of domestic innovations can substantially slow down transition and the difficulties in adopting new foreign technologies may cause further delay. These aspects point toward a challenge to manage energy transition in these countries, a challenge that has not received much attention: Which policy instruments are most effective to increase the speed of adoption of new foreign technologies?⁴ It is likely that an adequate answer to this question entails different (geographical) processes for different regions in the world (cf. Crescenzi, Rodriguez-Pose, & Storper, 2007).

While this paper aims to highlight that economic geographers and regional scientists can provide important insights to support managing sustainability transition, such works are still in their infancy. This is likewise visible in the limitations of this contribution. While it is not uncommon to start analyzing a phenomenon at the country level, naturally, one would like to study smaller entities as well. Currently, datasets related to sustainability transition with a fine-grained spatial dimension are largely missing. Moreover, even country-level data is often limited to certain regions like Europe or North America. The dataset used for this paper is limited to European Union member states that agree on joint goals for energy transition, share similarities in their institutions, and are relatively geographically and culturally proximate. While this excludes a variety of alternative explanations that can potentially influence transition, it also restricts the generalizability of the research findings to other contexts. From a global perspective, policymakers may face a trade-off between deployment of (foreign) technologies and building and protecting of domestic renewable technology markets (Kirkegaard et al., 2010). Hence, the indirect influence of renewable energy innovation may be less pronounced in regions where trade barriers are more common. Of special interest are also developing countries with lacking own innovation capabilities. In this respect, it might be very interesting to study use of foreign technologies that support sustainability transition in other parts of the world. Moreover, this paper studies innovation in the renewable energy sector in general, neglecting possible heterogeneity in technologies. In this respect, future research may benefit from a more fine-grained analysis of the impact of innovation on sustainability transition. Hence, future efforts aiming to develop new datasets may allow deeper insights into the intersection of quantitative geography and sustainability transition.

ACKNOWLEDGEMENTS

I am grateful to *JRS* editor Mark D. Partridge for excellent guidance and valuable comments. I would also like to express my gratitude to three anonymous reviewers for their careful reading of my manuscript and for providing constructive and insightful comments on this work.

⁴ While there is limited knowledge of complementary policy instruments to stimulate adoption in the context of renewable energy, Fabrizio and Hawn (2013) present empirical evidence of the interrelationship between policy and complementary inputs supporting solar power adoption.

REFERENCES

- Agrawal, A. (2002). Innovation, growth theory and the role of knowledge spillovers. *Innovation Analysis Bulletin*, 4(3), 3–6.
- Agrawal, A., Kapur, D., & McHale, J. (2008). How do spatial and social proximity influence knowledge flows? Evidence from patent data. *Journal of Urban Economics*, 64, 258–269.
- Belotti, F., Hughes, G., & Mortari, A. P. (2013). *XSMLE: Stata module for spatial panel data models estimation, statistical software components S457610*. Boston: Boston College Department of Economics.
- Binz, Ch., Truffer, B., & Coenen, L. (2014). Why space matters in technological innovation systems—Mapping global knowledge dynamics of membrane bioreactor technology. *Research Policy*, 43, 138–155.
- Blonigen, B. A., Davies, R. B., Waddell, G. R., & Naughton, H. T. (2007). FDI in space: Spatial autoregressive relationships in foreign direct investment. *European Economic Review*, 51(5), 1303–1325.
- Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, 39, 61–74.
- Boschma, R., & Frenken, K. (2010). The spatial evolution of innovation networks: A proximity perspective. In R. Boschma & R. Martin (Eds.), *The handbook of evolutionary economic geography*. Cheltenham: Edward Elgar.
- Brown, L. (1968). *Diffusion dynamics*. Lund, Sweden: C.W.K. Gleerup.
- Böhringer, C., Fischer, C., & Rosendahl, K. E. (2013). Cost-effective climate policy design: Size matters. *Journal of Economic and Environmental Management*, 67(3), 318–339.
- Carlsson, B. (1997). *Technological systems and industrial dynamics*. Boston: Kluwer Academic.
- Carlsson, B. (2006). Internationalization of innovation systems: A survey of the literature. *Research Policy*, 35, 56–67.
- Crescenzi, R., Rodriguez-Pose, A., & Storper, M. (2007). The territorial dynamics of innovation: A Europe–United States comparative analysis. *Journal of Economic Geography*, 7(6), 673–709.
- Coenen, L., Benneworth, P., & Truffer, B. (2012). Toward a spatial perspective on sustainability transitions. *Research Policy*, 41, 968–979.
- Comin, D. A., Dmitriev, M., & Rossi-Hansberg, E. (2012). *The spatial diffusion of technology*. NBER Working paper No. 18534.
- Elhorst, P. (2013). Spatial panel models. In M. M. Fischer, P. Nijkamp (Eds.), *Handbook of regional science*, Chapter 82. Berlin: Springer.
- Elhorst, P. (2014). *Spatial econometrics. From cross-sectional data to spatial panels*. Berlin: Springer.
- Fabrizio, K. R., & Hawn, O. (2013). Enabling diffusion: How complementary inputs moderate the response to environmental policy. *Research Policy*, 42(5), 1099–1111.
- FS-UNEP Collaborating Centre for Climate & Sustainable Energy Finance. (2014). *Global Trends in Renewable Energy Investment 2014*. FS-UNEP Global Trends Reports.
- Garud, R., & Karnoe, P. (2003). Bricolage versus breakthrough: Distributed and embedded agency in technology entrepreneurship. *Research Policy*, 32 (2), 277–300.
- Gibbons, S., & Overman, H. G. (2012). Mostly pointless spatial econometrics. *Journal of Regional Science*, 52, 172–191.
- Hess, D. J. (2014). Sustainability transitions: A political coalition perspective. *Research Policy*, 43(2), 278–283.
- Huber, J. (2008). Pioneer countries and the global diffusion of environmental innovations: Theses from the viewpoint of ecological modernisation theory. *Global Environmental Change*, 18(3), 360–367.
- Jaffe, A. B. (1989). Real effects of academic research. *American Economic Review*, 79(5), 957–970.
- Jaffe, A. B., & Trajtenberg, M. (2002). *Patents, citations, and innovations: A window on the knowledge economy*. Cambridge: MIT Press.
- Kates, R. W., & Parris, T. M. (2003). Long-term trends and a sustainability transition. *Proceedings of the National Academy of Sciences of the United States of America*, 100(14), 8062–8067.
- Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42(3), 752–782.
- Kemp, R., Schot, J., & Hoogma, R. (1998). Regime shifts to sustainability through processes of niche formation: The approach of strategic niche management. *Technology Analysis & Strategic Management*, 10 (2), 175–195.
- Kirkegaard, J., Hanemann, T., Weischer, L., & Miller, M. (2010). *Toward a sunny future? Global integration in the solar PV industry*. Working paper Series10-6, World Resources Institute and Peterson Institute for International Economics.
- Kroeber, A. L. (1940). Stimulus diffusion. *American Anthropologist New Series*, 42 (1), 1–20.
- LeSage, J. P., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Boca Raton: CRC Press Taylor & Francis Group.
- Meadowcroft, J. (2009). What about politics? Sustainable development, transition management, and long term energy transitions. *Policy Sciences*, 42, 323–340.

OECD Environment Statistics. (2014). *Environmental policy instruments*. DOI :10.1787/data-00696-en

European Commission. (2008). *Memo on the renewable energy and climate change package*, Memo/08/33. Retrieved from http://europa.eu/rapid/press-release_MEMO-08-33_en.htm?locale=en

Sagar, A. D., & van der Zwaan, B. (2006). Technological innovation in the energy sector: R&D, deployment, and learning-by-doing. *Energy Policy*, 34(17), 2601–2608.

Veugelers, R. (2012). Which policy instruments to induce clean innovating? *Research Policy*, 41(10), 1770–1778.

Verbong, G., & Geels, F., 2006. The ongoing energy transition: Lessons from a socio-technical, multi-level analysis of the Dutch electricity system (1960–2004). *Energy Policy*, 35(2), 1025–1037.

Verdolini, E., & Galeotti, M. (2011). At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. *Journal of Environmental Economics and Management*, 61(2), 119–134.

How to cite this article: Noseleit F. Renewable energy innovations and sustainability transition: How relevant are spatial spillovers? *J Regional Sci.* 2018;58:259–275. doi:10.1111/jors.12340.

APPENDIX

TABLE AI Summary statistics

	Mean	Std. Dev.	Min	Max
Renewable energy generation capacity (ln)	1.445	1.616	−3.079	4.191
Renewable energy patents	36.987	74.469	0	576.657
Absorptive capacity (ln)	9.425	1.697	5.862	12.888
Energy prices (ln)	−2.249	0.289	−2.875	−0.399
Tax revenues (ln)	8.845	1.508	6.239	11.251
Population (ln)	2.571	1.335	−0.878	4.413
GDP per capita (ln)	10.313	0.314	9.548	11.395
Feed-in-tariff (1 = yes)	0.642	0.481	0	1
Quota/TGC (1 = yes)	0.192	0.394	0	1
Tender (1 = yes)	0.113	0.317	0	1
Tax incentives (1 = yes)	0.163	0.37	0	1

TABLE AII Correlation table

	1	2	3	4	5	6	7	8	9	10
1 Renewable energy generation capacity (ln)	1									
2 Renewable energy patents	0.40	1								
3 Absorptive capacity (ln)	0.49	0.53	1							
4 Energy prices (ln)	0.06	0.25	0.22	1						
5 Tax revenues (ln)	0.50	0.41	0.58	0.27	1					
6 Population (ln)	0.75	0.41	0.62	0.11	0.87	1				
7 GDP per capita (ln)	−0.33	0.19	0.18	0.35	−0.23	−0.45	1			
8 Feed-in-tariff (1 = yes)	0.08	0.15	−0.18	0.13	0.05	0.01	0.01	1		
9 Quota/TGC (1 = yes)	0.11	0.03	0.25	0.21	0.20	0.24	0.10	−0.50	1	
10 Tender (1 = yes)	−0.12	−0.13	−0.02	−0.11	0.11	0.09	−0.18	−0.17	−0.17	1
11 Tax incentives (1 = yes)	−0.01	−0.12	0.14	−0.21	−0.13	−0.12	−0.01	−0.45	−0.10	−0.16