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A spatial perspective on green technology adoption in China: insights from patent licensing data

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ABSTRACT

In the transition to more sustainable regional economies, the widespread adoption of green technologies is crucial. However, little is known about the geography of green technology adoption and the relationship between regional demand and supply of green technologies. In this paper, we shed light on the (regional) factors explaining whether innovation adopters use green technologies that have been developed locally or green technologies that have been developed in other places. We analyze a unique data set of 8825 licensing agreements for Chinese patents in green technologies, which we use as an indicator to measure innovation diffusion. Our results suggest that the regional context plays a key role in predicting whether innovation adopters use local or non-local green technologies. We show, among other things, that the use of locally developed green technologies is more likely in regions characterized by green technology specializations and high innovation capacity than in less innovative regions.

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Innovation diffusion; green technology; China; environmental innovation; patent licensing

1. Introduction

To combat pressing environmental crises such as pollution, environmental degradation and climate change, economies must transition to cleaner and more sustainable modes of production and consumption. A major ingredient of such a sustainability transition is the use of clean and environmentally friendly technologies, usually referred to as *green technologies*. Green technologies are technological innovations in environment-related domains, often also labelled environmental innovations or eco-innovations (Haščič and Migotto 2015; Kemp et al. 2019). We will use these terms interchangeably throughout this paper. Due to the grand societal challenges resulting from environmental crises, both academia and practitioners are increasingly concerned with the development and diffusion of green technologies. Over the past two decades, considerable knowledge has been gathered regarding the conditions under which green technologies emerge and the conditions under which they diffuse. Traditionally, the scholarly literature distinguishes

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between three groups of determinants that influence the development and use of green technologies: technology push factors, demand pull factors, and regulatory factors (Barbieri et al. 2016; Hojnik and Ruzzier 2016; Horbach 2008, 2019; Rennings 2000). In recent years, researchers have also paid increased attention to regional factors, both in terms of the regional context influencing the conditions under which green technologies emerge and the regional context influencing the adoption and diffusion of green technologies (Antonioli, Borghesi, and Mazzanti 2016; Barbieri et al. 2022; Horbach 2014; Losacker 2022; Losacker, Horbach, and Liefner 2023; Montresor and Quatraro 2020; Santoalha and Boschma 2021). This growing literature on regional determinants of environmental innovation, however, has not yet provided meaningful insights into the underlying diffusion patterns of green technologies. In fact, we argue that we (as scholars) can make quite informed claims about how the regional context contributes to the adoption of green technologies, but we know very little about where those green technologies actually come from.

Against this background, this paper seeks to determine which factors explain why some green technologies are adopted in the region where they have been developed and others are not. In other words, this paper examines the factors that influence whether green technology adopters use technologies that have been developed locally or technologies that have been developed in other places. From an empirical perspective, we therefore follow a simple binary classification of the geography of green technology adoption as proposed by Tödtling, Trippl, and Frangenheim (2021). In the first scenario, an innovation adopter in a given region uses a green technology that has been developed or produced within the same region, and in the second scenario, an adopter uses a green technology that has been developed or produced elsewhere.

For the empirical part of this paper, we make use of patent licensing data as an indicator for innovation adoption. We use the novel Chinese online platform IncoPat which matches patent and licensing data, providing us with a data set that contains geographic information for 8825 green technology license agreements in China regarding where the technology originates from (licensor region) and where it is adopted (licensee region). We use two-level mixed effects models to investigate what factors influence the probability that patents will be licensed within the region in which the patent was developed compared to in-licensed patents that were developed elsewhere. We consider technological factors on the patent-licensing level, such as quality and scope of an innovation, and determinants on the regional level (Chinese prefectures), such as green regional specializations and regional innovation capabilities.

The remainder of this paper is organized as follows. In Section 2, we summarize the current state of research and justify the main research question explored in this paper. In Section 3, we provide information on our data sources and explain the empirical approach used to answer the research question. We describe and discuss results in Section 4, while Section 5 provides a summary of the paper along with implications for both future research and policy.

2. Background literature

2.1. Environmental innovations: peculiarities and global trends

The widespread diffusion of green technologies is crucial to address mounting environmental crises. It is therefore highly relevant to study environmental innovations and green technologies, in particular from a social science and innovation studies point of view. In fact, environmental innovations come with some special characteristics compared to regular innovations. Obviously, environmental innovations have a positive impact on environmental quality when compared to existing alternatives, which is also reflected in established definitions. For instance, Kemp et al. (2019, 35) define an environmental innovation as a '[…] new or improved product or practice of a unit that generates lower environmental impacts, compared to the unit's previous products or practices, and that has been made available to potential users or brought into use by the unit'. Moreover, environmental innovations feature a distinct peculiarity from an innovation economics perspective. That is to say, they are exposed to two types of externalities. In the developmental phase, environmental innovations, as with all other types of innovations, suffer from the problem that R&D leads to costs for the developers, while knowledge development will also benefit others. In the diffusion phase, and this is peculiar to environmental innovations, adopters contribute to reducing negative impacts on the environment, while society as a whole benefits. Consequently, there are little economic incentives for both inventors and adopters to invest in environmental innovations, giving rise to market failures. This phenomenon is commonly referred to as the double-externality problem, making environmental innovations dependent on regulatory support (Jaffe, Newell, and Stavins 2005; Nordhaus 2011; Rennings 2000). However, stringent regulations may not only induce environmental innovation, but may even enhance the competitiveness of firms and regional economies (Porter and van der Linde 1995). Therefore, green technologies are particularly susceptible to regulation and market intervention.

In addition, empirical research has uncovered a number of stylized facts on green technologies and environmental innovations. Most importantly, green technologies differ from non-green technologies in terms of complexity and impact. On the one hand, they rely on more diverse knowledge and combine more technological components. They therefore require a higher degree of R&D cooperation and external knowledge in the developmental phase (De Marchi 2012; Ghisetti, Marzucchi, and Montresor 2015) On the other hand, they have a stronger impact on future innovations (Barbieri, Marzucchi, and Rizzo 2020). Taken together, these characteristics make green technologies particularly interesting because, although they are inherently complex in their development and application, they can eventually create win-win situations by contributing to the solution of environmental problems while at the same time stimulating technological progress and economic development. Many countries and regions are therefore attempting to develop green industries, not only for environmental reasons, but also for economic reasons (Grillitsch and Hansen 2019; Jänicke 2012; Quitzow 2013).

At the global level, it is evident that emerging economies are increasingly successful in the development and production of green technologies and that existing patterns in the global technology landscape are shifting. Many emerging economies, particularly China, benefit from so-called green windows of opportunity in that regard (Konda 2022; Lema, Fu, and Rabellotti 2021; Pegels and Altenburg 2020). In that sense, China is no longer dependent on foreign knowledge for the development of green technologies and is no longer taking the usual approach of technological catch-up. Instead, China is increasingly able to reshape the global innovation landscape in many environmentally relevant technology fields and is actively configuring global socio-technical regimes (Gosens, Binz, and Lema 2020; Losacker and Liefner 2020; Yap et al. 2022; Zhou, Miao, and Urban 2021). In light of these trends, there is growing interest in analyzing the international diffusion of green technologies. A key insight from this literature is that the diffusion of green technologies occurs mainly between high-income countries, rather than from high-income countries to developing countries. The diffusion of green technologies to less developed countries, on the other hand, is increasingly driven by emerging economies, in particular by China, because technologies developed in emerging economies tend to be tailored to the demand conditions of poorer countries. However, less developed countries often depend on the transfer of green technologies because they lack indigenous innovation capabilities (Conway et al. 2015; Herman and Xiang 2019; Popp 2006; Probst et al. 2021).

2.2. A regional perspective on green technology diffusion

From a geographical perspective, the literature mentioned above has left a number of questions unanswered. First and foremost, it remains unclear how diffusion patterns of green technologies translate to the subnational level. In order to shed light on this issue, we draw on an emerging body of literature that deals with the geography of environmental innovations and sustainability transitions (Hansen and Coenen 2015; Hansmeier 2021; Losacker et al. 2021). This literature emphasizes that markets for green technologies often emerge by means of local user-producer interactions, indicating that the early phase of technology diffusion might take place in the region where the technology is developed (Dewald and Truffer 2012; Rohe 2020). The use of locally developed green technologies is in fact straightforward, as some directly address local environmental issues, such as pollution or climate change adaptation. However, some green technologies respond to global market needs, for example technologies that contribute to solving global environmental problems, i.e. climate change mitigation technologies. For these kinds of green technologies, markets do not emerge in the region where the technology is being developed, but rather elsewhere (Binz and Truffer 2017). The difference between local and non-local technology use can thus be attributed in particular to characteristics of the technology itself or to the technological innovation system in which the technology is embedded.

In addition to these technology-specific factors, the regional context in which a technology is to be adopted is also important. For example, the level of economic development and the innovation capabilities of a region are likely to play an important role in determining whether an innovation adopter in that region will use technologies developed locally or whether the adopter will be dependent on technologies developed in other regions. Typically, urban regions are responsible for technology development, while peripheral and structurally weak regions are dependent on technology transfer. This pattern is particularly evident for China, as technological capabilities are highly concentrated in a small number of regions (Kroll and Neuhäusler 2020; Losacker 2022; Seo and Sonn 2019). Beyond this, there are other factors at the regional level that are directly related to the use of (green) technologies. For example, it is well established that the diffusion of environmental innovations depends on the extent to which a region develops its own green industries (Hansen and Coenen 2015). Regions with a strong focus on green technologies and green industries are more likely to have a higher level of legitimacy and acceptance for green technologies than regions with a less green industry mix (Rohe and Chlebna 2021). It is therefore likely that regions specializing in green technologies will also make use of green technologies that have been developed locally. Furthermore, demonstration effects are very important for the diffusion of green technologies. In regions where green technologies are already widely used or where many green technologies are developed, local demonstration and learning effects can emerge, leading to an increased adoption of green technologies by other users in the region (Antonioli, Borghesi, and Mazzanti 2016; Graziano and Gillingham 2015; Horbach and Rammer 2018). In summary, it appears that both technology-specific and region-specific factors need to be considered to explain the diffusion patterns of green technologies. However, it is unclear to what extent these factors are actually significant. In fact, most studies consider either technological factors or regional factors when analyzing green technology diffusion, neglecting the multilevel structure of this relationship. Given these research gaps, this paper aims to answer the following research question:

> RQ: Which (regional) factors determine whether green technology adopters use technologies that have been developed locally or technologies that have been developed in other places?

3. Data and methods

For the empirical part of this paper, we make use of patent licensing data as an indicator for innovation diffusion and adoption. Patent licenses are contracts in which one party (the licensee) acquires the rights to use a patented technology held by another party (the licensor). Licensing agreements are therefore useful indicators to study the diffusion process of innovations, providing information on where a technology was developed (licensor) and where it is used (licensee). Moreover, licensed patents are proxies for actual innovations rather than for inventions that are not introduced to the market, overcoming one of the usual caveats when using patent data to measure innovation (Archibugi 1992; Nelson 2009). Unfortunately, licensing information is not easily available in most countries and it is thus seldom used in empirical research (Buenstorf and Schacht 2013; Kani and Motohashi 2012). However, this restriction does not hold for the Chinese case, as the Chinese National Intellectual Property Administration (CNIPA) registers and discloses information on patent licensing agreements.

Against this background, we retrieved matched patent-licensing data for Chinese patents from the novel IncoPat database (www.incopat.com), which processes unstructured licensing data from CNIPA. We collected information on all license agreements and their respective patent documents with license commencement dates between 2008 and 2019. We filtered green technology patents using the ENV-TECH classification, which links IPC (International Patent Classification) and CPC (Cooperative Patent Classification) classes to eight green technology domains (Haščič and Migotto 2015). These include environmental management technologies, water-related adaptation technologies, technologies relating to capture, storage or disposal of greenhouse gas emissions, and climate change mitigation technologies in different sectors (i.e. energy, transportation, buildings, waste, production and processing of goods). In order to study the spatial diffusion of green technologies, we geocoded both licensor and licensee locations. For licensor locations, geocoding is straightforward, as licensor (i.e. patent applicant) addresses are mentioned in the patent documents. We were thus able to process the address information in a geographical database (www.geonames.org). For licensee locations, however, geocoding was more challenging, given that the licensing agreements do not contain any geographic information. We therefore made use of automated web search queries for licensee names via the application programming interfaces (API) of Google Maps and Baidu Maps. This approach enabled us to retrieve geographic information for about 90% of all licensees in our data set. Our final data set lists data on 8825 licensing agreements for green technology patents, including locations for licensors and licensees at the prefectural level. We are therefore able to match additional data on the regional level to our data set. Further information on this unique data set is provided by Losacker (2022) and Losacker, Horbach, and Liefner (2023). In summary, the data set enables us to track the diffusion process of an innovation over time and space. In other words, we know where an innovation is adopted (licensee location) and we know where that innovation was developed in the first place (licensor location). In that regard, we can distinguish between two basic scenarios, following a simple binary classification of the geography of green technology adoption used by Tödtling, Trippl, and Frangenheim (2021). An innovation adopter can choose either to use a locally developed technology (intraregional licensing) or to use a technology that was developed in another region (interregional licensing). This simple analytical approach is shown in Figure 1.[1]

For the data set employed in this paper, Figure 2 visualizes the extent to which the share of intraregional licensing differs between regions (see also Losacker 2020). In more detail, the graph indicates for each region how many technologies that are adopted in the region were also developed locally (green bar, left side) compared to the number of adoptions in the region where the technology was developed elsewhere (grey bar, right side). It is evident that the share of intraregional licensing differs considerably between regions. In some regions, adopters predominantly make use of locally developed technologies (upper end), while in other regions, adopters seem to rely on non-local technologies (lower end). For example, most innovation adopters in Chongqing use green technologies that have also been developed in Chongqing (88.02%), while in Suzhou the share of intraregional licensing is considerably smaller (26.91%). For further insights on the spatial distribution of green patent licensing agreements in China, we provide several maps in Figure A1 in the Appendix.

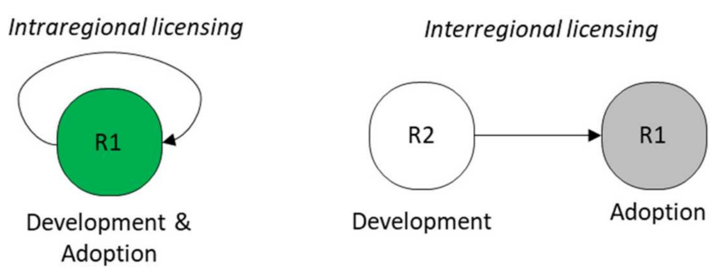

Figure 1. Analytical framework to distinguish between intraregional licensing and interregional licensing.

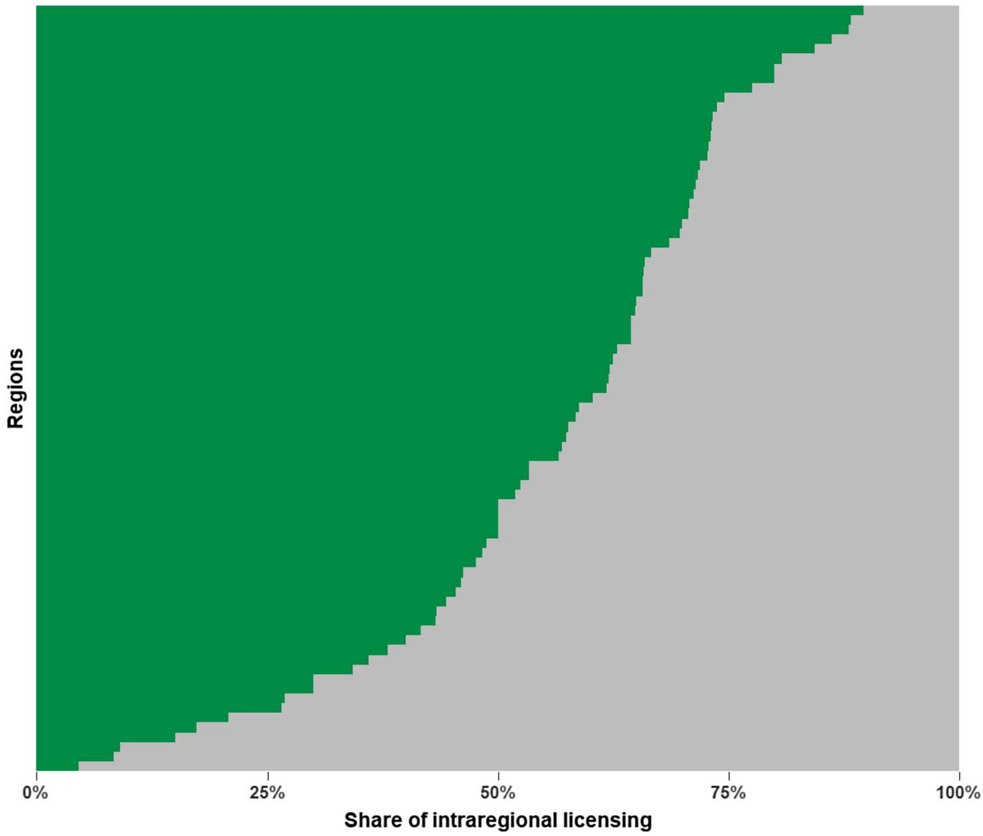

Figure 2. Share of intraregional licensing by region, 2008–2019.

Based on these observations, our econometric approach aims to explore the (regional) determinants of why some green technologies are adopted in the region where they have been developed and others are not. As outlined above, our data set includes variables on two different levels. It firstly includes variables on the patent-licensing level, which are unique to each licensing observation, and secondly includes variables on the regional level, with multiple licensing observations found in each region. Therefore, the data is structured in a hierarchical format, with two levels at which patent-licensing observations are nested within regions. In more detail, our data set consists of $j = 1, \ldots, 202$ prefecture-level regions, with regions j consisting of $i = 1, \ldots, n_j$ licensing observations.

For our econometric estimation strategy, we need to consider this hierarchical structure, as licensing observations might be correlated within a region, violating the assumption of independence. In order to overcome this issue, we estimate two-level mixed effects probit models, which read as follows:

$$intrapref_{ij} = \beta_0 + \beta_1 reg_j + \beta_2 lic_{ij} + \mu_j + \varepsilon_{ij} \quad (1)$$

The model estimates the probability of the binary response variable $intrapref_{ij}$ being 1 as a function of several predictors. That is, the model includes a vector of regional variables reg_j with fixed slopes β_1 and a vector of variables on the patent-licensing level lic_{ij}

with fixed slopes β_2. β_0 denotes the intercept, μ_j denotes random effects on the regional level and ε_{ij} is the error term.

The binary response variable *intrapref* distinguishes between *intra*regional licensing agreements, where licensor and licensee are located in the same prefecture, and *inter*regional licensing agreements, where licensor and licensee are located in different regions (1 if intraregional, 0 otherwise). On the patent-licensing level, we add several independent variables that are likely to affect the diffusion process. That is to say, we use the number of 4-digit IPC classes listed on a patent (*ipc*) to measure the technological scope of an innovation, and we use the number of average forward citations per year (*fwd_cit*) as an indicator for innovation quality, which is standard in the pertinent literature. We include a categorical variable indicating different types of licensors, where we distinguish between firms (*firm*, reference group), individuals (*indiv*), and universities and research institutes (*uni*). We control for exclusive rights in licensing agreements (*excl*; 1 if exclusive, 0 otherwise) and we add dummies for each ENV-TECH domain to capture technology-specific heterogeneity. In addition, we control for the year of licensing in order to isolate unobservable effects of innovation diffusion patterns over time.

In the next step, we construct a further set of variables on the level of prefectural regions. These variables capture the regional context in which the technology adopter (i.e. the licensee) is embedded. Given that the values for many variables on the regional level vary over time, we split the data set into three overlapping periods (period one: 2008–2012; period two: 2010–2015; period three: 2013–2019) and calculate the regional variables for each period. We include a dummy variable *eco_reg* that indicates whether the Chinese Ministry of Environmental Protection lists a prefecture as a ‘key environmental protection model’ in the observed period (1 if yes, 0 otherwise). The variable aims to capture the environmental regulation stringency of regions as well as governmental support for environmental innovation. Listed regions need to comply with several pollutant control tasks, they show better environmental performances than non-listed regions and they serve as testbeds for green technologies (Brehm and Svensson 2020). Moreover, we assume a general effect of the regional innovation capacity for green technologies on adoption patterns. We thus include a variable (*reg_green_tech*) that quantifies the number of licensed patents in green technologies which applicants located in a region have filed during the observed period. The variable is expressed in relative values to the regional population. One of our main variables of interest is the technological specialization of regions, for which we calculate the relative patent activity (*rpa*) in green technologies. For each period, the *rpa* is based on the number of licensed patents p in technology t (green vs. non-green) with applicants located in region r. The *rpa* indicates whether a region develops more or less green technologies compared to what would be expected given the level of national green technology development. Values range from −1 to 1, with positive values indicating regional specialization in green technologies.

$$rpa_{rt} = \tanh\left[\ln\left(\frac{p_{rt}/\sum_t p_{rt}}{\sum_r p_{rt}/\sum_{rt} p_{rt}}\right)\right] \tag{2}$$

We use the regional population density (*pop_dens*), which we derived from the Chinese census (2010), to control for agglomeration economies. We control for the geographical size of a region (*size*), as the share of intraregional adoptions is of course likely to depend on how large a prefecture is. For instance, the fact that the share of intraregional licensing in Chongqing is very high can be explained to a large extent by its geographical size. We also include a variable that captures the number of universities and colleges per region (*edu*). This variable provides insights into the educational resources available in each region, allowing for an examination of its potential impact on licensing patterns. The variable is based on the national list of universities and colleges published by the Chinese Ministry of Education. Finally, we use the regional GDP per capita to control for the level of economic development (*gdp_pc*), and we account for the regional industry mix by including a variable that captures the importance of the manufacturing sector as a share of regional GDP (*manuf*). This variable also reflects the regional exposure to national environmental regulations to some extent, as regions with a high share of manufacturing industries are more affected by national and sectoral environmental regulations than regions with a low concentration of manufacturing industries (Castellani et al. 2022). Note that the two GDP-related variables are only available for one year (2007). However, we assume that the interregional variance of both factors is relatively stable over time. We provide descriptive statistics as well as short descriptions for all variables in Table 1.

4. Results and discussion

4.1. Technology-specific factors

For the econometric estimations, we mean-centred all variables (grand mean-centreing), which is a standard procedure when estimating mixed effects models. We estimate a separate set of models for utility model patents and for invention patents, as they have quite distinct features. That is to say, utility model patents have a shorter term (10 years) and they often involve less radical technologies with shorter life cycles. Technologies protected under utility model patents therefore have different diffusion patterns when compared to technologies protected under invention patents (Losacker, Horbach, and Liefner 2023). We also removed some observations (i.e. outliers, regions with low patent activity) for the econometric analyses (see number of observations and number of regions in Table 2).

Table 2 presents results (marginal effects) of six different regression models. Models 1, 2 and 3 include invention patents, while models 4, 5 and 6 include utility models, each model covering one period. In the first step, we employ the intraclass correlation coefficient (ICC) to gain insights into the extent to which the dependent variable is contingent on region-specific variation. The ICC shows moderate values across our data sets, suggesting that a considerable part of the variance in the dependent variable is attributable to differences between regions. In more detail, we find that for invention patents, about 22.6% (23.1%; 32.5%) of the variance in adoption patterns during the first (second; third) period can be attributed to region-specific factors. For utility model patents, regional differences are even more important, corresponding to 44.5% (37.3%; 43.1%) of the variance of the dependent variable. Likelihood-ratio tests support the fact that there is sufficient variability between regions to favour mixed-effects probit models over ordinary probit models.

Table 1. Variable descriptions and descriptive statistics.

Variable	Description	Mean	SD	Min	Max
Dependent variable					
intrapref	Intraregional licensing with licensor and licensee being located in the same prefecture (1 if yes)	0.64		0	1
Patent-licensing level					
ipc	Number of IPC classes	2.53	1.56	1	14
fwd_cit	Average number of forward citations per year	0.32	0.51	0	12.80
indiv	Applicant is an individual (1 if yes, ref. firm)	0.53		0	1
uni	Applicant is a university (1 if yes, ref. firm)	0.17		0	1
excl	Exclusive license agreement (1 if yes)	0.96		0	1
Regional level					
eco_reg	Prefecture is listed as key environmental protection model city during the observed period (1 if yes)	0.25		0	1
reg_green_tech	Number of licensed patents in green technologies which applicants located in a region have filed during the observed period, per 10,000 inhabitants (regional innovation capacity for green technologies)	3.69	6.09	0	41.03
rpa	Relative patent activity in green technologies for observed period (green specialization)	−0.01	0.62	−1	0.98
pop_dens	Population per km^2	566.53	594.09	18.42	5,404.02
size	Area in km^2	13,448.27	11,231.57	1,035.94	82,439.06
edu	Number of colleges and universities	8.87	15.18	0	92
manuf	Share of manufacturing sector of regional GDP	0.44	0.11	0.19	0.83
gdp_pc	Regional GDP per capita in CNY	21,944.14	13,273.10	12,292.12	81,796.29

Descriptive statistics are based on data for period one, including both invention patents and utility models ($n = 5099$). Statistics for regional variables are based on 202 regions for period one. All statistics are based on the raw data before rescaling and mean-centreing.

Table 2. Regression results, two-level mixed effects probit models, dependent variable intrapref (1/0).

	Invention patents						Utility models					
	Period one (1)		Period two (2)		Period three (3)		Period one (4)		Period two (5)		Period three (6)	
Patent-licensing level												
ipc	−0.003	(−0.465)	−0.008	(−1.735)	−0.001	(−0.033)	−0.007	(−1.367)	−0.003	(−0.743)	−0.002	(−0.206)
fwd_cit	−0.018	(−1.360)	−0.033***	(−3.006)	−0.048***	(−2.796)	0.003	(0.122)	−0.027	(−1.293)	−0.050	(−0.864)
indiv	0.125***	(3.532)	0.201***	(6.708)	0.174***	(4.188)	0.196***	(8.608)	0.181***	(8.924)	0.191***	(5.489)
uni	−0.219***	(−6.734)	−0.136***	(−5.036)	−0.036	(−1.245)	0.140***	(3.159)	0.152***	(3.987)	0.329***	(1.779)
excl	0.265***	(5.398)	0.133***	(3.777)	0.076**	(2.467)	0.079*	(1.654)	0.188***	(5.149)	0.250***	(4.940)
Regional level												
eco_reg	−0.009	(−0.284)	0.034	(0.971)	−0.005	(−0.109)	−0.022	(−0.449)	0.034	(0.928)	0.076	(0.982)
reg_green_tech	0.168	(0.781)	0.584**	(2.267)	0.789**	(2.050)	0.756**	(2.401)	0.839***	(3.177)	1.265***	(2.093)
rpa	0.159***	(4.757)	0.150***	(4.266)	0.190***	(3.897)	0.238***	(5.133)	0.143***	(4.177)	0.226***	(3.372)
pop_dens	0.032	(1.584)	0.038*	(1.673)	0.047	(1.524)	−0.009	(−0.308)	−0.034	(−1.276)	−0.005	(−0.101)
size	0.298**	(2.253)	0.202	(1.512)	0.687***	(3.114)	0.146	(0.813)	−0.025	(−0.186)	0.137	(0.401)
edu	0.391***	(5.082)	0.436***	(5.106)	0.416***	(3.335)	0.302***	(2.798)	0.215**	(2.476)	0.329*	(1.779)
manuf	0.365*	(1.882)	0.552***	(2.724)	0.498*	(1.665)	1.280***	(4.450)	0.533***	(2.728)	0.584	(1.384)
gdp_pc	0.118	(0.727)	−0.188	(−1.124)	−0.045	(−0.206)	−0.124	(−0.541)	−0.185	(−1.005)	−0.216	(−0.549)
Model info												
Green domain dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Obs.	1,819		2,193		1,299		3,263		3,711		1,582	
Regions	171		185		155		174		184		144	
ICC	0.226 (0.128; 0.287)		0.231 (0.148; 0.295)		0.325 (0.196; 0.378)		0.445 (0.357; 0.514)		0.373 (0.270; 0.439)		0.431 (0.312; 0.518)	
σ^2_μ	0.960		0.986		1.583		2.640		1.961		2.488	
Log Lik.	−1,007.912***		−1,267.136***		−748.893***		−1,672.881***		−2,031.069***		−877.423***	
AIC	2,065.823***		2,586.271***		1,549.785***		3,395.761***		4,114.137***		1,806.846***	

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. The table shows marginal effects and the corresponding *z*-values in parentheses. Variables were rescaled and centred (grand-mean centreing) before modelling. The marginal effects for the continuous independent variables were calculated at their means. Concerning dummy variables, the values report changes in probability for discrete changes of the dummy variables from 0 to 1. Intercept and regional random effects included but not reported. σ^2_μ denotes the variance of the random intercept at the regional level. For the ICC, 95% confidence intervals based on bootstrapped samples are reported in parentheses. In all models, variance inflation factors are below three.

With regard to the regression models, the results for variables at the patent-licensing level tell a quite similar story for utility models and for inventions. For example, the number of IPC classes listed on a patent (*ipc*) does not appear to affect the likelihood of a patent being licensed in the region where it was developed. In other words, a broad scope of application is not important for where an innovation will be adopted. The quality of an innovation, which is measured by the number of annual citations of a patent (*fwd_cit*), plays a limited role in the spatial diffusion process of green technologies. Only models 2 and 3, which include invention patents for the later periods, reveal a significant negative effect. This means that invention patents with a higher quality are more likely to be used in other regions than in the region where the invention was developed. However, the number of forward citations may not be the best available indicator for measuring the quality of a licensed patent, as the licensing agreement itself can be considered as a filter for high quality inventions. As our database unfortunately does not report information on licensing fees or on renewal rates, we tested an alternative indicator of patent quality, namely the number of licenses per patent. Due to the fact that this indicator is only meaningful for non-exclusive licensing agreements, we use this variable as a robustness test rather than for the main results presented in Table 2. In short, we find that the number of license agreements for a patent (both for invention patents and for utility models) has a negative and significant effect on the probability that the patent will be licensed locally. This finding holds for all model specifications reported in Table 2 and does not change the effects of the other variables considerably. To some extent, this finding supports the claim that high-quality patents will be licensed in regions other than the region where the patent was developed. It thus supports our findings for invention patents when using forward citations as a quality indicator. In addition, the type of innovator is a crucial factor determining whether an innovation is used locally or elsewhere. Patents filed by individuals (*indiv*) are more likely to be licensed in the region where the invention was developed, when compared with patents filed by firms. This result is robust across all models. Patent applications by individuals are a quite common phenomenon in China, mainly representing small privately owned firms or start-ups (Sun et al. 2021). These small firms might find it more difficult to reach non-local markets and thus commercialize their technologies within their home region. These technologies might also be niche innovations, not fitting into the existing socio-technical regime at the national level. Related studies point to the fact that patents filed by individuals will also diffuse more quickly, supporting our argument on the local adoption of technologies developed by small firms (Losacker, Horbach, and Liefner 2022). In contrast, our analysis yields mixed results for invention patents compared to utility model patents filed by universities or research institutes (*uni*). We find that green invention patents developed by universities are more likely to be adopted in other regions (models 1 and 2) when compared to invention patents developed by firms, while we find the opposite for utility model patents (models 4–6). This finding can be attributed to the different types of technologies that utility models and invention patents protect. Utility model patents often include technologies with a shorter life cycle, where demand might be very localized and of short duration, for example as reflected in many university-industry collaborations. Invention patents filed by universities, on the other hand, i.e. inventions with a higher quality and a longer life cycle, are more likely to be demanded by specialized firms in other regions. However, the effect for invention patents has become less relevant in the recent past, as model 3 indicates. Finally, our findings show that technologies acquired through an exclusive licensing agreement (*excl*) are more likely to be sourced locally. This is mainly due to the fact that geographic proximity and trust between licensor and licensee are necessary conditions for many (exclusive) license agreements to be concluded (Bidault and Fischer 1994; Mowery and Ziedonis 2015; Shen, Coreynen, and Huang 2022). Exclusive licenses can also result from locally commissioned R&D projects, which is another argument as to why exclusive licenses are more likely to be a local phenomenon.

4.2. Regional factors

So far, we have discussed factors on the patent-licensing level that relate to the local or non-local adoption of green technologies, including technology-specific characteristics. In order to answer the research question of this paper, however, the variables at the regional level are of major interest. In contrast to our expectations, the fact that a region is listed as a key environmental protection model does not seem to affect the use of locally developed green technologies in our analysis (*eco_reg*). It thus seems to be the case that environmental regulations do not play a role for the question of where an adopted green technology comes from. Of course, it is a general consensus in the literature that regulation will drive the adoption of green technologies (Barbieri et al. 2016; Hojnik and Ruzzier 2016). However, this does not imply that adopters will choose to make use of green technologies that have been developed locally rather than technologies that have been developed elsewhere. We thus conclude that while regulations are important for the adoption of green technologies, they might not matter for the creation of local markets where technology development and technology use take place in the same region.

Other than that, our expectations are met with regard to two important factors. Both *rpa* and *reg_green_tech* reveal positive and significant effects across all model specifications (except for model 1). This means that both specialization in green technologies and high regional innovation capacity correlate with an increased use of locally developed technologies. This finding is very much in line with the pertinent literature on the geography of innovation and established concepts such as regional innovation systems and regional clusters (Asheim, Grillitsch, and Trippl 2016). These concepts highlight the importance of regional technological specializations, local user-producer interactions and knowledge spillovers for the successful market entry of innovations. Once a region can provide such conditions, it is likely that the early adoption of a new technology will also take place in the region where the technology was developed (Dewald and Truffer 2012). Given that patent licensing explicitly captures the early adoption of an innovation, our results correspond well to the existing literature. The findings can also be translated into the fact that in innovative and specialized regions, the demand for green technologies can be met by the local industry. These regions have the potential to become lead markets, eventually driving the national and global diffusion of green technologies (Losacker and Liefner 2020). In contrast, regions that are not specialized in green technologies and are generally less innovative are more likely to rely on technology transfer from other regions. When comparing the size of the marginal effects, we find that both the regional innovation capacity and the regional specialization in green technologies play a more important role for the intraregional licensing of utility model patents than for the intraregional licensing of invention patents. This result is quite plausible, as regions with a strong green industry also provide markets for non-radical green technologies with a short life cycle. This type of technology is usually protected with a utility model patent and not with a regular invention patent. Invention patents, on the other hand, are more likely to be transferred to other regions.

In addition to the effects of specialization and regional innovation capacity, agglomeration advantages, which occur primarily in urban regions with high population densities (*pop_dens*), are found to not affect the adoption patterns of green technologies (only in model 2). The control variable *size*, measuring the geographic area of a region, shows a positive and significant effect for invention patents. The adoption of local green technologies is thus, as expected, dependent on distance. However, this effect does not seem to be important for utility model patents. One explanation for this result might be that regional specialization and green innovation capacity are more important for utility models. For utility models, it is rather a matter of the region actually maintaining strong green industries so that the technology is licensed within the region, while the size of the region is independent of these factors. In contrast, we find positive and significant effects for *edu*, meaning that better educational infrastructure as indicated by the number of universities and colleges in a region increases the probability that innovation adopters make use of locally developed technologies. This result holds for all model specifications. We also tried to control for transport infrastructure, given that it is likely to affect local licensing patterns. We thus calculated regional motorway and railway densities using OpenStreetMap data. However, due to a significant correlation (>0.9) with population density, indicating multicollinearity, we excluded these variables from the final analysis. Furthermore, we find some evidence that the regional industry mix, as given by the share of the manufacturing sector of regional GDP (*manuf*), has a positive impact on the adoption of locally developed green technologies (except for model 6). Regions that are characterized by high shares of polluting industries (i.e. manufacturing) are thus more likely to make use of locally invented green technologies. Finally, we find that the level of economic development (*gdp_pc*) does not affect the use of locally developed green technologies.

In summary, our results demonstrate that both technology-specific factors at the patent-licensing level and regional factors help to explain whether adopters use local or non-local green technologies. The regional characteristics lead to the fact that in some regions, many locally developed green technologies are adopted, while other regions rely on technology transfer. In this context, regional specialization in green technologies as well as the technological capabilities of a region arguably play a pivotal role.

4.3. Limitations and robustness

The results presented are subject to some limitations. Firstly, it is worth recalling that our research is on the adoption of *green* technologies. We are therefore unable to judge to what extent the results only apply to green technologies, whether they are also valid for non-green technologies, or whether there are significant differences between green and non-green technologies. At the same time, our research design does not allow us to study peculiarities of different green technology domains (e.g. climate change mitigation vs. environmental management) given the limited number of licensing observations. Therefore, we are only able to control for green technology domains using dummy variables in our models, whereas it would certainly have been more intriguing to run separate sets of regression models on subsets of each green technology domain. Secondly, there is a somewhat similar limitation concerning the Chinese context. That is to say, it is difficult to judge the extent to which our results hold true for other countries and regions. While major patterns in innovation diffusion are likely to be very similar across space, the emerging position in the global technology landscape, coupled with persistent regional disparities in innovation capacity, make China a rather unique case (Liefner et al. 2021). Furthermore, there are some distinctive features of the Chinese IPR system, such as the importance of the utility model patent, the comparatively low patent quality and patent subsidies, to name but a few (Prud'homme 2017; Sun et al. 2021). Thirdly, some variables have shortcomings in terms of measurement, for example the GDP-related variables, which are only available for one year. In this regard, we face the dilemma of focusing on a very granular geographical level (prefectures), which means that we can take fewer factors into account than studies conducted at the provincial level. However, we feel confident that the advantages of our granular approach outweigh its disadvantages. Another important remark relates to the differences of the regression results between the three time periods reported in Table 2. The effects of some variables vary over time, in particular period one shows distinct patterns when compared to period two and three. We believe that these differences are mainly because innovators and adopters followed different licensing strategies when CNIPA started keeping official (and public) records of patent licensing contracts in 2008. Finally, our empirical approach carries a potential endogeneity problem, given the possibility that innovators may choose to locate close to places where their developed technologies are needed. For example, a firm that develops cleaner production technologies may choose to locate in a pollution-intensive region because of the geographic proximity to its customers. There might hence be a reverse causal effect in our empirical approach, driven by regional demand for green technologies. However, we argue that endogeneity is only a minor issue in our study for two main reasons. Firstly, many green technologies in our data set do not respond to local demand conditions, but rather to global environmental problems, for instance climate change mitigation technologies. Secondly, our data set also includes inventions from universities that generally do not relocate, thus limiting the endogeneity problem explained above.

Notwithstanding these limitations, we have performed a number of robustness tests to validate our findings, such as adjusting the time periods, running the regressions in a panel setting with time effects (intercepts and slopes) or using subsets with several regions or technologies excluded. The results of the robustness checks are in line with the results presented in Table 2. We decided to show the regression results for three different periods in order to highlight changes over time in an accessible way. As additional robustness checks, we have used other modelling techniques besides mixed effect probit models, including mixed effect logit models and non-hierarchical probit and logit models with regionally clustered standard errors. Overall, our results are robust to these tests. All statistical outputs are available from the authors upon request.

5. Conclusion

The aim of this paper was to study which factors determine whether adopters of green technologies use either technologies that have been developed locally or technologies that have been developed in other places. To answer this question, we analyzed a unique data set on licensing agreements for Chinese patents in green technologies. To this end, we considered not only factors at the patent-licensing level, but also, and in particular, factors at the regional level. Our results suggest that the regional context plays a key role in predicting whether innovation adopters will use local or non-local green technologies. Among other things, we show that the use of locally developed green technologies is more likely in regions characterized by green technology specializations and high innovation capacity than in less innovative regions. The latter rely on green technology transfer from other regions.

Our results hold two main implications for regional innovation policy. On the one hand, regions specialized in green technologies, where local demand can be satisfied by local technology supply, should exploit their lead market potential and build a competitive advantage through transferring and exporting local technologies. On the other hand, peripheral regions that lack significant green industries and that are dependent on technology transfer should strengthen local user-producer interactions and support local learning processes in order to foster green regional path development (Grillitsch and Hansen 2019; Tödtling, Trippl, and Frangenheim 2021). From a sustainability perspective, our results need to be interpreted in a somewhat different way. That is to say, the overall (e.g. national, global) goal of policymakers should be to accelerate and scale the diffusion of green technologies in order to curb environmental harm. In this context, it does not matter whether a green technology is adopted in the region where it was invented or whether it is adopted elsewhere, as long as using the technology contributes to reducing environmental damages (Altenburg and Pegels 2012). In this regard, policymakers need to think carefully about how to align the supply side (green technology development) and the demand side (green technology use) in regional sustainability strategies.

Further research is needed in particular concerning the following issues. Firstly, our analysis unfortunately does not allow any conclusions to be drawn about the strategic motives of the innovation adopters. Additional – notably qualitative – studies are needed to answer this unresolved aspect of the research conducted in this paper. Secondly, further quantitative studies following our approach are necessary to explore peculiarities of different green technologies, as even within one technological domain such as renewable energies, the spatiality of market formation is very heterogeneous, for example when comparing solar PV and wind power (Binz and Truffer 2017; Li, Heimeriks, and Alkemade 2022; Rohe 2020).

Note

1. For a detailed analysis of interregional licensing flows, see Losacker (2022).

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Appendix

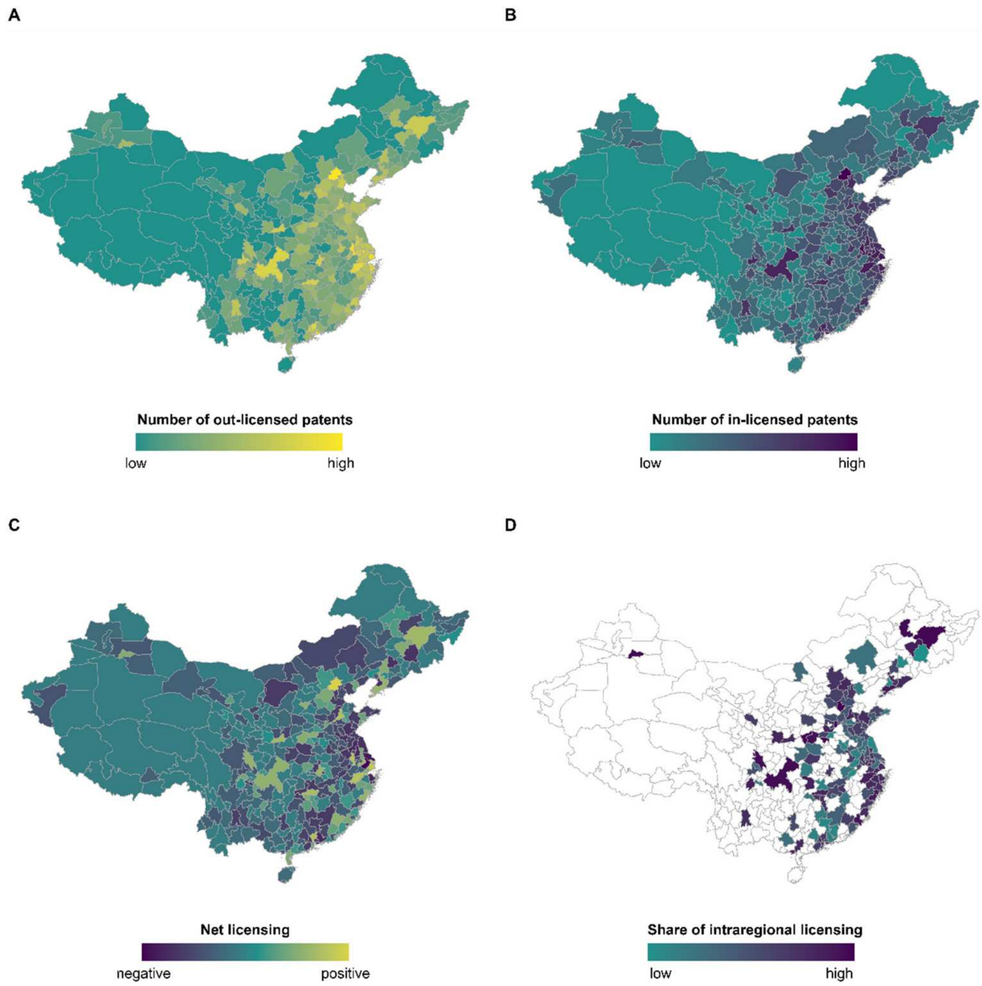

Figure A1. Spatial distribution of green patent licensing agreements, prefectural level, pooled data 2008–2019. (A): Number of out-licensed patents per region. (B): Number of in-licensed patents per region. (C): Net licensing per region. Net licensing is the difference between out-licensed and in-licensed patents per region, with positive values indicating that a region has a higher number of out-licensed patents than in-licensed patents. (D): Share of intraregional licensing per region. This map is an alternative visualization to Figure 2. Please note that we excluded regions with low numbers of licensing agreements for this map (<20).