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The impacts of technological overlap on international collaboration in China's green innovation endeavors

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North-South cooperation in green innovation activities is an essential avenue for promoting global climate governance. This study examines the impact of technological overlap on the scale of international cooperation in environmental technologies (ETs) between Chinese and foreign geographical units. The results show that technological overlap significantly increases the scale of international cooperation in ETs. The main international cooperation partners are located in the G7 countries, with the United States being the most significant partner. Technological overlap has not only promoted China to send many patent inventors to other countries but also encouraged China to introduce more foreign inventors. Further research reveals a significant interaction effect between the scale of existing inventor cooperation, local technological advantages, and technological overlap, which expands the scale of international cooperation. This paper calls for strengthened ET cooperation between developed and developing countries to address climate change.

Keywords Technological overlap, Environmental technologies, China, Developing countries, International cooperation

This study attempts to integrates tools from documentation and information science into geographic innovation research[1,2] by utilizing published patent documents and adopting the perspective of citation coupling[3]. From the vantage point of patent documents, it quantitatively assesses the concept of knowledge relatedness[4] within the framework of innovation geography. Traditional research has mainly focused on exogenous factors influencing the cross-border innovation team construction, such as spatial distance[5], labor returns[6–8], and investment factors[9]. In contrast, this study delves into the endogenous factors driving cross-border innovation cooperation, aiming to uncover the micro-foundations of how innovation actors in emerging countries, propelled by their own innovation successes, navigate the global innovation network to find and collaborate with appropriate overseas partners. Furthermore, the study provides an in-depth exploration of Marshallian externalities, often referred to as the "black box"[10]. Given China's notable achievements in innovation within the environmental technologies (ETs), this study particularly examines the status of Chinese innovation actors' engagement in cross-border innovation cooperation in ETs.

The concept of technological overlap refers to the extent to which two inventors share knowledge at a particular time, focusing on exploring the knowledge linkage between innovation subjects from the perspective of commonality[11]. Relevant studies have indicated that the higher the overlap degree of internalized codified knowledge among innovation subjects, the more similar the technical expertise between the subjects[11–13]. This familiarity with related technologies and knowledge help to mitigate friction and information asymmetry before and after transactions. While existing research has mainly focused on micro-innovation entities such as enterprises, the spillover effect of knowledge means that its influence may extend beyond the organization. Extending this indicator to geographical space may be feasible, given the high spatial concentration of innovation activities[14]. In this context, codified knowledge of geographical units is critical in allocating innovation resources, and bilateral or multilateral knowledge linkage becomes a driving force for the spatial flow of innovative talents.

As the world is becoming increasingly aware of the detrimental impact of climate change and the edge of climate disasters, there is a growing consensus among the international community to prioritize green and low-carbon transformation. Studies have shown that environmental technology (ET) innovation plays a crucial

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role in global climate governance[15–18], and it is the most significant factor affecting long-term governance costs[19]. However, most existing literature has focused on ET innovation in developed countries or North-South technology transfer[17,20,21], and there has been less attention given to the factors that promote ET innovation in developing countries[22]. Developing countries are often in a position of higher energy consumption due to the long-established international industrial chain. Therefore, cooperation and support from developed countries are crucial for these countries to achieve green and low-carbon transformation. It is only through collaborative dialogues and utilizing each country's contributions and comparative advantages that effective synergy can be achieved to address climate change[23].

Apart from directly importing equipment that materializes knowledge and introducing advanced technology to acquire knowledge, cross-border inventions through international cooperation are also crucial for developing countries to gain knowledge from developed countries[24,25]. The global innovation network, led by European Union and North American multinational corporations, has formed the characteristics of "Local Hotspot, Global Networks"[26], guiding the flow of global innovation resources. Therefore, relying on this network to allocate overseas innovation resources is a practical and long-term choice for developing countries. It is also an important channel for them to generate influential ideas and long-term benefits for inventors in the future[27]. Under the pressure of the international community to reduce emissions and achieve green economic growth, developing countries are now more willing to acquire knowledge through joint research and cooperation to achieve green economic growth. This is because knowledge can be spread faster in this way. However, the microscopic basis of international cooperation for developing countries in ETs still needs more exploration. Previous studies have shown that co-invention through utilizing external knowledge is determined by two factors: the partners' familiarity with each other's technical expertise (Technological Overlap) and their experience in previous technological collaborations[22,28–30].

Given that China is both a critical emerging node in the global innovation network and a significant carbon emitter, this study explores the relationship between technological overlap and the scale of international cooperation in ETs. By using patent data, we develop an indicator to measure the bilateral knowledge linkage between China and global innovation hotspots. Humans are the vital vessels through which knowledge is transmitted, and the diversification of individual skills has crafted a highly organic and meticulously integrated structure of human capital that fuels innovative activities. Innovative talents, endowed with exceptional skills in specific fields and armed with the latest cutting-edge knowledge, converge at particular spatial nodes, where they vigorously drive the progression of innovative endeavors. Given the pivotal role that innovation plays in stimulating economic growth, coupled with the striking agglomeration of high-skilled labor in certain spatial areas, the mobility of high-skilled labor (especially innovative talents) has emerged as a central focus. The extensive and far-reaching impacts of high-skilled labor mobility have become prominent topics of discussion and key areas of research across multiple fields of economics in recent years[8].From the perspective of spatial agglomeration characteristics, the matching effect of technological overlap on cross-border innovation teams is in line with the sorting effect[31], leading to the spatial agglomeration of high-skilled labor associated with innovation in the "new" new economic geography. Therefore, we utilize the sorting effect and the synergistic effects between the sorting effect, agglomeration effect, and selection effect within the framework of the 'New' new economic geography theory to address four key research questions. Firstly, can the technological overlap between China and other innovation hotspots facilitate ET cooperation with foreign regions? Secondly, is there a significant difference in the impact of technological overlap on the scale of international cooperation in different regions? Thirdly, Beijing, Shanghai, and Shenzhen are China's three active innovation regions. What are the differences in the impact of technological overlap on international cooperation among these regions? Finally, we explore the effects of other innovation activities in the "regional hotspots" on linking technological knowledge and allocating cross-border innovative talents.

This paper offers three significant contributions in comparison to the existing literature. Firstly, this study aims to present the bilateral knowledge linkage of patented innovation activities by using co-cited patents between innovation nodes, distinguishing the common perspectives of unilateral absorptive capacity and bilateral technological distance. Empirical evidence is provided on how ET knowledge linkage affect international cooperation. Secondly, this study focuses on ET cooperation between China and global innovation hotspots and highlights the heterogeneity of technological overlap affecting international cooperation at multiple geographical latitudes, unlike current research on ET innovation in developed countries or North-South technology transfer. Finally, it provides targeted suggestions for developing countries to participate in international cooperation in green innovation activities based on the resource allocation effect of knowledge linkages. This paper recognizes the significance of cross-border joint research and development (R&D) cooperation between global innovation hotspots and China from the perspective of bilateral or multilateral knowledge linkage and points out the strategy of international cooperation in the future.

The rest of this paper is structured as follows: section "Literature review" is a literature review; section "Theoretical model and research hypotheses" is model setting and data processing; section "Data source, variable construction, and model setting" is an analysis of empirical results; sections "Results and discussion" and "Heterogeneity analysis" are heterogeneity and interaction effects analysis; The final section presents the conclusions and policy implications of the study.

Literature review

The impact of Spatial agglomeration sorting effects on high-skilled labor mobility

The Roys model in the field of labor economics emphasizes both the selection effect, wherein high-skilled workers are chosen by the market, and the sorting effect, which pertains to how these workers select their employment locations. This model provides a solid micro-foundation for understanding the optimal geographic choices made by highly skilled labor. Given the well-documented phenomenon of innovative endeavors and highly skilled labor concentrating in a few major cities, Kerr and Kerr highlight the importance of spatial factors in elucidating the mobility patterns of such workers[8]. Behrens et al. further emphasize, from a dynamic perspective, that the spatial dynamics governing labor allocation are intricately linked with agglomeration, selection, and sorting effects[32].

The sorting effect underscores the alignment between labor skill levels and the productivity advantages offered by large cities, driven by spatial agglomeration. This alignment manifests in three primary ways. First, there is an alignment between labor skills and skill premiums. By capitalizing on the productivity advantages created through the selection effect, companies in major cities attract high-skilled workers with higher salaries[33]. Furthermore, the superior infrastructure of large cities, including healthcare and education, offers additional non-financial benefits to employees[8]. Consequently, skill premiums in big cities become a significant draw for highly skilled labor. Second, there is an alignment between labor skills and knowledge spillovers. The knowledge spillover effect is a pivotal aspect of agglomeration dynamics and plays a crucial role in the location decisions of highly skilled workers. Building on the concept of absorptive capacity, Davis and Dingel argue that highly skilled labor has an advantage in internalizing knowledge spillovers[34]. Therefore, to maximize this advantage, skilled workers opt for large cities with abundant innovative activities where knowledge spillovers are more pronounced; empirical evidence from Davis and Dingel also supports the notion that larger cities host a higher concentration of highly skilled workers and skill-intensive production[33]. Lastly, there is an alignment among various labor skills. Departing from the traditional high-low skill dichotomy, Eeckhout et al. suggest that skill complementarity helps explain the coexistence of diverse skill levels in big cities[35]. They further note that this complementarity can exist among high-end skills, as seen in learning exchanges and skill knowledge complementarity among heterogeneous high-skilled workers (e.g., top-skill complementarity like coaches and athletes in professional sports), as well as between high-end and general skills, evident in the complementarity of specialized labor division and service functions among diverse workers (e.g., extreme-skill complementarity like the synergy between highly skilled workers and domestic service labor).

Davis and Dingel argue that, while assuming labor can freely benefit from knowledge spillovers, Marshallian externalities from spatial agglomeration are often overlooked[34]. Existing empirical studies frequently use wages as a proxy for labor skill levels[6]. However, wages only reflect skill levels and do not disclose the skill composition of labor. Due to the scarcity of data on knowledge types or structures, there has been limited empirical exploration of how knowledge structures influence the location choices of highly skilled workers. By quantifying the knowledge embedded in cities, this paper presents a methodology to describe the skill composition of urban labor, thereby contributing empirical insights into how sorting effects drive the geographic choices of highly skilled workers. This represents a valuable attempt to unravel the mysteries of externalities, a core issue in urban economics.

Measurement of technological overlap and its impact on cross-border innovation collaboration

Technological overlap, or knowledge base overlap, refers to the degree of shared knowledge stock between two innovating entities at a given time, emphasizing the knowledge linkage between innovators from a commonality perspective. Related concepts encompass technological distance, technological similarity, and technological relatedness. Research indicates that greater technological overlap leads to more similar professional knowledge among innovators, enhancing familiarity with relevant technologies and knowledge. This, in turn, aids in reducing various frictions and challenges stemming from information asymmetry both before transactions (e.g., searching and matching between transacting parties) and after transactions (e.g., assimilating and applying external technologies or knowledge). This concept is frequently discussed in studies of firms acquiring external knowledge resources (e.g., technological mergers and acquisitions, R&D partnerships)[11,13]. Corporate finance research suggests that technological overlap also fosters economies of scale in innovative resources following M&A transactions[12].

Given the insights into knowledge flows provided by patent citation data[36] and the improved data accessibility due to the digitization of patent information, constructing technological overlap indicators based on shared patent citations in patent applications by two innovating entities (e.g., two firms) has become commonplace in empirical research[12,13].

Regarding the impact of technological overlap on innovation, existing research primarily focuses on its effect on innovators' absorption of external knowledge. Chesbrough notes that R&D and innovation activities of entities such as firms are increasingly trending towards openness, but integrating external ideas or knowledge is neither automatic nor cost-free[37]. Both Ahuja & Katila and Bena & Li indicate that the relevance (i.e., technological overlap) between acquired external knowledge and the existing knowledge base of the acquiring entity can influence its innovative output after acquiring external knowledge resources[11,12].

Overall, research suggests that technological overlap influences innovative activities through multiple mechanisms. First, it helps mitigate frictions caused by information asymmetry. For instance, Graebner et al.[38] argue that technological overlap enhances firms' absorptive capacity and lowers barriers to assimilating external knowledge resources. Second, it contributes to achieving economies of scale and scope in innovative resources. Since technological overlap represents the common ground in the existing knowledge bases of transacting parties, Henderson and Cockburn suggest that M&A transactions can help avoid redundant innovative resources or enable broader utilization of these knowledge assets[39]. Third, it facilitates specialized labor division in innovation. Redundant innovative resources from overlapping resources among participants also prompt innovation alliances to reconfigure these resources, allowing participants to allocate more resources to technical areas where they excel, thereby enhancing specialization[40].

Existing literature primarily constructs the technological overlap indicator at the micro-level of innovating entities (e.g., firms). However, the spillover effects from knowledge's natural externalities suggest that the influence of firms' knowledge may extend beyond their internal operations, especially for codified knowledge like patents. Thus, extending this indicator to geographical space could be a promising approach, aligning with the highly clustered nature of innovative activities. Furthermore, the knowledge linkage between two innovating entities, encapsulated by technological overlap, aligns well with the "like attracts like" principle of the spatial agglomeration sorting effect. Given that inventors are key knowledge carriers, constructing technological overlap indicators between geographical units and examining their impact on international innovation collaboration can provide valuable insights into how technological overlap affects innovative activities from a spatial perspective.

In summary, there is currently limited research exploring the micro-foundations of emerging country innovators' engagement in international R&D collaboration within smaller geographical areas such as provinces or states, based on the highly clustered nature of innovative activities. As emerging countries increasingly participate in the global innovation network, reshaping the global science and technology innovation landscape, investigating how technological overlap enables Chinese innovators to achieve targeted international scientific and technological collaboration in ETs holds significant practical importance.

Theoretical model and research hypotheses

This paper analyzes the impact of technological overlap on patent R&D collaboration through a simple theoretical model. Suppose inventor i ($i=1,2$) can independently develop a patent with value π_i with probability P_i. If both parties collaborate, the probability of successful patent development is P, and the value is π. However, R&D collaboration is not cost-free; inventors must incur a search cost C_i^{se} to find collaboration partners and an absorption cost C_i^{ab} during the collaborative R&D process to effectively utilize the partner's knowledge. Further, it is assumed that C_i^{se} and C_i^{ab} are functions of technological overlap, with $d(C_i^{se})/d(Overlap)<0$ $d(C_i^{ab})/d(Overlap)<0$, because technological overlap, determined by shared knowledge, helps mitigate various frictions caused by information asymmetry in the collaboration process, thereby reducing these two costs. Additionally, it is assumed that the value distribution of the collaborative patent will be P_1^* and P_2^*. Therefore, the payment matrix corresponding to this game is shown in Table 1, with the mixed-strategy Nash equilibrium being $\rho\ (\rho^*_1, \rho^*_2)$, where $\rho^*_1=C_2^{se}/(P_1^*\pi - C_2^{ab} - P_2\pi_2)$ and $\rho^*_2=C_1^{se}/(P_2^*\pi - C_1^{ab} - P_1\pi_1)$.

In this game, when inventor 1's willingness to collaborate, ρ_1, satisfies $\rho_1>\rho^*_1$, inventor 2's expected benefit from collaborative R&D exceeds that from independent R&D. Similarly, when inventor 2's willingness to collaborate, ρ_2, satisfies $\rho_2>\rho^*_2$, inventor 1's expected benefit from collaboration exceeds that from independent R&D. Therefore, collaboration is the optimal choice for both parties only when ρ_1 and ρ_2 simultaneously satisfy $\rho_1>\rho^*_1$ and $\rho_2>\rho^*_2$. Assuming that inventors' exogenous willingness to collaborate, ρ_i, follows a uniform distribution on [0, 1] and is mutually independent, the probability of both parties choosing to collaborate, P_{coop}, and $P_{coop}=(1-\rho^*_1)(1-\rho^*_2)$. By leveraging symmetry, it is easily derived that $d(P_{coop})/d(C_i^{se})<0$ and $d(P_{coop})/d(C_i^{ab})<0$ ($i=1,2$), further leading to $d(P_{coop})/d(Overlap)>0$. In other words, as technological overlap increases, so does the probability of inventors' R&D collaboration. Based on the sorting effect, within the framework of the 'New' new economic geography theory, the following hypothesis is proposed:

Hypothesis 1: Technological overlap can facilitate cross-border R&D collaboration between patent inventors (Sorting Effect).

When further discussing this game model within the context of exogenous spatial agglomeration, this paper considers two spatial factors that influence inventors' decisions in R&D collaboration games. First, geographical proximity enhances the convenience of information dissemination; existing R&D collaboration relationships among other local inventors generate spillover effects, helping to reduce the search costs, C_i^{se}, for local inventors seeking partners. Second, local technological advantages in specific fields or industries deepen the thickness of relevant professional knowledge, and spatial proximity increases the availability of relevant knowledge spillovers for local inventors, helping to reduce the absorption costs, C_i^{ab}, they face in internalizing external knowledge during R&D collaboration. Based on the synergistic effects between the sorting effect, agglomeration effect within the framework of the 'New' new economic geography theory, the following hypothesis is proposed:

Hypothesis 2a: The scale of existing local inventor collaborations interacts with technological overlap to promote R&D collaboration between patent inventors (the synergistic effects between sorting effect and agglomeration effect).

Hypothesis 2b: The scale of local technological advantages interacts with technological overlap to promote R&D collaboration between patent inventors (the synergistic effects between sorting effect and selection effect).

Data source, variable construction, and model setting

Data source

The data utilized in this research is sourced from two patent databases, REGPAT[41] and Citations[42], which have been compiled by the Organization for Economic Cooperation and Development (OECD). The REGPAT database includes the geographical location of patent inventors, while the Citations database offers patent citation details. This paper focuses on international cooperation in ETs, and it specifically identifies ET patents

		Inventor 2	
		Cooperative R&D	**Independent R&D**
Inventor 1	Cooperative R&D	$(P_1^*\pi - C_1^{se} - C_1^{ab})$, $(P_2^*\pi - C_2^{se} - C_2^{ab})$	$(P_1\pi_1 - C_1^{se})$, $P_2\pi_2$
	Independent R&D	$P_1\pi_1$, $(P_2\pi_2 - C_2^{se})$	$P_1\pi_1$, $P_2\pi_2$

Table 1. The payment matrix for the cooperative game among inventors.

that involve both Chinese and foreign inventors, using the patent International Patent Classification (IPC) and technical field comparison table issued by the World Intellectual Property Office (See https://www.wipo.int/ipstats/en/docs/ipc_technology.xlsx).

Variable selection and descriptive statistics

Dependent variable

The dependent variable is the scale of international cooperation ($InvCo_{ijt}$), measured by the cooperation times of 18,166 Chinese and foreign geographical unit pairs of bilateral patent inventors in ETs between 1998 and 2017. The REGPAT database provides the geographical information of patent inventors, enabling us to identify the ET patents that feature both Chinese and overseas inventors. We then calculate the cooperation times of these 18,166 pairs, which serves as an indicator of the scale of international cooperation between Chinese and foreign geographical units (Kogler et al. examined international collaboration among inventors in European countries through the co-occurrence of inventors[43]).

Independent variable

The independent variable is the degree of technological overlap ($Overlap_{ijt}$). To construct $Overlap_{ijt}$, the first step involves selecting NUTS2-level geographical units (31 provinces in mainland China and 586 provinces or states in foreign countries, hereinafter referred to as province) based on the inventor's geographical information of the Patent Cooperation Treaty (PCT) patents disclosed in the REGPAT database between 1998 and 2017. This results in 18,166 pairs of Chinese and foreign geographical units. The second step sums up the backward citation patents of patent inventors participating during the period *t* as the knowledge source database of the geographical units (for data smoothing, we used a period of three years to construct each indicator in the benchmark regression and performed a rolling calculation), with the province being the unit. The final step extracts the same patents in the knowledge source databases of the two geographical units of the Chinese and foreign provincial pairs and calculates the total amount, which is used as the technological overlap indicator of the Chinese and foreign geographical unit pairs. It is worth mentioning that only non-cooperative ET patents, meaning those not jointly including Chinese and overseas inventors, are used to alleviate endogenous bias caused by reverse causality in subsequent regression analysis (as shown in Fig. 1).

Control variables

We utilize conventional variables that may impact international cooperation as control variables: the previous period's scale of bilateral inventor cooperation ($InvCo_{ijt-3}$) in the previous observation period (lag by one standard observation period consider as three years), to control for the impact of tacit knowledge linkages between the two regions, which are derived from their past cooperation experiences; the current period's scale of inventors in Chinese provinces ($Invnum_{it}$), and the current period's scale of inventors in foreign provinces ($Invnum_{jt}$), to control for the impact of regional innovation activity intensity. $InvCo_{ijt-3}$ is calculated by the number of inventors taking part in joint patent cooperation between Chinese and foreign provinces. $Invnum_{it}$ is calculated by the number of inventors taking part in the joint patent cooperation in Chinese provinces. $Invnum_{jt}$ is calculated by the number of inventors taking part in the joint patent cooperation in foreign provinces. These control variables are used to control for the impact of agglomeration effects on the scale of cross-border innovation cooperation[14].

Descriptive statistics

As G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) have expressed their commitment to promoting green innovation and sharing climate technologies with developing countries, we divide the cooperation objects into the G7 countries and non-G7 countries. Table 2 presents descriptive statistics which reveal that China participates mainly in international cooperation with G7 countries. The scale of international cooperation is on average 16 times larger than that with non-G7 countries. Furthermore, China's PCT cooperation in ETs with BRICS countries is minimal, averaging only 0.0005. In contrast, China's PCT cooperation in this field with Japan and South Korea is notably high, averaging 0.0787, which is second only to its cooperation level with the United States at 0.0851. Additionally, the technological overlap between China and G7 countries is close to 0.03 patents, while with non-G7 countries it is only 0.0036. The average values for this indicator are 0.0443 for the United States and 0.0485 for Japan, respectively, indicating a significant overlap in the background knowledge bases of Chinese inventors in ETs field with their peers in the United States and Japan.

Figure 2 illustrates the annual fluctuations in the scale of cross-border innovation cooperation in the ETs between mainland China's inventors and foreign inventors from 2001 to 2017. The dark blue indicates the cooperation scale with G7 countries, showing a relatively stable growth trend throughout this period. Notably, collaboration saw significant increases during certain years, particularly from 2009 to 2011 and after 2016. In contrast, the orange line represents cooperation with non-G7 countries, which also exhibited growth but on a smaller scale overall. Throughout the entire period, cooperation with G7 countries consistently dominated, highlighting their importance and influence in cross-border innovation cooperation with Chinese mainland inventors, especially within the ET field.

Model setting

This paper aims to study the impact of technological overlap on the scale of international cooperation in ETs between China and foreign geographical units. To estimate this, a high-dimensional fixed-effects model is used. The Hausman test results, based on the regression data, reveal a test statistic chi2(4) value of 18149.76, accompanied by an extremely low p-value of 0.0000. This leads us to accept the alternative hypothesis, which states that there are significant differences in the coefficients between the fixed effects model and the random

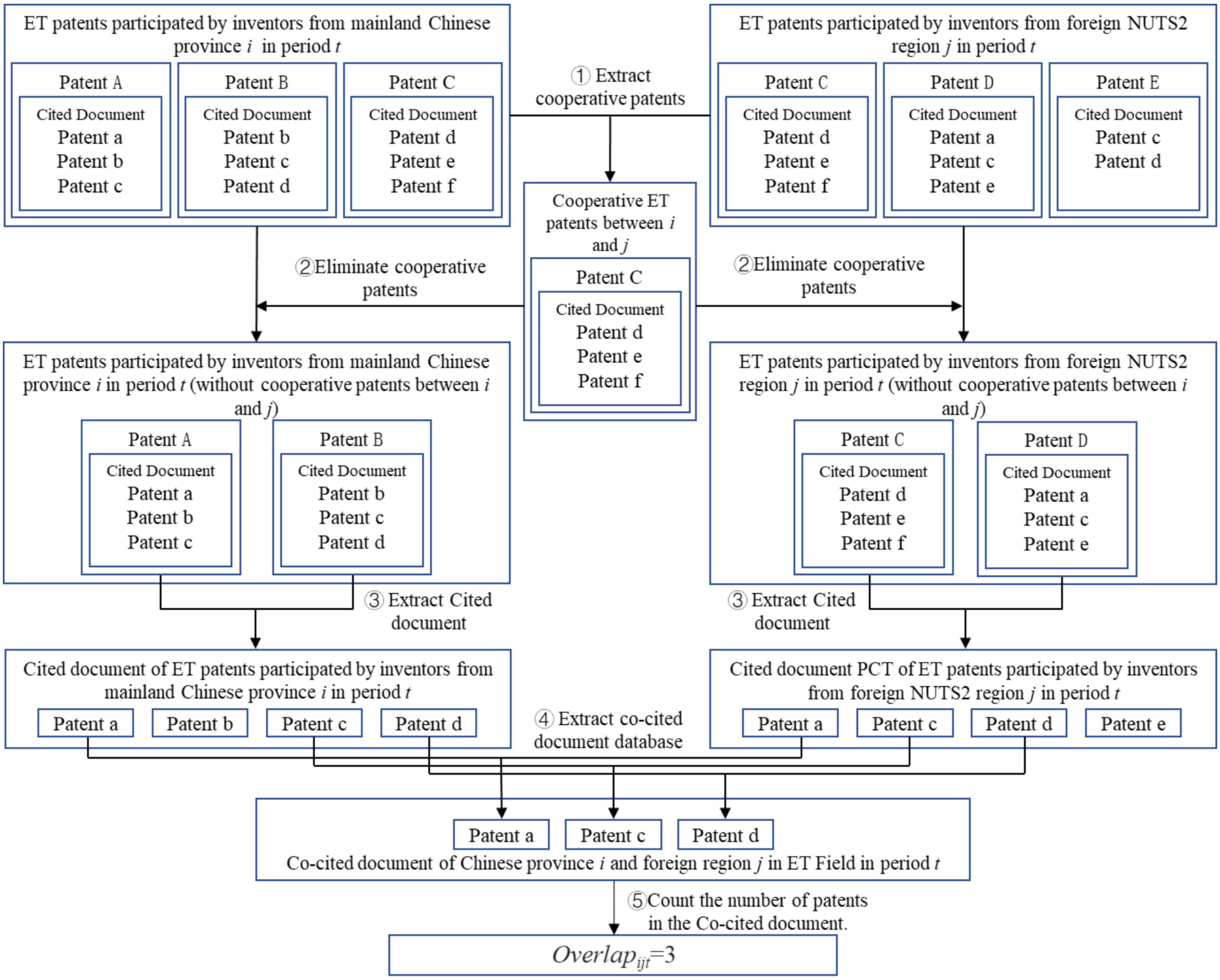

Fig. 1. Construction of co-cited documents and technological overlap between geological units.

effects model. Given these findings from the Hausman test, opting for the fixed effects model appears to be more suitable. The benchmark measurement equation is as follows:

$$InvCo_{ijt} = \alpha + \beta_1 Overlap_{ijt-3} + X\eta + FE_{it} + FE_{jt} + FE_{ij} + \varepsilon_{ijt} \tag{1}$$

Where $InvCo_{ijt}$ represents the scale of international cooperation between China's province i and foreign province j in period t. To alleviate endogenous bias, we lag our explanatory variable and some control viables by one standard observation period (three years) in our benchmark regression. In the robustness tests, we also used different lengths of observation periods to construct those variables and adjusted the lag lengths of the corresponding variables according to the lengths of the observation periods. $Overlap_{ijt-3}$ represents the degree of technological overlap of Chinese and foreign geographical unit pairs in period t-3. X represents a string of control variables. The control variables include the scale of bilateral inventor cooperation in period t-3, which is denoted as $InvCo_{ijt-3}$, the scale of inventors in Chinese provinces in period t ($Invnum_{it}$), and the scale of inventors in foreign provinces in period t ($Invnum_{jt}$).

To control for biases stemming from omitted variables, the estimation equation includes joint fixed effects for provinces and years in mainland China (FE_{it}), which account for the impact of policy and economic changes within each province in mainland China; joint fixed effects for provinces and years in foreign countries (FE_{jt}), which account for the impact of policy and economic changes within each foreign provinces; and fixed effects for pairs of Chinese and foreign geographical units (FE_{ij}), which address factors like geographical distance, linguistic and cultural differences, and enduring political relations between the two regions.

Results and discussion

Benchmark results and explanation

Table 3 displays the benchmark results. Both columns (1) and (2) control for Chinese provinces, foreign provinces, and years fixed effects to eliminate any confounding factors with province or time that could affect

Dependent variable	$InvCo_{ijt}$				
	Obs	Mean	Std.Dev	Min	Max
From All Countries	272,490	0.0151	0.569	0	113
From G7	79,980	0.0449	1.023	0	113
From Non-G7	192,510	0.0028	0.150	0	32
From US	23,715	0.0851	1.207	0	53
From BRICS	66,960	0.0005	0.043	0	5
From JK	7905	0.0787	2.239	0	113
Independent variable	$Overlap_{ijt-3}$				
	Obs	Mean	Std.Dev	Min	Max
From All Countries	272,490	0.0115	0.175	0	14
From G7	79,980	0.0305	0.297	0	14
From Non-G7	192,510	0.0036	0.081	0	7
From US	23,715	0.0443	0.358	0	14
From BRICS	66,960	0.0008	0.039	0	5
From JK	7905	0.0485	0.362	0	12

Table 2. Statistical characteristics of the scale of international Cooperation and technological overlap in ETs between China and foreign countries. Data sources: OECD REGPAT database, OECD Citations database. Unless otherwise specified, the same is below.

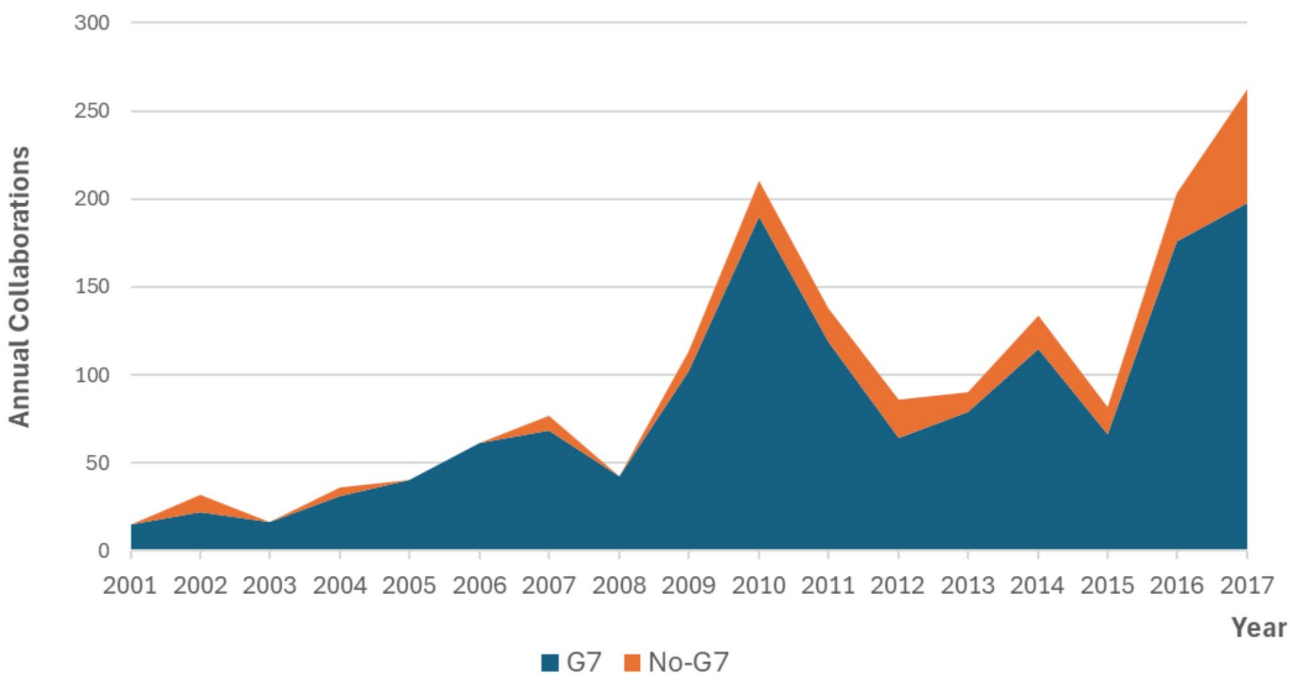

Fig. 2. Annual cross-border innovation cooperation in PCT Patents related to ETs between inventors from mainland China and international partners.

the estimation of the core explanatory variable coefficient. Column (1) reveals the regression results when only introducing the technological overlap ($Overlap_{ijt-3}$) of Chinese and foreign geographical unit pairs. It is apparent that technological overlap significantly promotes the scale of international cooperation in ETs. To account for factors such as the existing scale of cooperation and the scale of inventors of both parties that could affect the scale of international cooperation, column (2) of Table 3 controls for the scale of bilateral inventor cooperation in period t–3 ($InvCo_{ijt-3}$), the scale of inventors in Chinese provinces in period t ($Invnum_{it}$), and the scale of inventors in foreign provinces in period t ($Invnum_{jt}$). The estimated coefficient of $Overlap_{ijt-3}$ remains significantly positive at the 1% level. Due to the limited availability of relevant variables affecting innovation activities at the geographical unit level, especially foreign provinces or states, column (3) introduces the joint fixed effects of provinces and years in mainland China (FE_{it}), the joint fixed effects of provinces and years in foreign countries (FE_{jt}), and the fixed effects of Chinese and foreign geographical unit pairs (FE_{ij}). It is still

Variables	$InvCo_{ijt}$ (1)	(2)	(3)
$Overlap_{ijt-3}$	0.745*** (3.44)	0.431*** (3.30)	0.335*** (3.49)
$InvCo_{ijt-3}$		1.718*** (3.75)	− 0.257 (− 0.57)
$Invnum_{it}$		− 0.002 (-0.74)	
$Invnum_{jt}$		− 0.002 (− 1.17)	
FE_t,FE_i,FE_j	Yes	Yes	
FE_{it},FE_{jt},FE_{ij}			Yes
N_clust	18,166	18,166	18,166
r2_a	0.071	0.110	0.315
N	272,490	272,490	272,490

Table 3. Effects of technological overlap on the scale of international Cooperation in ETs. Note: All standard errors are clustered standard errors at the Chinese and foreign geographical unit pairs level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Unless otherwise specified, the same is below.

	Panel A: the length of the observation period			Panel B: Weighted technological overlap
	Two years	Four years	Five years	
Variables	(1)	(2)	(3)	(4)
$Overlap_{ijt-2}$	0.318*** (2.76)			
$Overlap_{ijt-3}$		0.229** (2.30)		0.202*** (2.61)
$Overlap_{ijt-4}$			0.240** (2.15)	
FE_{it},FE_{it},FE_{ij}	Yes	Yes	Yes	Yes
N_clust	18,166	18,166	18,166	18,166
r2_a	0.220	0.409	0.507	0.314
N	290,656	254,324	236,158	272,490

Table 4. Robustness test. Note: We adjusted the lag lengths of the explanatory variable and control variables according to the lengths of the observation periods in Panel A; the independent variable in Panel B is the weighted technological overlap by cited times.

apparent that technological overlap, which represents bilateral ET knowledge linkage between Chinese and foreign geographical units, significantly promotes the scale of international cooperation in ETs.

Overall, the estimated coefficient of the key explanatory variable $Overlap_{ijt-3}$ is robust under different model setting environments. We use column (3) of Table 3 as a baseline estimate. This means that the number of co-cited patents of Chinese and foreign geographical unit pairs in ETs increases by 10, and the scale of international cooperation increases by 3.35 person-times. This result suggests that technological overlap can be the foundation for China's participation in international cooperation in ETs, as it incorporates knowledge linkage between two innovation subjects. This result supports our Hypothesis 1.

Robustness test

In order to test how the length of the observation period of the backward citation patents of patent inventors participating affects the results of the regression analysis, this study varies the observation period to 2, 4, and 5 years. The independent and dependent variables are adjusted accordingly. The results, displayed in Panel A of Table 4, show that the estimated coefficients of technological overlap are consistently positive. Additionally, as the length of the observation period increases, the scale of bilateral international cooperation remains relatively stable.

To calculate technological overlap again, this study uses a weighted indicator based on the number of citations of bilaterally co-cited patents. This accounts for the fact that the number of citations may differ between the two provinces, reflecting the extent to which knowledge from these patents is utilized in local innovation activities. The result, shown in Panel B of Table 4, indicates that the estimated coefficient of $Overlap_{ijt-3}$ decreases slightly but remains significant at 0.202. This result means that if the co-cited patents between Chinese and foreign geographical units increase by 10, the scale of bilateral international cooperation in ETs increases by 2.

Overall, the robustness of the results is confirmed by changing the observation period and using a weighted technological overlap indicator based on the number of citations.

Heterogeneity analysis

It's interesting to note that innovative activities tend to be concentrated in certain geographical units due to varying abilities to allocate innovation resources. For instance, Switzerland and the United States are net importers of high-skilled immigrants, while China and India are net exporters[7]. Given the goals of energy conservation, emissions reduction, and response to climate change, China must allocate innovation resources on a global scale to maintain its green innovation strength. As an influential player in the global innovation network, which countries' inventors may China seek to collaborate in ETs by leveraging technological overlap? The top 100 global innovation agglomerations include Shenzhen-Hong Kong-Guangzhou, Beijing, and Shanghai[44]. It's worth examining whether there are any differences in the effects of ET cooperation among these three regions in China.

Country comparison of international cooperation partners

This study aims to compare China's partners in international cooperation in ETs based on technological overlap. To achieve this, the patents that contain Chinese and foreign inventors are classified by country, and a sample of cooperation between China and other countries patent inventors is constructed. The baseline regression method is used to estimate the results. Table 5 reports the regression results of technological overlap on the scale of international cooperation between Chinese and foreign geographical units. The positive correlation between technological overlap and the scale of international cooperation in ETs is more significant in the G7 countries sample, as shown in column (1). However, from column (4), it can be seen that the coefficient in the non-G7 country sample is not significant. By decomposing the G7 countries into the United States and the G7 countries excluding the United States, it is found that the regression coefficients of the variable $Overlap_{ijt-3}$ are significantly positive, but relatively higher in the United States sample. Furthermore, technological overlap can also increase the scale of international cooperation in ETs between China and JK countries (Japan and South Korea), BRICS countries (Brazil, Russia, India, China, and South Africa).

Through an analysis of the impact of technology overlap on international cooperation between Chinese and foreign geographical units, we have discovered that Chinese inventors tend to collaborate with the United States, Japan, and South Korea in ETs. This is due to the fact that the United States has been a global leader in R&D investment for ETs, particularly energy conservation and emissions reduction technology, new energy technology, carbon capture technology, and carbon dioxide recovery and storage technology. Additionally, China and the United States share similar goals in developing green and clean energy and addressing climate change, making it a natural foundation for their cooperation in ETs. Moreover, since the first Tripartite Environment Ministers Meeting (TEMM) was held in 1999, the tripartite environmental cooperation centered on TEMM has fostered multi-level cooperation mechanisms among government departments, scientific research institutes, and civil society, thereby promoting collaboration among the three countries in ETs.

Based on the technological overlap, we examine the differences in the scale of international cooperation between inventors of the three major innovation clusters in mainland China and those foreign countries. The results, shown in columns (7)–(9) of Table 5, reveal that technological overlap has a greater impact on promoting the scale of international cooperation between Shanghai and Shenzhen with foreign inventors. However, technological overlap did not show a significant impact on advancing the scale of international cooperation between Beijing and foreign inventors. This may be attributed to the fact that Beijing boasts a higher density of top-tier universities compared to Shanghai and Shenzhen. These universities may have substituted the codified knowledge associations, as represented by technological overlaps, with their tacit knowledge flows. Additionally, since most China's high-level universities are publicly funded and policy-supported, Beijing's innovation activities, which rely heavily on these universities, exhibit a more noticeable residual influence from the command-based planned economy era. In contrast, Shanghai and Shenzhen, fueled by market dynamics, demonstrate a more prominent performance in emerging technology (ET) intellectual property cooperation (Beijing, Shanghai, and Shenzhen have distinct innovation advantages due to differing numbers of high-level universities. Beijing, with more top institutions, offers stronger theoretical support, while Shanghai and Shenzhen excel in market-driven applied innovation[45]).

Comparison of inventor flow in international cooperation

To examine the differences between China, European Union, and North American in using technological overlap to attract overseas innovation resources, this paper classifies all patents containing Chinese and foreign inventors

	G7	U.S.	G7 excluding U.S.	Non-G7	JK	BRICS	Beijing	Shanghai	Shenzhen
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Overlap_{ijt-3}$	0.394*** (3.48)	0.674*** (3.75)	0.253** (2.27)	− 0.005 (− 0.10)	0.324*** (2.60)	0.031** (2.49)	0.075 (1.00)	0.591*** (3.68)	0.042*** (3.25)
r2_a	0.318	0.546	0.169	0.317	0.160	0.381	0.267	0.509	0.314
FE_{it},FE_{jt},FE_{ij}	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
FE_t,FE_j	No	No	No	No	No	No	Yes	Yes	Yes
N_clust	5332	1581	3751	12,834	527	4464	586	586	586
N	79,980	23,715	56,265	192,510	7905	66,960	8790	8790	307,650

Table 5. Country comparison of international cooperation partners.

based on the country of the patent applicant. We then extract the patents of the inflow of foreign inventors, and the outflow of Chinese inventors (The ownership of intellectual property rights typically lies with the patent applicant. When a patent has inventors from both China and foreign countries, it is classified as an "inventor-inflow" patent if at least one applicant is from China, and an "inventor-outflow" patent if one applicant is from outside of China. It should be noted that the classification is based on the national attribution of intellectual property rights, not the inventor's nationality. For instance, if a patent has only Chinese applicants, the property rights of the innovation belong exclusively to China. On the other hand, if the applicants are from China and the United States, then the property rights are jointly owned by both countries. This definition aligns with the current 'not looking for everything, but looking for use' approach to flexible talent introduction). We construct the scale of patent inventor cooperation and estimate it using the benchmark regression setting. Results from columns (1) of Table 6, show that the estimated coefficient of technological overlap is significantly positive in all countries' samples, indicating that co-cited patents have significantly promoted the outflow of Chinese patent inventors to foreign countries or regions, positively contributing to global ET cooperation and innovation. In economic terms, the number of co-cited patents between Chinese and foreign geographical units increase by 10, and the number of domestic inventors who flow out of China increase by nearly 1.4.

Furthermore, we analyze the outflow samples of Chinese patent inventors and categorize them into G7 and non-G7 countries. Our findings reveal that Chinese inventors primarily flow into G7 countries, with the United States being the most preferred destination among the seven countries. Moreover, we observe that technological overlap plays a significant role in promoting the flow of Chinese inventors to Japan and South Korea, but it has no significant impact on the BRICS countries. Overall, the G7 countries, which are the world's major innovation hotspots, are the primary targets of Chinese inventors for ET cooperation, with the United States being China's main partner for international cooperation. This indicates that the two largest economies are committed to promoting international cooperation in ETs and guiding the cross-border flow of innovative talents, thus demonstrating the joint efforts and responsibilities of developed and developing countries in addressing climate change.

The impact of technological overlap on the scale of international cooperation in ETs also exists within China. In Columns (8)–(10) of Table 6, we observe that the inflow of foreign inventors to Shenzhen is significantly promoted by technological overlap, but it did not have the same effect in Beijing and Shanghai. This suggests that Shenzhen is unique in its ability to utilize overseas inventor resources in ETs.

Overall, the results indicate that technological overlap has a positive effect on both the outflow of Chinese inventors (Panel A of Table 6) and the inflow of foreign inventors (Panel B of Table 6). This demonstrates that China has been successful in sending a large number of patent inventors to other countries, while also attracting more foreign inventors. This mutually beneficial relationship creates a win-win situation for all involved.

Interaction effect of spatial agglomeration power on international cooperation

As previously stated, the technological overlap indicator, which is based on co-cited patents, illustrates the knowledge linkage between Chinese and foreign geographical units. Its impact on the international cooperation of patent inventors aligns with the classification effects of spatial agglomeration. However, the bilateral knowledge linkage of geographical units has a wider scope and can be observed in various aspects. This raises the question of whether these different knowledge linkages have a superimposed effect.

Behrens et al.[32] argued that in the exploration of the spatial agglomeration allocation of economic resources discussed in 'new' new economic geography, the traditional agglomeration effects are intertwined with selection effects and classification effects to form a linkage effect. The agglomeration effect is formed by the externalities resulting from the proximity of production factors, while the selection effect is the optimization of local factor resources that results from market competition. Therefore, in the process of ET cooperation, what type of linkage effect will be formed from these factors and technological overlap? To investigate this, we will use an interactive model with the following measurement model:

$$InvCo_{ijt} = \alpha + \beta_1 Overlap_{ijt-3} + \beta_2 M_{ijt} + \beta_3 M_{ijt} \times Overlap_{ijt-3} + FE_{it} + \ FE_{jt} + \ FE_{ij} + \varepsilon_{ijt} \quad (2)$$

	Panel A: outflow of Chinese inventors							Panel B: inflow of foreign inventors		
	All countries	G7	U.S.	G7 excluding U.S.	Non-G7	JK	BRICS	Beijing	Shanghai	Shenzhen
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Overlap_{ijt-3}$	0.142*** (2.80)	0.167*** (2.80)	0.325*** (2.80)	0.079** (2.02)	− 0.006 (− 0.17)	0.088** (1.99)	0.003 (0.12)	− 0.025 (− 0.47)	0.001 (0.11)	0.025*** (3.46)
r2_a	0.433	0.450	0.530	0.244	0.219	0.195	0.442	0.199	0.173	0.363
FE_{it},FE_{jt},FE_{ij}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
FE_t,FE_j	No	No	No	No	No	No	No	Yes	Yes	Yes
N_clust	18,166	5332	1581	3751	12,834	527	4464	586	586	586
N	272,490	79,980	23,715	56,265	192,510	7905	66,960	8790	8790	307,650

Table 6. Comparison of inventor flow in international cooperation.

	All countries	G7	U.S.	G7 excluding U.S.	Non-G7	JK	BRICS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Overlap_{ijt-3}$ $\times InvCo_{ijt-3}$	0.290*** (3.76)	0.314*** (4.08)	0.268*** (5.13)	0.266 (1.02)	– 0.133 (– 0.84)	0.009 (0.07)	0.291** (2.20)
r2_a	0.323	0.326	0.555	0.172	0.319	0.160	0.402
FE_{it},FE_{jt},FE_{ij}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N_clust	18,166	5332	1581	3751	12,834	527	4464
N	272,490	79,980	23,715	56,265	192,510	7905	66,960

Table 7. Interaction effect of the scale of existing inventor cooperation and technological overlap.

	All countries	G7	U.S.	G7 excluding U.S.	Non-G7	JK	BRICS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Overlap_{ijt-3}$ $\times Techadv_{it}$	0.381*** (2.81)	0.451*** (2.92)	0.671*** (3.91)	0.256 (1.64)	– 0.110 (– 1.38)	0.237 (0.89)	0.022 (1.62)
$Overlap_{ijt-3}$ $\times Techadv_{jt}$	0.396*** (2.87)	0.417*** (3.15)	0.603*** (3.02)	0.227** (2.05)	0.225 (0.93)	0.092 (0.28)	0.041** (2.33)
r2_a	0.318	0.321	0.550	0.170	0.320	0.160	0.382
FE_{it},FE_{jt},FE_{ij}	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N_clust	18,166	5332	1581	3751	12,834	527	4464
N	272,490	79,980	23,715	56,265	192,510	7905	66,960

Table 8. Interaction effect of local technological advantages and technological overlap.

Among them, the interactive item of the adjustment variables M_{ijt} and $Overlap_{ijt-3}$ is newly introduced to study the interaction effect of technological overlap and other influencing factors on the scale of international cooperation between Chinese and foreign geographical units.

Interaction effect of the scale of existing inventor cooperation and technological overlap

The cooperation between bilateral patent inventors has created a historical legacy that goes beyond their mutual understanding and connection. It also includes the dissemination of relevant information, such as personal and location data, which spreads through their social network. This spillover effect is amplified by the scale of existing inventor cooperation and their spatial proximity, which helps overcome geographical barriers that can hinder bilateral inventors from finding innovative partners. When inventors look for collaborators with the help of knowledge linkage formed by technological overlap, the agglomeration effect formed by network communication strengthens the influence of the classification effect, which positively forms a linkage effect.

To prove this mechanism, this paper introduces the interactive item $Overlap_{ijt-3}\times InvCo_{ijt-3}$, which shows the interaction effect of agglomeration and classification effects in cross-border inventor flow. As shown in column (1) of Table 7, in all countries' samples, the estimated coefficient of the interactive item $Overlap_{ijt-3}\times InvCo_{ijt-3}$ is significantly positive, which means that the scale of existing inventor cooperation and technological overlap have formed a positive relationship in the process of promoting the bilateral flow of patent inventors. The interaction effect only exists in G7 countries, with a focus on international cooperation between China and the United States. However, it significantly impacts ET cooperation between China and BRICS countries, with no significant impact on the ET cooperation between China, Japan, and South Korea. This result supports our Hypothesis 2a.

Interaction effect of local technological advantages and technological overlap

The local technological advantages reflect the uniqueness of a particular geographical space in terms of innovation environment, resource availability, and allocation efficiency. These factors can be considered as a region's spatial assets[46]. Local technological advantages can also play a significant role in reducing the information asymmetry that often occurs in innovation activities, thus becoming a critical factor in attracting highly-skilled workers.

From the perspective of 'new' new economic geography, the region's technological advantage is the comprehensive performance of local innovation resources after optimal allocation through market competition. Therefore, it serves as a proxy variable for the selection effect. The question remains whether the selection effect, represented by local technological advantages, and the classification effect, represented by technological overlap, will form an interaction effect. To measure local technological advantages, this paper uses the cumulative ranking of inventors participating in ET patents based on geographical units. If a region's cumulative number of inventors participating in ET patents ranks among the top 20% in the world during the same period, the sub-administrative geographic units $Techadv_{it}$ (inside China) and $Techadv_{jt}$ (outside China) are assigned a value of 1; otherwise, they are assigned a value of 0. The paper then introduces the interactive item $Overlap_{ijt-3}\times Techadv_{it}$ and $Overlap_{ijt-3}\times Techadv_{jt}$ in the baseline regression equation.

In Table 8, it is evident that the interaction effect of local technological advantages and technological overlap between Chinese and foreign geographical units has a significant impact on the scale of international cooperation in all countries' samples. Further analysis reveals that this effect is particularly pronounced in China's collaboration with G7 countries, with a focus on international cooperation between China and the United States. Moreover, the technological advantages of geographical units outside China play a crucial role in the selection of international cooperation partners by Chinese patent inventors. As a result, developing countries can leverage the strengths of overseas nations in clean energy and technology to enhance their ET innovation and strengthen R&D collaboration with developed countries. This approach can enable them to tackle climate change, expand cooperation, and address the challenge of climate change. This result supports our Hypothesis 2b.

Conclusion and policy recommendations

International cooperation in green innovation activities is crucial for achieving global coordinated emission reduction. In line with the promotion of green economic growth and energy conservation, China must actively introduce innovative talents from overseas to stimulate more green innovations than ever before. While the literature has explored the impact of international climate agreements on developing and developed countries' cooperation, few studies have delved into the basis of developing countries' participation in international cooperation in ETs. This paper examines the knowledge linkage between "Local Hotspots" as a bridge to attract bilateral innovative talents to international cooperation. By using patent data, we concretize the bilateral knowledge linkage into the technological overlap indicator of Chinese Province-Foreign Country pairs. Based on the 'new' new economic geography framework, we use a high-dimensional fixed effect model to focus on the impact of technological overlap on the scale of international cooperation between Chinese and foreign geographical units in ETs. Our findings show that technological overlap significantly promotes the scale of international cooperation in ETs, with the United States being the most critical partner. Furthermore, we find that the scale of existing inventor cooperation and local technological advantages and technological overlap formed a positive interaction effect that increases the scale of international cooperation, especially between China and G7 countries.

Our study offers practical implications for promoting in-depth cooperation between Chinese and foreign inventors. Firstly, the study finds that the technological overlap reflected in the co-cited patents can be an effective basis for allocating innovative foreign talents in ETs while promoting Chinese patent inventors to participate in global green technology innovation cooperation. This can lead to mutual benefits between developing and developed countries. Secondly, by utilizing information on technological overlap in ETs, targeted cooperation in ETs can be promoted between Chinese and G7 countries' inventors, especially between Chinese and United States inventors, to maximize the benefits of international cooperation.

Although this study provides empirical evidence on the impact of technological overlap on Chinese inventors' participation in cross-border innovative cooperation within the ET sector, we acknowledge that our analysis has its limitations. One limitation is that we solely rely on PCT patent data in the ET sector provided by the OECD to construct our technological overlap indicator. This may result in the technological overlap identified in this study not fully capturing the knowledge relatedness between China and other countries in ET sector. Another limitation is the lack of detailed information on the cited patents, which hinders our ability to explore the influence of the structural characteristics of technological overlap on Chinese inventors' engagement in cross-border innovative cooperation in ETs. Future research could integrate the co-cited patent database with other databases, such as the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), the China National Intellectual Property Administration (CNIPA), and the Japan Patent Office (JPO), to enhance the detailed information available on co-cited patents. Furthermore, attempting to measure codified knowledge relatedness through scientific publications holds significant value.

Data availability

The datasets used and analysed during the current study available from the corresponding author on reasonable request.

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Author contributions

L.J. completed the basic research framework and empirical research of this paper, and wrote the first, third, and fourth chapters. L.JB. wrote the manuscripts for the second and fifth chapters of this paper and was responsible for proofreading the manuscript. All authors reviewed the manuscript.

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Competing interests

The authors declare no competing interests.

Additional information

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