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Impacts of codified knowledge index on the allocation of overseas inventors by emerging countries: evidence from PCT patent activities in China

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Abstract
Based on the backward citation information of patents and the geographical information of inventors, this study constructed an overlap index of highly-cited patent technologies between 31 provinces in mainland China and 49 foreign countries (or regions) with active PCT patent inventors (1998–2017), in order to depict the bilateral codified knowledge relatedness index. It further investigates its impact on the scale of allocation of overseas inventors by Chinese patent activities. According to the results, the codified knowledge relatedness significantly increased the scale of overseas patent inventors imported to China, that is, for every 1000 patents added in the technological overlap of highly-cited patents, the number of local inventors introduced from foreign countries (or regions) to local high-quality patent activities in China increased by 14, and this effect is mainly concentrated in the active innovation areas around the world. Further study showed that the impact of the bilateral tacit knowledge linkage on the allocation of overseas inventors with the codified knowledge relatedness was substitutive, and this substitutability decreased with the improved quality of innovation activities.

Keywords Codified knowledge relatedness · Technological overlap · Patents · Overseas inventors

JEL Classification F43 · O15 · O32 · O53

Introduction

The global innovation network, which is led by multinational companies in Europe and the United States, has formed the characteristics of "Local Hotspot, Global Networks" (WIPO, 2019),[1] which guides the flow of global innovation resources. Europe and the United States

[1] The report of the World Intellectual Property Organization (WIPO) in 2019 noted that the geocoding data provided by millions of patent inventors and authors of scientific publications described to the world the remarkable characteristics of the global innovation geographical map in recent years: "Local Hotspot,

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are the leaders of the current global innovation network and the global innovation resource allocation competition, with particularly prominent positions in attracting overseas high-skilled laborers. For example, the United States and Switzerland are the largest net importers of high-skilled immigrants, with a considerable proportion from emerging countries, such as China and India (Kerr et al., 2016). At the same time, during the continuous extension and reshaping of the international innovation network, the innovation strength of emerging countries represented by BRICS has been greatly improved (Kogler et al., 2017; Lee et al., 2019; WIPO, 2020) and has gradually become a new important node in the global innovation network.[2] During this process, the allocation of overseas innovation resources based on the global innovation network, especially high-end technical talents, is an important approach for emerging countries to consolidate their independent innovation strength. As shown in Fig. 1, since the beginning of the twenty-first century, with the expansion of the global innovation network, the cross-border joint R&D cooperation between BRICS countries and G7 countries has been rapidly deepened, and the scale of PCT patents jointly developed by countries from both parties have increased from 31,000 (2001 to 2010) to 73,000 (2011 to 2017). Specifically, the cross-border cooperation patents between China and G7 countries have increased from 15,000 to 51,000 during the same period, which makes China a representative case of global emerging countries in allocating overseas innovation resources. Different from the "siphon effect" of traditional innovation highlands, such as Europe and the United States, on global innovative talents through long-term accumulated innovation strength and reputation, the micro basis for emerging countries to attract overseas high-end technical talents is a topic worth exploring. In view of China's outstanding performance in global innovation activities, this study focused on China's allocation of overseas innovation talents.

Current studies focusing on cross-border innovation talent flows are based on the perspectives of agglomeration effects and spillover effects, which explain why the traditional innovation highlands such as OECD countries, which constitute less than a fifth of the world's population, could host two-thirds of high-skilled migrants (Artuç et al., 2015; Kerr et al., 2016). Relevant studies indicate that traditional innovation highlands attract high-skilled laborers based on selection effects (Combes et al., 2012) with high monetary or non-monetary benefits (Davis & Dingel, 2020; Kerr & Kerr, 2018). Meanwhile, the highly skilled laborers choose to agglomerate to traditional innovation highlands, which are characterized by high innovation activity and high knowledge spillovers, based on their own comparative advantages in absorptive capacity (Cohen & Levinthal, 1990) and their capacity to internalize knowledge spillovers (Davis & Dingel, 2019). However, for emerging countries, neither the skill premium provided by productivity advantage, nor the knowledge spillover provided by agglomeration of innovation activities, can be compared to traditional innovation highlands. Obviously, current theories based on agglomeration and selection effects are not applicable to explaining why the emerging countries (such as BRICS countries), which are not advantaged in terms of both agglomeration and skill premiums, can accelerate the cross-border acquisition of highly skilled inventors from the traditional innovation highlands (such as G7 countries). Therefore,

Footnote 1 (continued)

Global Networks" with a slight sense of disobedience, that is, knowledge creation is highly concentrated in a few regional hotspot cities, but it is spreading to the wider international community.

[2] For example, Shenzhen-Hong Kong-Guangzhou, Beijing, and Shanghai in China have already entered the top ten of the top 10 global innovation clusters (WIPO, 2020).

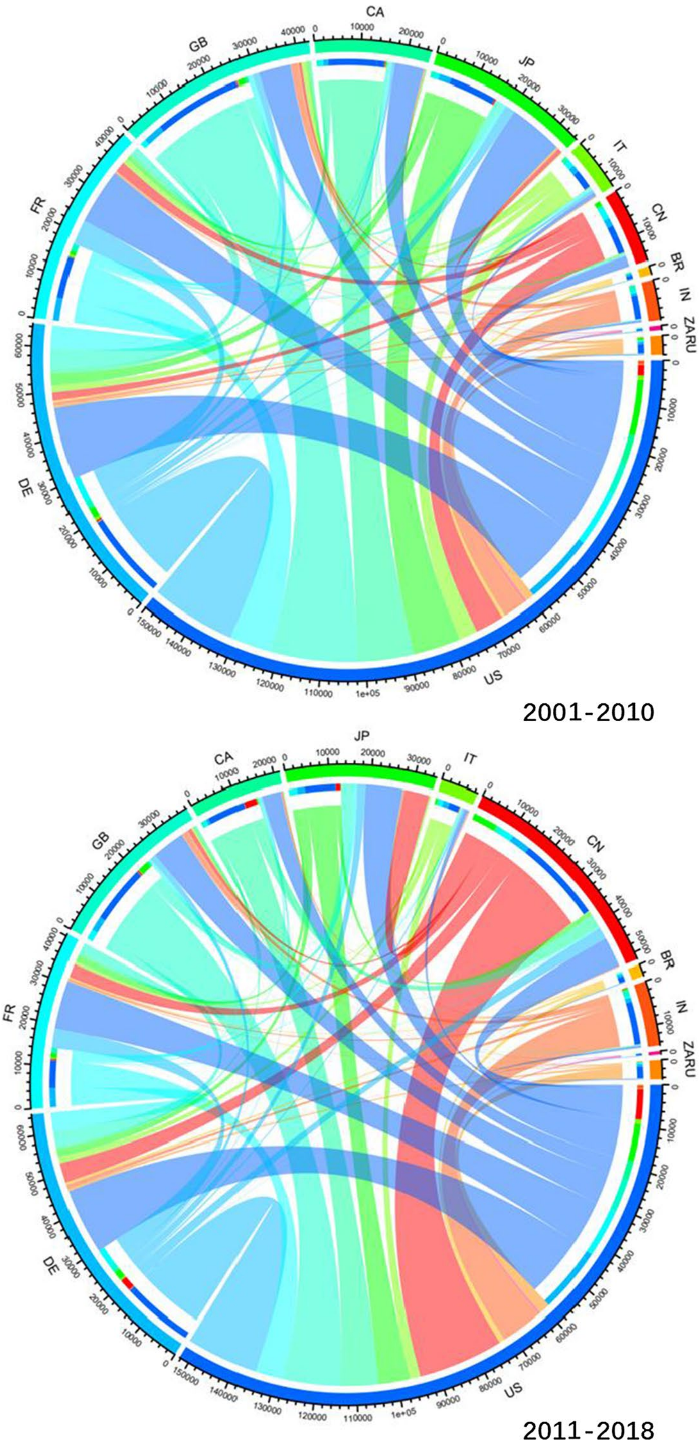

Fig. 1 Evolution of R&D collaboration between G7 and BRICS from 2001 to 2017

this study intended to explain how emerging countries acquire highly-skilled foreign talents (especially from the traditional innovation highlands) based on the perspective of knowledge relatedness.

Different from tacit knowledge, with the help of revolutionary communication technology, codified knowledge expressed in the form of academic journals and patents spread with unprecedented breadth, depth, and speed around the world. When they are learned, mastered and internalized by scientific and technical workers scattered around the world, they potentially become a professional "common language" for innovative personnel to exchange. Obviously, the higher the overlap degree of internalized codified knowledge among innovative personnel, the more professional the "common language" between them, which enhances the possibility of building innovative teams. During the gradual diffusion of the global innovation network, the widespread dissemination of such codified knowledge promotes the knowledge relatedness among nodes of the innovation network to be gradually strengthened, thus, creating conditions for the increased flow and cooperation of talents among such networks. Therefore, this study regarded codified knowledge as the microscopic basis for the allocation of overseas inventors by emerging countries. According to existing empirical studies, the technological overlap, which was often constructed based on patent citation data, can be regarded as codified knowledge relatedness among innovation subjects (Bena & Li, 2014; Sears & Hoetker, 2014). Moreover, from the perspective of space, the matching effect of knowledge relatedness on cross-border innovation teams is also in line with the sorting effect (Gaubert, 2018), which leads to the spatial agglomeration of resources in new economic geography. Therefore, combined with the spatial spillover characteristics of knowledge, this study constructed the technological overlap index of the geospatial dimension, as based on patent data. The bilateral codified knowledge relatedness between China and other parts of the world was drawn and presented, then, its impact on China's allocation of overseas patent inventors and its spatial heterogeneity was investigated. In addition, a large number of studies have emphasized the prominent role of tacit knowledge in innovation activities (Lecuona & Reitzig, 2014). Hence the question, does tacit knowledge play a moderating role in the process of attracting overseas inventors through the codified knowledge relatedness?

There are two main aspects of the marginal contribution of this paper. First, based on microdata at the patent level, a technological overlap index between 31 provinces in mainland China and 49 foreign geographical units (countries or regions) with active PCT patent inventors was measured in this study for the first time. The co-cited patents were used to present the bilateral codified knowledge relatedness among innovation nodes, and its impact on China's attraction of overseas patent inventors was investigated to provide new evidence and insights into how global emerging innovation nodes attract cross-border innovative talents. Second, this study measured the bilateral tacit knowledge linkage between China and foreign regions using the number of patent inventors flowing into different regions of China from overseas R&D partners. Then, this study investigated its moderating role in the process of allocating overseas inventors through the codified knowledge relatedness to provide evidence for the interactive effect between tacit knowledge and codified knowledge in the process of allocating cross-border innovation resources.

Literature review and research hypotheses

Technological overlap, also known as knowledge base overlap, refers to the overlap degree of the existing knowledge of two invention subjects at a certain time point and focuses on discussing the knowledge relatedness between innovation subjects from the perspective of commonness. A patent is a typical product of knowledge codification, and its citation information provides the flow footprint of related codified knowledge (Alcacer & Gittelman, 2006; Jaffe et al., 1993). Due to the improved availability of patent data by electronization, the technological overlap index has been constructed in many studies based on the same backward citation patent information, as found in the patent applications of two invention subjects (such as two enterprises). Thus, as the existing knowledge relatedness (Bena & Li, 2014; Sears & Hoetker, 2014) between invention subjects can be measured, technological overlaps can be used to measure the codified knowledge relatedness index between invention subjects.

According to relevant studies, the higher the overlap degree of existing codified knowledge among innovation subjects, the more familiar they are with relevant technologies and knowledge. This helps to alleviate the frictions and troubles caused by information asymmetry in the establishment of innovation teams (such as searching and matching both parties in mergers and acquisitions) and the post-establishment innovation activities (such as understanding and using external technologies or knowledge). Therefore, this concept is often discussed in studies of enterprises' behavior in acquiring external knowledge resources (such as technology mergers, acquisitions, and R&D alliances) (Ahuja & Katila, 2001; Kapoor & Lim, 2007; Makri et al., 2010; Sears & Hoetker, 2014). In addition, studies on corporate banking held that the overlap of existing codified knowledge also contributes to the formation of economies of scale of innovation resources after mergers and acquisitions (Bena & Li, 2014).

Meanwhile, some existing studies also focused on the impact of technological overlap on the internalization of external knowledge activities by innovation subjects. While Chesbrough (2003) noted that the R&D innovation activities of R&D subjects, such as enterprises presenting a trend of openness innovation, the internalization of external ideas or knowledge is not an automatic or free process. According to Cassiman and Colombo (2006), the essential purpose of technology-driven mergers and acquisitions is to coordinate internal and external technical resources to enhance innovation output. Both Ahuja and Katila (2001) and Bena and Li (2014) noted that the correlation between external knowledge acquired by R&D subjects through mergers and acquisitions, as well as their existing codified knowledge (i.e., technological overlap), can affect the quantity and quality of innovation output after acquiring external knowledge resources.

Generally speaking, as a measure of the bilateral codified knowledge relatedness, the mechanism of technological overlap affecting innovation activities mainly includes the following aspects. First, a technological overlap helps to alleviate the frictions caused by information asymmetry in the process of collaboration between internal knowledge and external knowledge. According to Graebner et al. (2010), technological overlap helps to improve the absorptive capacity of enterprises (Cohen & Levinthal, 1990) and reduces the barriers for enterprises to understand and use external knowledge resources. According to Kavusan et al. (2016), the higher the technological overlap, the more similar the innovation activity paradigms of all parties in the innovation alliance, which is conducive to the understanding and use of external knowledge by all parties, and further conducive to the smooth development of R&D cooperation. According to Bena and Li (2014), technological overlap helps buyers identify and discover the actual value of knowledge and technical resources. In this way, the search and match efficiency in the mergers and acquisitions market can be improved, and the related transactions can be promoted. Second, technological overlap helps to form economies of scale and the scope of innovation resources. According to Henderson and Cockburn (1996), since a technological overlap is the intersection of the existing knowledge of both parties, mergers and acquisitions help to preserve innovation resources, thus, forming economies of scale; or this knowledge can be used more widely to form economies of scale. Third, technological overlap helps to specialize innovation activities. In order to make more effective use of the surplus innovation resources, as derived from technological overlap, both parties of the innovation cooperation will reconfigure the combined innovation resources, and then, promote R&D activities in the technical field where they have advantages, thus, enhancing their specialization level (Cassiman & Colombo, 2006).

However, technological overlaps may also push the resistance and costs of internalizing the external knowledge of innovation subjects. Sears and Hoetker (2014) noted that a technological overlap may cause knowledge redundancy among R&D subjects, which will increase the cost and difficulty of effectively identifying each party's high-value knowledge; therefore, the excessive expansion of technological overlap may have a negative impact on the effect of the internalization of external knowledge by innovation subjects. According to Kavusan et al. (2016), the internalization effect of technological overlap on external knowledge presents an inverted U-shaped relationship, which is in conformity with the viewpoint of Sears and Hoetker (2014). Therefore, compared with the technological overlap constituted by high-value patents, the expansion of technological overlap constituted by general-value patents is not entirely beneficial for enterprises to search and identify external innovation human resources. As highly-cited patents are widely used as background knowledge sources for R&D subjects, they have wider recognition and deeper understanding among R&D groups, and thus, have a more significant impact in alleviating any inconsistencies caused by information asymmetry during R&D cooperation. Therefore, this study focused on the structural features of technological overlap, constructed corresponding technological overlap indicators based on highly-cited patents and non-highly-cited patents, and compared the impact of the two on the allocation of cross-border inventor resources.

High-quality innovation activities usually require innovative talents with higher skill levels, and such talents are highly irreplaceable. However, enterprises seeking external innovation resources may find it difficult to obtain suitable high-end technical talents locally, which is particularly obvious for emerging countries due to their relatively weak reserve of high-end technical talents. Therefore, in order to carry out high-quality innovation activities, emerging countries must expand their search scope of external inventor resources (Ahuja & Katila, 2004; Katila & Ahuja, 2002), and rely more on introducing them from global innovation hotspots. Meanwhile, more complex and cutting-edge knowledge must be invested in high-quality innovation activities (Akcigit et al., 2016), which leads to more serious information asymmetry in innovation teams carrying out such high-quality innovation activities (Wuchty et al., 2007). Therefore, in order to build effective cross-border innovation teams, bilateral codified knowledge relatedness can play a greater role in alleviating the impact of information asymmetry.

This study puts forward the following hypothesis:

H1 The technological overlap of highly-cited patent technologies can promote the scale of the introduction of overseas inventors to the high-quality R&D activities of emerging countries

In addition to codified knowledge, tacit knowledge also plays an important role in innovation activities. During the allocation of cross-border inventor resources with technological overlap, the tacit knowledge linkage (Latilla et al., 2018) can enrich the diversity of the cognitive dimensions among innovation team members (Nonaka & Krogh, 2009), thereby directly enhancing the team's creativity potential (Hoever et al., 2012; Kurtzberg, 2005). Moreover, in addition to transmitting the uncodified frontier knowledge in the technical dimension, the tacit knowledge linkage can affect the unique innovation behavior of R&D subjects through the cognitive dimension (Nonaka & Krogh, 2009). However, due to its abstractness and inexpressiveness, tacit knowledge is difficult to be codified, or it cannot be codified or disseminated in a timely manner due to its excessive advance. Therefore, the communication and sharing of tacit knowledge usually require face-to-face communication between people, meaning it relies more on those who participate in innovative activities (Dhanaraj et al., 2004), such as direct peer-to-peer interaction in private social networks (Lecuona & Reitzig, 2014).

During the innovation activities carried out using the codified knowledge contained in knowledge documents, innovation personnel must decode such knowledge documents. On one hand, the redundant knowledge (Sears & Hoetker, 2014), which is irrelevant to the theme of the current innovation activities in the codified knowledge search, is screened to eliminate its interference. On the other hand, when codifying the knowledge, distorted information can be restored (Arora et al., 2018; Roach & Cohen, 2013), and such factors will restrict the utilization efficiency of codified knowledge by the innovation team. However, during this process, the tacit knowledge possessed by innovation participants will play a reasonable role in interpreting relevant codified knowledge, thus, alleviating this restriction. Therefore, in an environment where emerging countries attract overseas innovative talents, tacit knowledge may enhance the attraction of codified knowledge to overseas inventors. Meanwhile, when the tacit knowledge attached to overseas inventors has a strong impact on the interpretation of codified knowledge, the role of codified knowledge in alleviating information asymmetry may be replaced, thus, the attraction of codified knowledge to overseas inventors may be weakened.

This study puts forward the following hypothesis:

H2 In the process of attracting overseas innovative talents from emerging countries, the tacit knowledge linkage plays a moderating role in the allocation effect of overseas patent inventors by the codified knowledge relatedness.

To summarize the above research hypotheses, the model framework of this study is shown in Fig. 2.

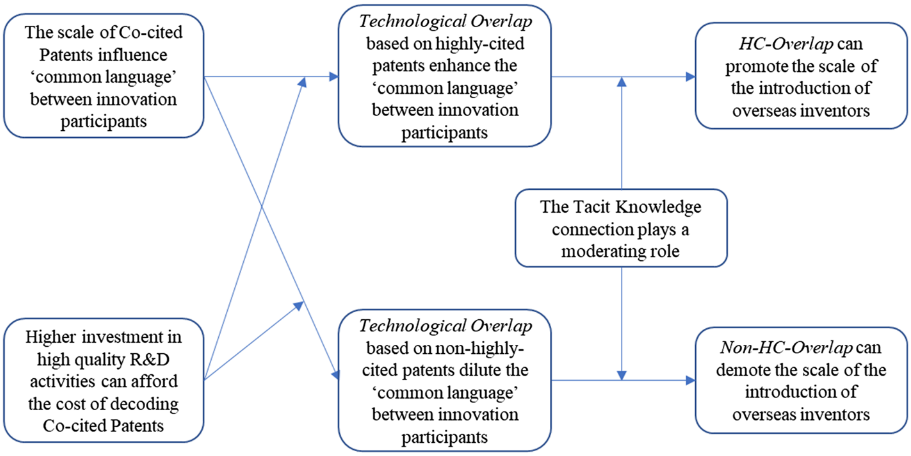

Fig. 2 Theoretical model of the main hypotheses

Data source, variable construction, and model setting

Data source and variable construction

The data used in this study came from two patent databases,[3] REGPAT and Citations, as compiled by the Organization for Economic Cooperation and Development (OECD), in which REGPAT provides the geographical location of patent inventors at the NUTS2 level, while Citations provides the forward- and backward-citation information of patents.

The key explanatory variable in this study is the technological overlap ($HC\_Overlap_{ijt}$), based on highly-cited patents, where subscript i represents provinces in mainland China, j represents foreign geographical units (countries or regions), and t represents the year of the territory. The specific construction steps are, as follows. First, according to the Citations database, all backward citation patents in the global PCT patent citation database were grouped according to priority years, and the patents cited in the top 10% in each priority year were defined as Highly-cited Patents, while other patents were regarded as Non-Highly-cited Patents. Second, according to the geographical information of PCT patent inventors, as published in the REGPAT database from 1998 to 2017, this study selected 31 provincial administrative regions in mainland China (hereinafter referred to as provinces) and 49 foreign countries or regions with active PCT patent inventors (hereinafter referred to as countries) as the geographical research units, in order to construct 1519 Chinese province-foreign country pairs to build the technological overlap index. Finally, this study took 31 Chinese provinces and 49 foreign countries as the geographical units, respectively, and the backward citations of the patents of the geographical units, as identified in period t,[4] were summed up as the knowledge source database of the geographical unit. Then, the

[3] The impact of relevant policy tools on private R&D in European Union region was investigated using REGPAT in Egger & Loumeau (2018).

[4] In order to smooth the process, each index was constructed in the benchmark regression with a period of three years, and rolling calculation was carried out.

co-cited patents of each Chinese province-foreign country pair were further extracted,[5] and the numbers of Highly-cited Patents and Non-Highly-cited Patents were calculated, respectively, in order to extract the key explanatory variable $HC\text{-}Overlap_{ijt}$ and the control variable $Non\text{-}HC\_Overlap_{ijt.}$

The dependent variable is the scale of the introduction of overseas inventors to China's provincial high-quality patent activities ($InvImportHQ_{ijt}$).[6] The construction steps of this variable are, as follows. First, this study constructed a patent width index for all PCT patents from 1998 to 2017 using the method inAkcigit et al. (2016),[7] and then, the patents were grouped according to priority years, that is, the patents with the same priority years were merged into the same group. The patents ranked in the top 10% of the patent width index in each group were defined as high-quality patents, while others were attributed to non-high-quality patents. Second, the scales of overseas inventors in high-quality patents belonging to 1519 Chinese Province-Foreign Country pairs were calculated, respectively. Specifically, in this study, based on the geographical information of patent inventors, as provided by REGPAT, the patents containing at least one applicant in China were identified from the high-quality patent database, and then, the number of inventors of foreign geographical units in this patent was summed up individually, which was regarded as the inflow scale[8] of overseas inventors to Chinese Province-Foreign Country pairs.

Other control variables in this study include the inflow scale of overseas inventors ($InvImport_{ijt-3}$) and the outflow scale of domestic inventors ($InvExport_{ijt-3}$)[9] in the previous observation period (lag by one standard observation period consider as three years), which were used to control the flow intensity of brain gain and brain drain between Chinese provinces and foreign countries (or regions); the similarity of the technical structure

5 Fig. 4 in the appendix shows a detailed description of the construction of the technological overlap index. In addition, of note in this study, the technological overlap index was only extracted based on non-cooperative patents (that is, excluding the patents of inventors from Chinese and foreign geographic unit pairs), to alleviate the endogenous errors caused by reverse causality in the regression analysis.

6 In view of the fact that the applicant is usually the owner of the intellectual property contained in the patent, the non-Chinese inventor in a patent including at least one Chinese applicant is considered in this study as the inflow of foreign inventors in China. Similarly, Chinese inventors in a patent with at least one non-Chinese applicant is considered as the outflow of domestic inventors in China.

7 A patent serves as an important carrier of innovation knowledge. The complexity of its knowledge can directly reflect the content of knowledge created by innovation behavior itself, and provide patent holders with higher monopoly power of innovation products to realize the commercial value of the patent by improving the difficulty of competitors' imitation and improvement under the patent protection system. Therefore, patent knowledge width, which can reflect the complexity and extensiveness of patent knowledge, is an ideal index to measure patent quality (Akcigit et al.,2016). The specific calculation method is $Quality = (1\text{-}HHI)$, where HHI is the Herfindal-Hirschman index of the IPC number of the patent, which distributes the weight at each Group level.

8 For example, suppose a patent had at least one applicant from Beijing, and three of the four inventors from the United States and one from Japan. In this study, the scale of *InvImport* obtained by Beijing from the United States was calculated as 3 person-times, and the scale of *InvImport* obtained by Beijing from Japan was calculated as 1 person-time. In the following robustness test, other methods were used to measure the scale of *InvImport* in this study.

9 The variable *InvExportij* measures the outflow of domestic inventors, which form Chinese province *i* to foreign country *j* as Brain Drain. For example, suppose a patent had at least one applicant from the United States, and four inventors from China (three from Beijing and one from Shenzhen). In this study, the scale of *InvExport* obtained by the United States from Beijing was calculated as 3 person-times, and the scale of *InvExport* obtained by the United States from Shenzhen was calculated as 1 person-time.

Table 1 Statistical characteristics of cross-border R&D cooperation scale and technological overlap samples of Chinese and foreign geographical unit pairs

Explanatory variable	$InvImportHQ_{ijt}$				
	Obs	Mean	Std. Dev	Min	Max
From All Countries	22,785	0.143	2.049	0	114
From G7	3255	0.782	5.209	0	114
From Non-G7	19,530	0.037	0.547	0	33
Explained Variable	$HC\text{-}Overlap_{ijt-3}$				
	Obs	Mean	Std. Dev	Min	Max
From All Countries	22,785	13.729	116.182	0	5151
From G7	3255	60.022	285.547	0	5151
From Non-G7	19,530	6.013	41.777	0	1314

OECD REGPAT database, OECD Citations database. Unless otherwise specified, the same is below

of Chinese and foreign geographical unit pairs (Co_tech_{ijt})[10] was used to control the correlation between the technical fields of bilateral innovation activities (Jiang et al., 2017).

Model setting

To test the abovementioned hypotheses, this study set the benchmark measurement equation,[11] as follows:

$$Inv\,Import\,HQ_{ijt} = \alpha + \beta_1 HC - Overlap_{ijt-3} + \beta_2 NC- Overlap_{ijt-3} + X\eta + FE_{it} + FE_{jt} + FE_{ij} + \varepsilon_{ijt} \tag{1}$$

where, the dependent variable is the scale of the introduction of high-quality patent activities to China's province i from foreign country j in t period; the key dependent variable is the technological overlap $HC{-}Overlap_{ijt-3}$ constructed based on highly-cited patents by Chinese and foreign geographical unit pairs in t-3 period. In addition to technological overlap $Overlap_{ijt-3}$, as constructed based on non-highly-cited patents in t-3 period, the control variable X also includes $InvImport_{ijt-3}$ and $InvExport_{ijt-3}$ in t-3 period and Co_tech_{ijt} in t period. To better control the errors caused by missing variables, the estimation equation introduces the joint fixed effect FE_{it} of provinces in mainland China and years, the joint fixed effect FE_{jt} of foreign countries (or regions) and years, and the fixed effect FE_{ij} of Chinese and foreign geographical unit pairs.

[10] In this study, the Pearson correlation coefficient of patent activities in 35 technical fields in each observation period of 1519 Chinese and foreign geographical unit pairs was calculated using the comparison table of patent IPC and technical fields set by WIPO, which was used as the proxy variable of similarity of innovation activities in technical fields of Chinese and foreign geographical unit pairs. For specific comparison table of patent IPC and technical fields, see https://www.wipo.int/meetings/en/doc_details.jsp?Doc_id=117672 (retrieval date: March 12, 2021).

[11] To alleviate endogenous bias, we lag our explanatory variable by one standard observation period (three years). In the robustness tests, we also used different lengths of observation periods to extract the those variables, and adjusted the lag lengths of the corresponding variables according to the lengths of the observation periods.

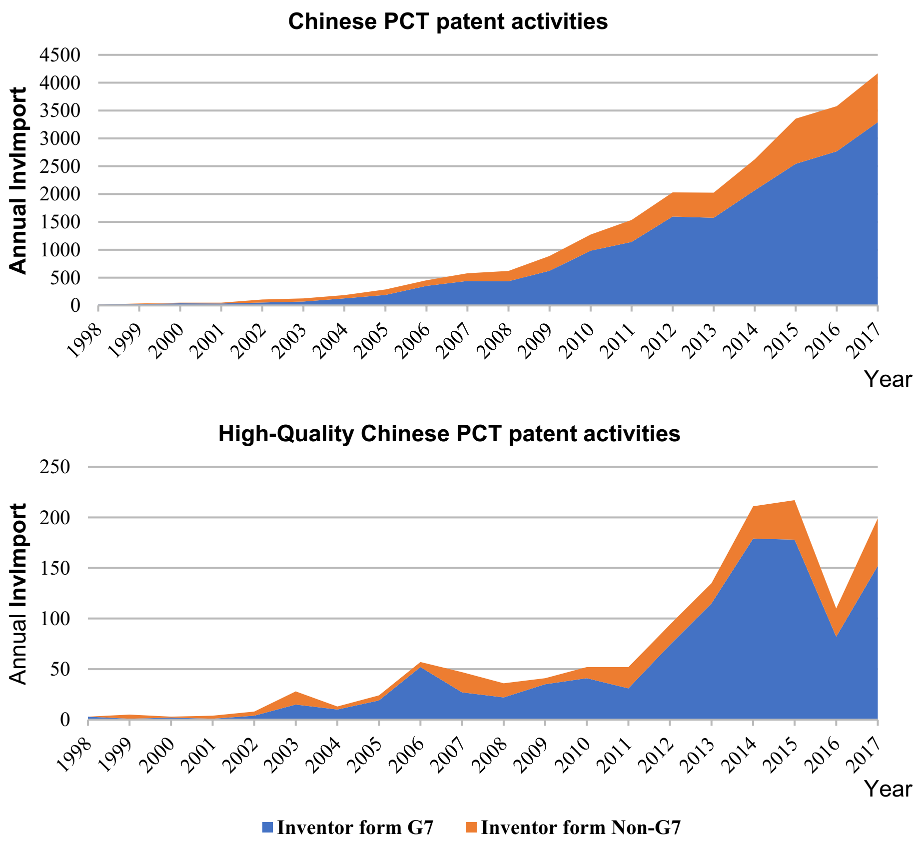

Fig. 3 Annual inventor import of PCT patents introduced to China from 1998 to 2017

Descriptive statistics

As shown in Table 1, the overseas inventors imported to China were mainly concentrated in G7 countries, and the average technological overlap of highly cited patent technologies in Chinese province-G7 country pairs exceeded 60 patents, while the index of Chinese province-non-G7 country pairs was only six patents.

From 1998 to 2017, the annual total scale of the inflow of foreign inventors to Chinese PCT patent activities maintained steady growth, with an average annual growth rate of over 30%, while the annual scale of the inflow of foreign inventors to Chinese high-quality PCT patent activities expanded rapidly from 2011, and then, quadrupled in two years. In addition, whether at the overall level or the high-quality innovation activity level, more than 75% of the inventor resources, as introduced by applicants-led PCT patent activities in China, came from G7 countries (as shown in Fig. 3).

Table 2 Introduction of overseas inventors to high-quality innovation activities promoted by overlap of highly-cited patents

Explained Variable	$InvImport_{ijt}$				$InvImportHQ_{ijt}$	$InvImportNQ_{ijt}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Overlap_{ijt-3}$	0.179***	0.158**	0.01			
	(2.80)	(2.48)	(0.17)			
$HC\text{-}Overlap_{ijt-3}$				0.041	0.014**	0.027
				(0.74)	(1.96)	(0.51)
$Non\text{-}HC\text{-}Overlap_{ijt-3}$				−0.23	−0.048**	−0.138
				(−0.67)	(−2.16)	(−0.40)
$InvImport_{ijt-3}$			1.386***	1.452***	0.040**	1.412***
			(4.55)	(4.06)	(2.09)	(4.04)
$InvExport_{ijt-3}$			−0.078	−0.088	−0.004	−0.087
			(−0.91)	(−1.12)	(−1.18)	(−1.13)
Co_tech_{ijt-3}			2.451	2.681	0.233	2.424
			(0.99)	(1.05)	(1.61)	(0.98)
FE_t, FE_i, FE_j	Yes					
$FE_{it}, FE_{jt}, FE_{ij}$		Yes	Yes	Yes	Yes	Yes
N_clust	31	1519	1519	1519	1519	1519
adj. R^2	0.368	0.585	0.802	0.803	0.63	0.809
N	22,785	22,785	22,785	22,785	22,785	22,785

All standard errors were the clustering standard errors between Chinese and foreign geographical units

$^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

Basic results and discussion

Benchmark results and explanation

Table 2 shows the benchmark regression results. First, column (1) of Table 2 only introduces the technological overlap ($Overlap_{ijt-3}$) of Chinese and foreign geographical unit pairs extracted, as based on the full reference database. In addition, in order to control the specific impact of the spatio-temporal dimension, the fixed effect of common years and geographical units was also introduced. According to the results, the estimated coefficient of $InvImport_{ijt}$ of the $Overlap_{ijt-3}$ pair was positive and significant at the level of 1%. To alleviate the estimation errors caused by missing variables, this study introduced the joint fixed effect of geographical units and years (FE_{it} and FE_{jt}) and the fixed effect of Chinese and foreign geographical unit pairs (FE_{ij}). The first two fixed effects help to control the affecting factors of the changes of Chinese and foreign geographical units over the years, such as the scale of patent inventors of each geographical unit over the years. Meanwhile, the last fixed effect could control the impact of the specific connection or relatedness between Chinese and foreign geographical units, such as the personnel flow cost due to the bilateral spatial distance. As shown in column (2), the adjusted R2 increased from 0.368 to 0.585, and up to 58.9%, which shows the rationality and effect of introducing the above fixed factors on relieving missing variables. Meanwhile, the estimated coefficient of $Overlap_{ijt-3}$ decreased to 0.158 but was still significant at 5%. Worthy of note, the inflow scale of foreign inventors ($InvImport_{ijt-3}$), the outflow scale of domestic inventors ($InvExport_{ijt-3}$) of both parties in the previous period, and the technical structure similarity index (Co_tech_{ijt-3}) of the innovation activities of Chinese and foreign geographical unit pairs were constructed based on the subdivision of technical fields and introduced into the equation as control variables. The third column shows that although the adjusted R^2 further increased from 0.585 to 0.802, which is up more than 37%, the estimated coefficient of the dependent variable $Overlap_{ijt-3}$ was no longer significant, while the coefficient of the control variable $InvImport_{ijt-3}$ was significant at 1%. These results mean that, at the overall level, Chinese innovation subjects were more inclined to attract overseas inventors from the same region by relying on the relationships with existing overseas inventors and utilizing the spatial agglomeration effect to allocate overseas inventor resources.

As highly-cited patents are widely used as the background knowledge sources of R&D subjects, they have a more significant effect in alleviating friction during R&D cooperation, thus, the dependent variable $Overlap_{ijt-3}$ was decomposed into $HC\_Overlap_{ijt-3}$ and $Non\text{-}HC\_Overlap_{ijt-3}$ in column (4). This study regarded the new estimation equation, $HC\_Overlap_{ijt-3}$ as the key dependent variable, and $Non\text{-}HC\_Overlap_{ijt-3}$ was used to control the knowledge redundancy caused by the technological overlap of non-highly-cited patents. According to the results, the coefficient of $HC\_Overlap_{ijt-3}$ was still not significant.

As mentioned above, the impact of the technological overlap of highly-cited patents on attracting overseas inventors to emerging countries was heterogeneous, thus, this study further divided the samples according to patent quality. Column (5) and column (6) represent the scale of overseas inventors of high-quality innovation patents ($InvImportHQ_{ijt}$) and non-high-quality patents ($InvImportNQ_{ijt}$), respectively. According to the results, the coefficient of the key dependent variable $HC\text{-}Overlap_{ijt-3}$ was significantly positive at the level of 5% in column (5), but not significant in column (6). This result means that the technological overlap of highly-cited patents significantly increased the inflow scale of overseas inventors; however, this effect only occurred in high-quality patent activities. The results support H1. In addition, worthy of note, the estimated coefficient of the control variable $InvImport_{ijt-3}$ in column (5) was obviously smaller than that in column (6), and while the self-accumulation of the inflow scale of overseas inventors had a significant impact on both high-quality and non-high-quality patent activities, it was stronger in non-high-quality patent activities.

Therefore, column (5) was taken as the benchmark estimate in this study, which means that for every 1000 more highly-cited patents in the co-cited patent database between Chinese and foreign geographical units, the number of overseas inventors participating in high-quality patent activities introduced from corresponding regions to Chinese provinces would increase by 14. Unlike current studies that explain the agglomeration of highly skilled laborers to traditional innovation highlands in terms of a premium for monetary and non-monetary benefits (Davis & Dingel, 2020; Kerr & Kerr, 2018), we find that the codified knowledge relatedness, as measured by technological overlap, is also a significant factor for emerging countries, such as China, to allocate foreign innovative talents, such as inventors.

Table 3 Robustness test

	Panel A			Panel B	Panel C	Panel D
	2 years	4 years	5 years	PPML	Patnum	nuts2
	(1)	(2)	(3)	(4)	(5)	(6)
$HC\text{-}Overlap_{ijt-2}$	0.009*					
	(1.82)					
$HC\text{-}Overlap_{ijt-3}$				0.001**	0.004**	0.005***
				(2.13)	(2.31)	(3.51)
$HC\text{-}Overlap_{ijt-4}$		0.014**				
		(2.21)				
$HC\text{-}Overlap_{ijt-5}$			0.013**			
			(2.23)			
$FE_{it}, FE_{jt}, FE_{ij}$	Yes	Yes	Yes	Yes	Yes	Yes
N_clust	1519	1519	1519	92	1519	18,166
adj. R^2	0.54	0.662	0.69		0.715	0.503
P. R^2				0.755		
N	24,304	21,266	19,747	977	22,785	272,490

We adjusted the lag lengths of the explanatory variable and control variables according to the lengths of the observation periods in Panel A; all standard errors were the clustering standard errors between Chinese and foreign geographical units

*$p<0.1$, **$p<0.05$, ***$p<0.01$

Robustness test

Robustness test 1

The length of the observation period was changed. In order to test the potential impact of fluctuation of the observation period on the regression results, this study further provided the results from observation periods of 2/4/5 years. Specifically, the key independent variable and the dependent variables were adjusted according to the length of the observation period. According to the estimation results given by Panel A in Table 3, the estimation coefficient of $HC\text{-}Overlap_{ijt-2}$ was significantly positive at 10%, and the estimation coefficient of $HC\text{-}Overlap_{ijt-4}$ and $HC\text{-}Overlap_{ijt-5}$ was significantly positive at 5%.

Robustness test 2

Different regression methods were used. Since innovation activities were highly concentrated at the geographical level, and knowledge spillover itself had highly regional characteristics, the variable of the inflow scale of overseas inventors to the high-quality patent activities constructed in this study was positive and had many zero values. Therefore, Poisson Pseudo-Maximum Likelihood Estimation (PPML) was used to re-test the benchmark regression model. According to the PPML estimation results given by Panel B in Table 3, the estimation coefficient of $HC\text{-}Overlap_{ijt-3}$ was still significantly positive at 5%.

Robustness test 3

The construction method of the inflow scale of overseas inventors was replaced. With reference to the construction method of Lee et al. (2019), this study measured the inflow scale of overseas inventors to high-quality patent activities according to the number of high-quality patent achievements,[12] and the estimation results are given in Panel C of Table 3. While the estimation coefficient of $HC\text{-}Overlap_{ijt-3}$ decreased to 0.004, it was still significant, meaning that when the number of co-cited high-quality patents of Chinese and foreign geographic units increased by 1,000, the number of cooperative patents of Chinese and overseas inventors could increase by nearly 4.

Robustness test 4

The geographical unit level was changed. In order to measure whether the benchmark regression results were still stable at the smaller geographical unit level, this study recorded 586 foreign NUTS2-level geographical units[13] with PCT patent activity from 49 foreign countries (or regions), which were further refined and identified, then, 18,166 Chinese and foreign province pairs were constructed on this basis, and the corresponding variables were recalculated. According to the estimation results given by Panel D in Table 3, even in NUTS2, which is a smaller geographical space, the estimation coefficient of $HC\text{-}Overlap_{ijt-3}$ was still significantly positive at 1%.

Overall, the estimation results of the correlation robustness test are consistent with those of the benchmark regression.

Heterogeneity analysis

With China's increasing economic strength and the transformation of high-quality growth pushed by the government, innovation has become the first driving force for development, and the purpose, methods, and partners of China's global intelligence introduction are increasingly diversified. Olechnicka et al. (2019) held that the innovation policies formulated by the Chinese government especially encourage international scientific research cooperation, among which the United States and Taiwan are the largest partners (Zheng et al., 2012). Zhou and Glänzel (2010) focused on scientific publications and held that the number of times of international cooperation between China and scientific and technical workers in the European Union and North America was gradually increasing, whereas that with emerging countries (such as Brazil and Turkey) was declining.

In order to investigate the spatial heterogeneity of the attraction of technological overlap to overseas inventors in the dimension of inventors' source locations, the samples in this

[12] Based on the cooperation scale of patent quantity measurement, the inventors of the same geographical unit were not calculated repeatedly; for example, there were 6 inventors in patent A, of which 2 were from Beijing, 2 were from the United Kingdom and 2 were from the United States, thus, the cooperation scale of Beijing-UK and Beijing-US was 1. Therefore, *Patnum* was smaller than the cooperation scale *InvImport*, as constructed based on the number of inflow of foreign inventors in benchmark regression.

[13] Eurostat set up the NUTS classification as a system for dividing up the EU's territory in order to produce regional statistics for the Community. The NUTS classification includes three geographical levels, NUTS1, NUTS2 and NUTS3. The NUTS2 regions represent the first administrative tier of subnational government; for example, the Province of Ontario in Canada. Refer to: https://ec.europa.eu/eurostat/web/nuts/background (retrieval date: March 12, 2021).

Table 4 Heterogeneity test (source locations of overseas inventors)

Geological Level	Panel A: Countries (or Regions)		Panel B: NUTS2	
Inventors From	G7	Non-G7	Hotspots	Non-Hotspots
	(1)	(3)	(4)	(5)
$HC\text{-}Overlap_{ijt-3}$	0.0220**	0.0015	0.0061***	−0.0002
	(2.45)	(1.37)	(3.73)	(−0.47)
$FE_{it}, FE_{jt}, FE_{ij}$	Yes	Yes	Yes	Yes
N_clust	217	1302	3100	15,066
adj. R^2	0.659	0.541	0.514	0.479
N	3255	19,530	46,500	225,990

All standard errors were the clustering standard errors between Chinese and foreign geographical units

*$p<0.1$, **$p<0.05$, ***$p<0.01$

study were classified at the national and NUTS2 levels. At the national level, this study constructed two sub-samples of G7 countries and non-G7 countries; at the NUTS2 level, two sub-samples of innovation hotspots and non-innovation hotspots[14] were constructed. As shown in Table 4, whether at the national level or the NUTS2 level, the promotion effect of technological overlap on China's introduction of overseas inventors was mainly concentrated in the global innovation active regions, such as G7 countries and NUTS2 regions with the top 100 global innovations (Table 4).

Interaction effect of tacit knowledge on the allocation of overseas inventors by technological overlap

As mentioned above, the technological overlap index describes the relatedness of the codified knowledge between geographical units, which alleviates information asymmetry in cross-border R&D cooperation. In fact, non-codified tacit knowledge also plays this role. Do interactive effects exist between the two types of knowledge relatedness when promoting the allocation of cross-border inventors?

Since the construction of a tacit knowledge dissemination network relies more on point-to-point interactions among individuals (Lecuona & Reitzig, 2014), geographical proximity provides the possibility of tacit knowledge dissemination. On one hand, the geographical proximity facilitates the construction and extension of innovation talents' personal social networks, thus, facilitating the flow of tacit knowledge among network nodes. On the other hand, the spillover effect of knowledge is further strengthened in the smaller geographical space, and both of these factors promote the dissemination of tacit knowledge. In addition, by attracting and gathering highly-skilled talents in specific technical fields or industries, geographical units can consolidate and strengthen local technical advantages in corresponding sub-fields and deepen the thickness of relevant professional knowledge,

[14] According to the geographical information of PCT patent inventors, as published in the REGPAT database from 1998 to 2017, this study calculated the accumulative inventor activity times of 586 geographical units with PCT patent activity records outside China during the observation period, and the top 100 with NUTS2 level were selected as innovation hotspots outside China, while the remaining regions were regarded as non-innovation hotspots outside China.

Table 5 The impact of the bilateral tacit knowledge linkage on the allocation of overseas inventors with codified knowledge relatedness

Innovation quality type	Total (1)	High-quality (2)	Normal-quality (3)
	Panel A: M_{ijt} as $InvImport_{ijt-3}$		
$InvImport_{ijt-3}$	2.098***	0.064***	2.058***
	(7.56)	(4.57)	(7.62)
$InvImport_{ijt-3}$#$HC\text{-}Overlap_{ijt-3}$	−0.001***	−0.000*	−0.001***
	(−2.80)	(−1.79)	(−2.81)
$InvImport_{ijt-3}$#$Non\text{-}HC\text{-}Overlap_{ijt-3}$	0.002**	0.000	0.001**
	(2.01)	(1.24)	(1.99)
Adj. R^2	0.849	0.659	0.855
	Panel B: M_{ijt} as $InvImport\_Total_{it-3}$		
$InvImport\_Total_{it-3}$ #$HC\text{-}Overlap_{ijt-3}$	−0.000	−0.000	0.000
	(−0.12)	(−1.34)	(0.02)
$InvImport\_Total_{it-3}$ #$Non\text{-}HC\text{-}Overlap_{ijt-3}$	−0.000	0.000	−0.000
	(−0.29)	(1.09)	(−0.50)
Adj. R^2	0.805	0.643	0.812
FE_{it}, FE_{jt}, FE_{ij}	Yes	Yes	Yes
N_clust	1519	1519	1519
N	22,785	22,785	22,785

All standard errors were the clustering standard errors between Chinese and foreign geographical units

*$p<0.1$, **$p<0.05$, ***$p<0.01$

thus, creating a favorable environment for external inventors to disseminate and share their tacit knowledge. In addition, this role will form a scale effect with the increase in the number of external inventors introduced.

Obviously, overseas inventors are an important carrier of their local tacit knowledge and have the function of disseminating tacit knowledge. Therefore, this study took the number of overseas inventors in the *t-3* period of Chinese and foreign geographical units ($InvImport_{ijt-3}$) as the proxy variable of the tacit knowledge of foreign geographical units, and then, introduced Eq. (1) as an interactive variable to check its regulatory effect on the allocation of overseas inventors by technological overlap. The specific measurement model is shown, as follows:

$$\begin{aligned} InvImportHQ_{ijt} = & \alpha + \beta_1 HC - Overlap_{ijt-3} + \beta_2 Non - HC - Overlap_{ijt-3} \\ & + \beta_3 InvImport_{ijt-3} + \beta_4 InvImport_{ijt-3} \times HC - Overlap_{ijt-3} \\ & + \beta_5 InvImport_{ijt-3} \times Non - HC - Overlap_{ijt-3} \\ & + X\eta + FE_{it} + FE_{jt} + FE_{ij} + \varepsilon_{ijt} \end{aligned} \tag{2}$$

The estimation results are given in Table 5 Panel A. In the total sample, the estimation coefficient of interactive variable $InvImport_{ijt-3} \times HC\text{-}Overlap_{ijt-3}$ was significantly negative. There was a significant substitution for the impact of the bilateral tacit knowledge linkage, as caused by the self-accumulation of the inflow scale of overseas inventors on the allocation of overseas inventors by the codified knowledge relatedness, which not only reduced the dependence of cross-border innovation activities on the effective part (*HC-Overlap*$_{ijt-3}$) of codified knowledge but also reduced the interference of the redundant part (*Non-HC-Overlap*$_{ijt-3}$) in codified knowledge. Columns (2) and (3) of Panel A further show that, while this substitution mainly focused on non-high-quality patent activities, it had no significant effect on high-quality patent activities.

Although codified knowledge relatedness could effectively alleviate information asymmetry, the interpretation of codified knowledge relatedness itself costs time and energy to eliminate the interference of redundant knowledge in codified knowledge (such as the identification of high-cited patents and general patents in the technological overlap). Regarding the general quality innovation activities that were more sensitive to cost constraints, compared with paying more to interpret the codified knowledge relatedness, the tacit knowledge of existing innovation partners is more inclined to be used to alleviate information asymmetry; on one hand, the high-quality innovation activities with higher input of innovation elements were less sensitive to the cost constraint of the codified knowledge relatedness; on the other hand, the specific high-skilled inventor resources needed in high-quality innovation activities were more irreplaceable, which would make it difficult to completely replace the role of the codified knowledge relatedness by using tacit knowledge alone. Therefore, in innovation activities with higher quality, the substitution effect of the bilateral tacit knowledge linkage on codified knowledge, as caused by the self-accumulation of the inflow scale of existing overseas inventors, would show a downward trend.

In addition, this study further replaced *InvImport*$_{ijt-3}$ with the scale of existing overseas inventors (*InvImport_Total*$_{it-3}$) in Chinese provinces, and the results are given in Table 5 Panel B. The coefficient of interactive item *InvImport*$_{ijt-3}$×*HC-Overlap*$_{ijt-3}$ was not significant in all subsamples, which reflects the unique "geographical stickiness" of tacit knowledge.

Discussion and conclusions

This study empirically investigates the impact of interregional codified knowledge relatedness on attracting foreign highly skilled talent to China. To the best of our knowledge, this is the first study to provide evidence that technological overlap between regions and countries enhances the cross-border flow of patent inventors from developed economies to emerging economies, and this is also the first study to investigate the interactive effect between the interregional codified knowledge relatedness and tacit knowledge linkage in the process of allocating cross-border innovative talents. We draw the following conclusions.

First, the interregional technological overlap, based on highly-cited patents, significantly boosts the scale of the inflow of local patent inventors from globally innovative countries or regions to 31 provinces in mainland China. In contrast, the technological overlap, based on non-highly-cited patents, does not have this role. The main reason is that highly-cited patents are more widely recognized and deeper understood among patent inventors than non-highly-cited patents, and thus, can more effectively mitigate the information frictions faced by cross-border R&D cooperation. Moreover, this effect of technological overlap on the inflow of foreign patent inventors shows obvious heterogeneity in terms of the origin of foreign inventors. Specifically, the technological overlap mainly helps China to attract foreign inventors from G7 countries or global innovation hotspots. The fact that most of the high-cited patents are created by developed countries is the reason for this phenomenon.

Second, the interregional tacit knowledge linkage, as measured by the number of existing foreign inventors, can negatively moderate the impact of the technological overlap on foreign inventors' inflow. However, this negative moderating effect is very slight for high-quality patenting activities. As mentioned earlier, specific highly skilled talents that match with high-quality innovation activities are more irreplaceable, thus, the moderating role of tacit knowledge linkage is limited.

The relevant conclusions have important practical significance and rich policy implications. First, when formulating and implementing industrial policies, the Chinese government should pay more attention to identifying cross-border collaborative R&D opportunities and technology areas, as based on knowledge relatedness between international and domestic innovation activities. It is well known that China, as an emerging country, participates in global innovation networks as a "catcher" and builds up its innovation strength by following traditional innovation highlands through "catch-up strategies" (Guo et al., 2019). Therefore, the Chinese government can mine information on cross-border knowledge linkages, as based on open information about global innovation activities (e.g., scientific papers, grants, and patents), and make this information available to domestic innovation agents seeking foreign innovation talents. Second, facing a more complex international political environment, Chinese companies need to rely on the knowledge relatedness formed by the global innovation network to precisely explore more opportunities to allocate innovation resources abroad.

Although this study provided empirical evidence on the impact of knowledge relatedness regarding the cross-border flow of highly skilled laborers, it is acknowledged that our analysis has limitations. One limitation of this study is that we only use PCT patent data to construct the technological overlap, which may lead to the possibility that the technological overlap constructed in this study may not provide a complete picture of the knowledge relatedness between China and other countries. Another limitation is that the detailed information of cited patents is not available, which prevents us from investigating the impact of the structural features of technological overlap on the allocation of overseas innovative talents by China. Future research can combine the co-cited patent database with the other databases, such as USPTO, EPO, CNP, and JPO, in order to improve the detailed information of co-cited patents. In addition, the attempt to measure the codified knowledge relatedness based on scientific publications is valuable.

Appendix

See Table 6.

Table 6 Geographical distribution with PCT patent activity records

Continent	Number of countries (or regions)	Number of NUTS2 regions	Country (or region) code and number of subdistricts (NUTS2 units)
Asia	7	88	Mainland China (CN,31), Chinese Hong Kong (HK,1), Chinese Taiwan (TW,1), Israel (IL,6), India (IN,32), Japan (JP,10), Korea(KR,7)
North America	3	96	USA(US,51), Canada(CA,13), Mexico(MX,32)
South America	2	41	Brazil (BR,26), Chile (CL,15)
Europe	35	361	Austria (AT,9), Belgium (BE,3), Bulgaria (BG,6), Switzerland (CH,7), Cyprus (CY,1), Czech (CZ,8), Germany (DE,38), Denmark (DK,5), Estonia (EE,1), Spain (ES,19), Finland (FI,5), France (FR,27), United Kingdom (GB,12), Greece (GR,13), Croatia (HR,2), Hungary (HU,7), Ireland (IE,2), Iceland (IS,2), Italy (IT,21), Liechtenstein (LI,1), Lithuania (LT,1), Luxembourg (LU,1), Latvia (LV,1), Monaco (MC,1), Malta (MT,1), Netherlands (NL,12), Norway (NO,7), Poland (PL,16), Portugal (PT,7), Romania (RO,8), Russia (RU,77), Sweden (SE,8), Slovenia (SI,2), Slovakia (SK,4), Turkey (TR,26)
Oceania	2	22	Australia (AU,8), New Zealand (NZ,14)
Africa	1	9	South Africa (ZA,9)

OECD REGPAT database

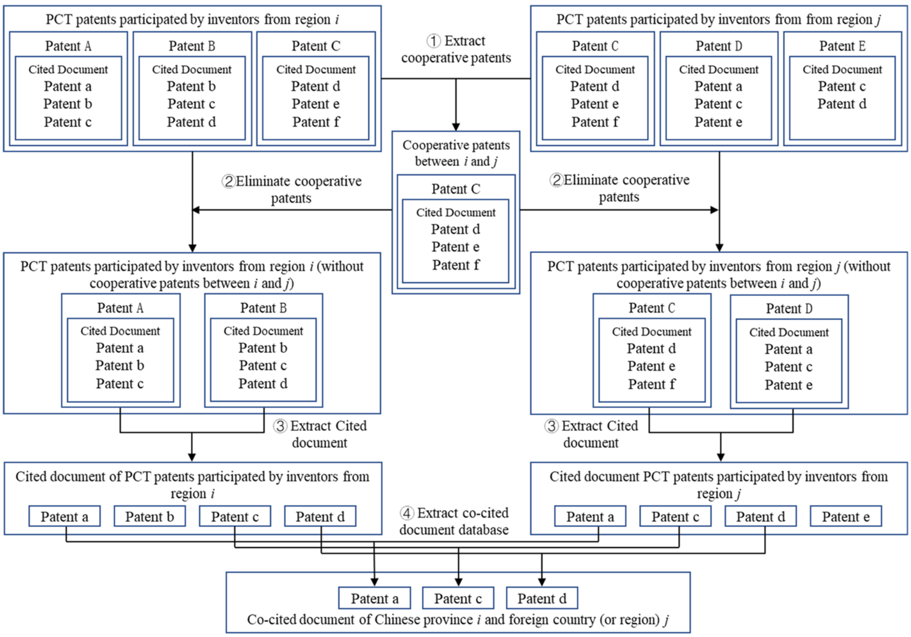

Fig. 4 Extraction procedure of co-cited database between Chinese and foreign geographical units

Construction of technological overlap

With reference to the concept of the extraction of technological overlap by Bena and Li (2014), the specific steps of extracting the main independent variable $Overlap_{ijt}$ in this study are shown in Fig. 4:

It was assumed that during investigation period *t*, the PCT patents participated by inventors from China province *i* were: A (cited document: a, b, c), B (cited document: b, c, d), and C (cited document: d, e, f); PCT patents participated by inventors from countries (or regions) outside mainland China *j* are: C (cited document: d, e, f), D (cited document: a, c, e), and E (cited document: c, d).

(1) According to the patent database (A, B, C) in which the inventors from China province *i* participated and the patent database (C, D, E) in which the inventors from foreign countries (or regions) *j* participated, the patent library (C) invented by the inventors *i* and *j* was identified;
(2) The patent library (C) invented by inventors *i* and *j* was excluded from the respective patent databases of regions *i* and *j*, to obtain patent database (A, B) and patent database (D, E), respectively;
(3) According to the patent database (A, B) and patent database (D, E), the cited document database (a, b, c, d) of Chinese province *i* and the cited document database (a, c, d, e) of foreign country (or region) *j* were extracted, respectively;
(4) According to the cited document database (a, b, c, d) of Chinese province *i* and the cited document database (a, c, d, e) of foreign country (or region) *j*, the overlap part was extracted as the co-cited database (a, c, d) of both parties during observation period t, and the number of patents within was counted to obtain the technological overlap of *i* and *j* in observation period t of 3.

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