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ORIGINAL PAPER

Unpacking technology flows based on patent transactions: does trickle-down, proximity, and siphon help regional specialization?

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Abstract

The spatial concentration of knowledge production leads to increased regional inequality, but technology flows have the potential to improve the distribution of innovation. This study examines the role of technology flows in regional specialization at the technology level in China during 2005–2016 using patent data. To unpack technology flows, we distinguish three directions based on patent transactions: trickle-down, proximity and siphon. Results show that regions are more likely to specialize in technological activities, which exhibit a greater number of external linkages characterized by relatively low relatedness and a limited number of strong links. Access to external technological linkages is identified as a key pathway for less innovative regions to achieve place breakthroughs. The technology flows of trickle-down help less innovative regions specialize in more complex technologies than their local knowledge base, while siphon does not significantly impact place breakthroughs in innovative regions.

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1 Introduction

The world exhibits significant imbalances, particularly in knowledge production. Within the global economic context, complex technologies tend to be spatially concentrated or sticky (Balland et al. 2020). The prevailing theory suggests that ubiquitous technologies are widely accessible, whereas intricate technologies tend to cluster within innovative cities, making their diffusion more challenging (Sorenson 2010). Currently, technological inventions have become the most important sources of growth, replacing land and energy (Romer 1986; Lucas 1988), but the future of innovation geography looks gloomy. Scholars have raised concerns that innovation may exacerbate regional disparities, which in turn could lead to social inequality. Recently, evolutionary economic geography (EEG) studies highlight the grim reality that not only is the current state of innovation unequal, but that in the future of regional diversification. Only the innovative regions will have the opportunity to diversify into highly complex activities, while less innovative regions focus on low-complex activities, resulting in a vicious circle of innovation inequality (Pinheiro et al. 2022). It is an inevitable law of development that some regions develop rapidly while others are locked in the dilemma of backwardness. However, in another point, the world is also balanced, especially in knowledge flows. Although innovation production is highly concentrated (Audretsch and Feldman 1996), technology flows improve the spatial distribution of knowledge. Once knowledge is codified (for example, patents), it means the reduction in the friction of space due to the improvements in information and communication tools (Bathelt et al. 2004), thus showing limited location reliance. Tradable intellectual property provides incentives for innovation development and diffusion (Spulber 2008), and patent markets facilitate the spatial extension of knowledge (Drivas and Economidou 2014).

Numerous studies have explored different forms of technology flows, such as foreign direct investment (Findlay 1978; Young and Lan 1997), commodity trade (Boschma and Iammarino 2009), patent cooperation (Santoalha 2019) and patent citations (Miguelez and Moreno 2017; Dosso and Lebert 2020). However, these indicators have three obvious disadvantages compared to patent transactions. First, these are unable to express whether knowledge is really transmitted from the source to the destination region (Breschi 2011). Technology flows are difficult to measure directly by patent citations due to the fact that early patents will be more significant than later ones (citation "inflation") (Hall et al. 2005). In addition, patent cooperation is an undirected network that cannot distinguish the direction of technology flows. A large number of studies have attributed recessive knowledge linkages in forms of capital or goods but ignored explicit technology. Patent transactions are then regarded as a traceable measure with determined agents and transfer records, thus they can reflect the actual trajectory of technologies. Second, the goal of inventions is to bring them to the market for commercialization (Walsh et al. 2016). However, invention cooperation is a process of knowledge exchange rather than a purely commercial activity (Zhang et al. 2016), and patent citations reflect more the intellectual value of the invention rather than the economic value (Liu et al. 2022). Patent transactions have become an important channel for acquiring knowledge through the act of trading (Choi et al. 2015), and transactions involving technology packages (patents, patent licenses, and other intellectual property and proprietary knowledge) may lead to the exchange of knowledge among transaction agents. The willingness of a firm to buy a patent depends on the knowledge contained in the patent (Anton and Yao 1994). Through the establishment of contact with the seller to obtain the knowledge of "how to use", patent transactions can therefore reflect explicit technology flows of commercialization. Lastly, geographical distance presents minimal constraints on informal flows like patent citations and collaborations, whereas it holds significance for formal, market-driven flows like technology transactions. While ample research has been conducted on informal, non-market channels, formal market-based knowledge transfer channels remain relatively understudied (Drivas and Economidou 2014).

The theory of external linkages can be used to illustrate the influence of technology flows on regional specialization. In the long run, regions with diverse capacities are supposed to have more opportunities for derived activities to achieve regional upgrades, and external linkages will enable regions to remain innovative and acquire novelty rather than being overly embedded (Boschma and Lambooy 1999). For less innovative regions, due to weak relatedness and lack of innovation resources, it is difficult to diversify into complex activities, and more external linkages are needed (Zhu et al. 2017; Balland et al. 2019). However, little attention has been paid to the direction of technology flows, that is, how the source of external linkages affects specialization of the receiving region. Zhu et al. (2017) showed for export data of Chinese firms that extra-regional linkages such as FDI have a positive effect on regional specialization varying across the regions and industries. Balland and Boschma (2021) demonstrated a similar positive effect of external linkages that are complementary to local capacity on the probability of regions to diversify, especially in peripheral regions. Miguelez and Moreno (2017) showed that the degree of relatedness between knowledge that is brought from "outside" (patent citations) and the local knowledge base affects regional innovation performance, which reflects that the heterogeneity of knowledge from different regions has different spillover effects on local innovation. Santoalha (2019) showed for 226 EU regions that cooperation between regions is an important determinant of regional diversification, and its impact depends on the region's level of development. Overall, the degree of relatedness, complementarity of external linkages with the local will affect the probability of regional specialization. However, these studies all focus on the unified characteristics of external linkages, but ignore where knowledge comes from. Establishing links with regions of different levels to introduce external technologies may have significant heterogeneity on the establishment of local specialization advantages.

In this research, China is considered a fast-growing innovation powerhouse with uneven innovation development and large knowledge flows. Cross-regional patent transactions are large in size and less constrained by different national systems, technology protection and other factors compared with European. Based on Chinese patent transaction records in ten years, the aim of this article is to discuss the impact of the directions of technology flows based on patent transactions on specialization in regions at different levels. To this end, we unpack three technology flows by comparing the innovation capacity gap between the source and destination regions, including trickle-down, proximity and siphon directions. Our main findings show that technology flows actually helped innovation backward regions in China to specialize and experience growth in more complex knowledge (place-based breakthrough) over the period 2005–2016 to avoid the diversification lock-in dilemma. Knowledge from regions with strong innovation capacities (trickle-down) or regions with similar innovation capacities (proximity) helps the region to establish a comparative advantage in this technology field, while knowledge from regions with relatively weak innovation capabilities has no significant effect on specialization in innovative regions.

This paper makes a significant contribution by incorporating patent transactions into the analysis of the EEG concerning regional specialization, which complements the perspective of the direction of technology flows. Here, we explore the influence of technology flows from varied sources, each characterized by varying degrees of relatedness and complexity. By utilizing technology domains as a foundational framework, we delve into the influence of these technology flows on regional specialization across different locations. This approach enables us to advance our understanding of the role of technology flows in regional specialization, particularly in less innovative regions. The remainder of this paper is structured as follows. The second section discusses the theoretical background of this paper. The third section describes the data and process of measuring, and the next section discusses the empirical results. The last section provides a brief conclusion and discusses some remaining research questions.

2 Theoretical background

2.1 Relatedness, external linkages and regional specialization

Considerable attention has been paid to how local capacities affect regional branching (Neffke et al. 2011; Boschma 2017). The relatedness based on a co-occurrence matrix was first proposed by Hidalgo et al. (2007). They found that regions are more likely to jump into industries related to local capacity. The principle of relatedness has been emphasized by lots of scholars in economic geography in various domains such as careers, products, industries, technologies and scientific research (Hidalgo et al. 2018; Guevara et al. 2016; Jefferson et al. 2021; Jun et al. 2020; Kogler et al. 2013; Boschma et al. 2014; Breschi et al. 2003). Furthermore, there appears to be broad consensus regarding the growing significance of external linkages (Balland and Boschma 2021; Santoalha 2019; Zhu et al. 2017). The local tends to diversify related industries or technologies, while external linkages are always thought to bring unrelated knowledge to supplement the local knowledge base (Frenken et al. 2007; Boschma 2017). Castaldi et al. (2015) found general innovation benefits from related variety while radical innovation is concerned with unrelated variety. Knowledge flows from different but related technologies facilitate the generation of new knowledge, while the more diverse and unrelated the technologies in a region, the higher the output in terms of high-quality innovations. Access to external linkages is a breakthrough approach for regions to seek beyond local dependence.

Evolutionary economic geography (EEG) have discussed multiple properties of external linkages. Industries or technologies that are more related to the local are more conducive to building connections, but as mentioned above, external linkages usually bring knowledge unrelated to the local. Regarding the strength and diversification of external linkages, Zhu et al. (2021) further clarified the performance of relatedness in that unrelated industries with a small number of strong links tend to have better economic performance and related industries with a large number of weak links are more likely to grow rapidly in an unfriendly environment. The advantages in technology fields may be derived from a wide range of regional partners and diverse knowledge, but more connections are beneficial to regions that can reorganize knowledge only when they have sufficient absorption capacity. To avoid the uncertainty and high risk of unrelated fields, regions should focus on a small number of strong links to increase the probability of returns, rather than seeking to diversify sources, which consumes a lot of time and resources. Based on the above, studies suggest that regions are more likely to specialize in technological activities, which exhibit a greater number of external linkages characterized by relatively low relatedness and a limited number of strong links.

2.2 Unpacking technology flows: three directions

EEG studies tend to look at how the relatedness properties of technology flows affect regional diversification, while the directions of flows are often overlooked. The development economist Hirschman (1958) proposed the polarization-trickle effect to explain the economic interaction and influence between developed and less developed regions. In the early stage of development, the developed regions produced a siphon effect on the less developed regions. But as time goes by, advanced technology, management methods, ideas, values and behavior and other economic and social progress factors of the developed trickled down to the less developed, will have a multifaceted promotion of the less developed 's economic progress. Refer to Hirschman's definition, the directions of technology flows could be divided into trickle-down and siphon to measure knowledge linkages between developed and less developed regions.

Technology flows of trickle-down may benefit specialization in less developed regions, and late-developing advantage, is often discussed at the country level to explain the uneven distribution of the economy (Kemeny 2011; Grossman and Helpman 1994; Storper 1997). Developed economies are committed to pushing technological frontiers outward, while developing economies can possibly diminish the technology gap if links with leaders are effective (Kemeny 2011). In this way, for countries without efficient endogenous innovation capacities, technology transfer can potentially bridge the technology gap, and become the strategy to keep up with the developed. From the perspective of regional knowledge diffusion, complex technologies produced in developed regions have become ubiquitous over a long period while reducing the complexity of technology flowing to edge regions (Hu et al. 2005). The absorption capacity of regions is also an important factor influencing whether knowledge spillovers can occur as a result of technology inflows.

When regions engage in innovation activities, they are easier to absorb and understand external knowledge (Griffith et al. 2003). Studies have found that the less economically developed regions are the ones benefiting the most from the geographical diffusion of knowledge, while developed regions benefit more from the inflows of knowledge workers (Miguélez and Moreno 2015). Based on the above, we thus hypothesized that:

Hypothesis 1 Regions are more likely to specialize in complex technological activities, which exhibit a greater number of external linkages from regions with relatively strong innovation ability (Trickle-down).

Proximity is also one of the directions of technology flows, which is a vital factor in acquiring external knowledge. Technology flows from regions with proximity are beneficial for innovative regions to absorb external technologies to effectively pursue regional diversification (Feldman et al. 2015). Some studies thought that the larger the technology gap, the more significant the technology spillover will be. However, Findlay (1978) verified that there is an inverted U-shaped relationship between the technology gap and technology spillover, which means over-large and over-small technology gap have obvious negative effect on technology spillover. The technology gap needs to be kept within bounds. Proximity of technology flows is based on the common knowledge base between regions (cognitive proximity), and contributes to broaden the knowledge space of the region. As Boschma (2005) puts it, "With the notion of cognitive proximity, it is meant that people (regions) sharing the same knowledge base and expertise may learn from each other. This is not only a matter of speed and efficiency of the acquisition of information, but also, and even more so, of extending the scope of cognition." The proximity of regional innovative capacities means that there are more firms with similar market needs between regions, as well as more frequent technology flows and tacit knowledge interactions between parent companies and subsidiaries, which is conducive to promoting the establishment of new complex technological advantages in the region. Based on the above, we thus hypothesized that:

Hypothesis 2 Regions are more likely to specialize in complex technological activities, which exhibit a greater number of external linkages from regions with similar innovation ability (Proximity).

The effect of technology flows in the siphon direction on the specialization in developed regions is still inconclusive. The role of the polarization effect is mainly reflected in the early stage. In this process, the economic growth of developed regions attracts labor, capital and talents from surrounding areas to the core, which effectively stimulates the growth of developed regions (Hirschman 1958). However, from the perspective of regional knowledge diffusion, the innovation capacities of less developed regions is not enough to produce complex technologies, but more ubiquitous technologies (Balland et al. 2020). A large technology gap also leads to different innovation needs among regions, and developed regions lack incentives to acquire novel technologies through siphon. The above make it difficult for technology flows of siphon direction to expand the technology space of developed regions. Based on the above, we thus hypothesized that:

Hypothesis 3 Regions have no significant role in specializing in complex technological activities, which exhibit a greater number of external linkages from regions with relatively weak innovation capabilities (Siphon).

3 Research design

3.1 Data

The data for patent applications and transactions were collected from the China National Intellectual Property Administration (CNIPA). In this study, the raw data includes nearly 12 million invention patent applications and 540,000 patent transactions from 2005 to 2016. It is important to note that China's GDP growth rate maintained a high rate of about 8% from 2005 to 2016, which was a period of vigorous development of national city clusters such as the Beijing-Tianjin-Hebei region, the Yangtze River Delta and the Guangdong-Hong Kong-Macao Greater Bay Area, and technology transactions between regions were extremely frequent. However, due to data limitations, we did not take into account technology flows from 2016–2023, which may affect whether the findings are applicable to the present. But at the same time, this study avoids the impact of China's economic slowdown, Sino-US trade blockade, COVID-19 and other events on domestic technology flows.

In the data processing section, firstly, each patent is matched to the technology field (four-digit of the IPC classification) and application city according to its main IPC classification and geographical address of application. We counted the number of patent applications in different technology fields of cities in order to measure the local technology specialization and regional complexity.

In addition, this paper uses patent transactions to represent technology flows. A legally valid assignment (generally a legal agreement) transfers all or part of the right, title, and interest in a patent from an existing owner (an assignor) to a recipient (an assignee) (Marco et al. 2015). Our patent transactions data involves the year of transfer, the main IPC classification and the cities where the right holder was located before and after the transfer (note that due to data limitations, we used the address of the applicant instead of the inventor), which depicts the linkages between two cities with the information of direction and intensity of each technology field, e.g., four patents of H04W flew from Shanghai to Beijing in 2016.

3.2 Measuring region-tech complexity

Economical complexity was developed by Hidalgo and Hausmann (2009), and later Balland and Rigby (2017) applied it to compute knowledge complexity. Drawing on

Hidalgo's vivid metaphor, if we liken a product to a LEGO model constructed with various building blocks, then complex technologies are akin to the uniquely shaped or critically connecting blocks within the model. The knowledge complexity index quantifies the quality of "knowledge". Complex products are often difficult to produce and imitate, requiring abundant and unique local capabilities that are embedded in a region's technological strength and institutional-cultural environment. These capabilities tend to be concentrated in cities with higher levels of innovation. Therefore, the level of regional innovation capacity can be evaluated by examining the complexity of regional knowledge output types.

The method of Reflections (MR) has been used by many studies about products and knowledge (Whittle and Kogler 2019; Balland and Boschma 2021). However, some criticisms about the application of the MR are mostly discussed that it underestimates the importance of highly diversified countries because MR measures complexity as the average of the complexities of the products and shows the result of a linear algebra exercise (Mariani et al. 2015; Sciarra et al. 2020). In contrast, Tacchella et al. (2012) proposed a nonlinear approach named Fitness and Complexity algorithm (FC), which is based on the fact that a less competitive country exporting a given product should unavoidably downgrade the product's complexity. Recently, Sciarra et al. (2020) reconciled the MR and FC approaches with a mathematically sound, multidimensional framework. Figure 2 and Table 9 in appendix compare the rationality and stability of three metrics, and the results show that the Generalized Economic Complexity Index (GENEPY) is more robust.

We calculate the GENEPY of cities and technology fields in China each year. The core of knowledge complexity is the two-mode network. Based on the empirical observation that innovative regions have diversified and cutting-edge technologies whereas less developed regions only have ubiquitous technologies, we represent the geography of knowledge production as a two-mode matrix. The GENEPY index for regions is created as follows:

$$\text{Genepy}_{c,t} = \left(\sum_{i=1}^{2} \lambda_i X_{c,i}^2 \right)^2 + 2 \sum_{i=1}^{2} \lambda_i^2 X_{c,i}^2 \tag{1}$$

where $X_{c,1}$ and $X_{c,2}$ are the eigenvectors corresponding to the first two largest eigenvalues λ_1 and λ_2 of the relatedness matrix.

$$\begin{cases} N_{cc^*} = \sum_i W_{c,i} W_{c^*i} = \sum_i \frac{M_{c,i} M_{c^*i}}{k_c k_{c^*} k_i'^2}, & \text{if } c \neq c^* \\ N_{cc^*} = 0 & \text{if } c = c^* \end{cases} \tag{2}$$

First, to interpret the symmetric squared matrix **N** as the mathematical description of the weighted topology of an undirected network, and second, to interpret the eigenvectors of **N** as the (multidimensional) eigenvector centrality of the nodes in the network. All diagonal elements are set to zero. This approach combines the eigenvectors into unique metrics. $X_{c,1}$ has a high correlation with FC and $X_{c,2}$ correlates with MR. Thus, we calculate the complexity of Chinese cities and all technology fields.

In order to distinguish the directions of trickle-down, proximity and siphon, we use the regional complexity index to evaluate the cities before and after technology transfer, so as to cluster the level of regional innovation in China. We supplement the correlation analysis between region complexity and the number of urban patents granted, which shows that they are highly correlated. Furthermore, we use the K-means clustering algorithm to divide the complexity of cities into 4 clusters each year.

K-Means clustering is an unsupervised algorithm commonly used in machine learning. The purpose is to divide the feature matrix of **N** samples into K disjoint clusters. Firstly, K samples are randomly selected as the initial centroids. Each sample point is assigned to the nearest centroid, and K clusters are generated. Secondly, the mean of all sample points in each cluster is calculated as the new centroid. The loop iterates until the sum of squares in the cluster is the smallest, and finally determines the centroid and sample points for each cluster. The intra-cluster sum of squares is used to measure the distance from the centroid of the sample point to the cluster, which is measured by the Euclidean distance. The calculation formula is:

$$\mathrm{CSS} = \sum_{J=0}^{m} \sum_{i=1}^{n} (x_i - u_i)^2. \tag{3}$$

where x_i is the sample points in the cluster, u_i is the centroid in the cluster, n is the number of features of the sample points, i is each feature that composes point x, m is the number of samples in the cluster, and j is each sample number.

Table 1 reflects regional innovation capacities during 2004–2015, which is consistent with the urban hierarchy in China. Beijing, Shenzhen and Shanghai are in the first tier (Cluster 4), and eight other sub-provincial cities followed (Cluster 3), which we combined into level3. The reason is that this paper focuses more on trickle-down and siphon, that is, technology flows between innovative and relatively less innovative regions, and these cities basically constitute the most innovation production regions in China. Cluster2 (level 2) also includes the major regional innovation centers in China, and Cluster 1 (level 1) is composed of other 276 cities with relatively backward innovation levels.

3.3 Visualizing three directions of technology flows

As argued in the literature review, it is critical to divide different directions of technology flows. The left graph in Fig. 1 reflects the geographic distribution of intercity technology flows in China, showing that the regional complexity and size of technology flows weakening outward from the center. Technology flows based on patent transactions are concentrated in the connections between Beijing, Shanghai and Shenzhen and other innovation regions. We make statistics on the directions of technology flows, as shown in the Fig. 1 on the top right. For the quantitative statistics of technology flows at different gaps between source and destination regions, Fig. 1 shows an inverted U-shaped relationship between

Table 1 Average regional technological complexity in China from 2004 to 2015

Level	Cluster	Regions (Regional complexity index)	Nums
Level3	Cluster4	Beijing (1.023), Shenzhen (0.889), Shanghai (0.852)	3
	Cluster3	Nanjing (0.327), Xi'an (0.319), Chengdu (0.290), Hangzhou (0.286), Tianjin (0.277), Guangzhou (0.263), Suzhou (0.262), Wuhan (0.228)	8
Level2	Cluster2	Ha'erbin (0.167), Qiandao (0.159), Wuxi (0.158), Hefei (0.149), Changsha (0.144), Shenyang (0.140), Dongguan (0.139) ……	33
Level1	Cluster1	Baoding (0.056), Taizhou (0.055), Lanzhou (0.054), Quanzhou (0.053), Zhongshan (0.053), Yantai (0.051), Nan-Chang (0.050) ……	276

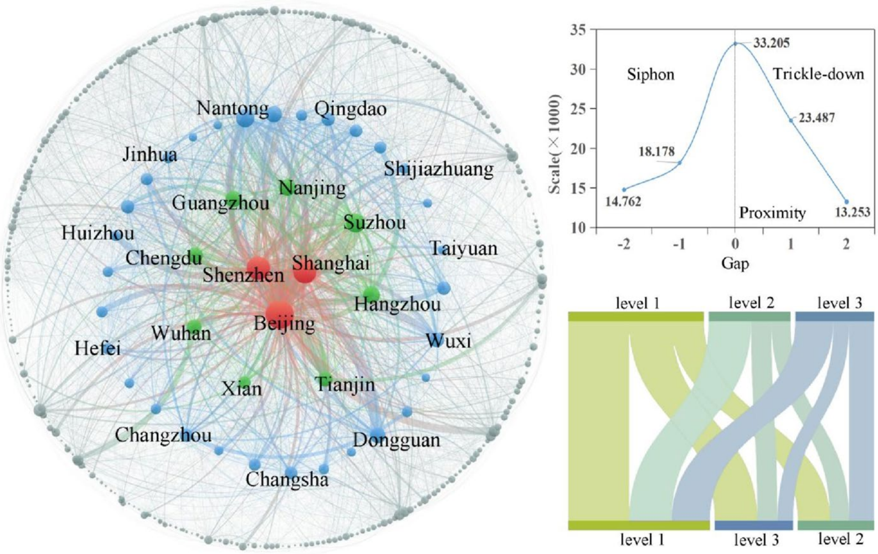

Fig. 1 The directions and sizes of technology flows during 2004 to 2015. *Notes* The colors of the dots in the left image represent different clusters, which are divided into high-to-low levels from the inside to the outside (Red and green are level 3, blue is level 2, and gray is level 1). The size of the dots indicates the weighting degree, and the width of the lines indicates the relative intensity of linkages between cities. (Drawing by Pajek and VOS Viewer)

Table 2 Size of technology flows in different directions from 2004 to 2015

Direction	Overall				Maximum flow			
	Flows	Gap	Weight	Percent	From	To	IPC	Weight
Trickle-down	level3 → level1	2	13,253	12.88%	Shenzhen	Huizhou	A24F	188
	level3 → level2	1	8730	8.49%	Shenzhen	Nantong	H04L	76
	level2 → level1	1	14,757	14.34%	Tianjin	Taizhou	F25D	265
Proximity	level3 → level3	0	5428	5.28%	Shanghai	Beijing	H01L	247
	level2 → level2	0	6635	6.45%	Dongguan	Nantong	A61K	65
	level1 → level1	0	21,142	20.55%	Linyi	Nantong	A61K	125
Siphon	level1 → level2	− 1	11,145	10.83%	Shenyang	Nanjing	H04N	155
	level1 → level3	− 2	14,762	14.35%	Jiaozuo	Beijing	H02G	68
	level2 → level3	− 1	7033	6.84%	Nanjing	Shenzhen	H04l	62

The complexity of a region in each year is calculated based on the number of patent applications in that year, so regions may fall into different levels in different years

the inter-region gap and the size of technology flows. It can be seen that the size of technology flows at the same level is the largest, and it gradually decreases with the expansion of the gap between regions. The sankey sub graph depicts the technology flows between regions of different levels. The length of the rectangle represents the inflow or outflow sizes of three levels, and the specific values are shown in the Table 2. In general, the size of technology flows in different directions is roughly similar: trickle-down (36,740) > proximity (33,205) > siphon (32,940).

3.4 Variables

3.4.1 Dependent variable

Our dependent variable refers to the region's capacity to specialize in technology at year t, which is calculated by the revealed comparative advantage (RTA) of the technology field. The formula is:

$$\mathrm{RTA}_{c,i,t} = \frac{\mathrm{patents}_{c,i,t} / \sum_i \mathrm{patents}_{c,i,t}}{\sum_c \mathrm{patents}_{c,i,t} / \sum_c \sum_i \mathrm{patents}_{c,i,t}} \tag{4}$$

where $\mathrm{RTA}_{c,i,t}$ represents the revealed comparative advantage of the technology field i of city c in year t, and $\mathrm{patents}_{c,i,t}$ is the number of patent applications attributed to the technology field i of city c in year t. We define our dependent variable takes the value of 1 if city c specializes in a technology t at time t ($\mathrm{RTA}_{c,i,t} >= 1$) and 0 otherwise.

3.4.2 Measuring relatedness and variety

Following the method adopted by Hidalgo et al. (2007), we measure the relatedness between the transferred technology field and the region's existing knowledge structure. Firstly, the relatedness is computed with the minimum of the pairwise conditional probabilities of two technology fields specializing in the same region. The formula is:

$$\phi_{i,j,t} = \min\{P(\mathrm{RTA}_{c,i,t} >= 1 | \mathrm{RTA}_{c,j,t} >= 1), P(\mathrm{RTA}_{c,j,t} >= 1 | \mathrm{RTA}_{c,i,t} >= 1)\} \tag{5}$$

where$\varphi_{i,j,t}$ is the relatedness of technology field i and j at year t. It is high when technology field i and j collocate in many regions in year t. Furthermore, relatedness density, which measures the relatedness of the technology field and local knowledge portfolio, is defined as:

$$\mathrm{Density}_{c,i,t} = \frac{\sum_i x_{i,t}\varphi_{i,j,t}}{\sum_i \varphi_{i,j,t}} \tag{6}$$

where $x_{i,t} = 1$ if $\mathrm{RTA}_{c,i,t} >= 1$ and 0 otherwise. A high density value means that city c has abundant developed technologies surrounding the transferred technology field i.

In addition to the sum of relatedness between technology field i and local capability, variety of relatedness developed by Zhu et al. (2021) attempts to measure the strength and variety of linkages because relatedness density ignores the number of linkages between technology and local technology portfolio. For example, when the technology field i is related to two technology fields in a city with a relatedness density of 1 and field j is related to five technology fields with the same relatedness density. The former are a small number of strong links (two links of 0.5), while the latter are a large number of weak links (five links of 0.2). Following the method adopted by Zhu et al. (2021), we calculate the ratio of the relatedness between technology field i and j to the sum of relatedness between technology i and the technology portfolio of city c, defined as:

$$q_{c,j,t} = \frac{\phi_{i.,j,t}}{\sum_{j \in S_V} \phi_{i,j,t}} \tag{7}$$

where S_v is composed of four-digit technologies in which city c has an RTA. Then, the variety of relatedness of technology field i in city c with entropy measured below:

$$\text{Variety}_{c,i,t} = \sum_{j \in S_V} q_{c,j,t} \ln\left(\frac{1}{q_{c,j,t}}\right) \tag{8}$$

A high (low) variety of relatedness means that the technology field i is weakly (strongly) related to a large (small) number of technologies. Zhu et al. (2021) verified that variety of relatedness is compatible with relatedness density because both indicators define different aspects.

3.5 Model

The following conditional linear model is estimated:

$$\begin{aligned} \text{RTA}_{c,i,t+1} = {} & \beta_0 + \beta_1 \ln \text{linkage}_{c,i,t} + \beta_2 \text{Gap}_{c,i,t} + \beta_3 \text{Density}_{c,i,t} \\ & + \beta_4 \text{Variety}_{c,i,t} + \beta_5 \text{RTA}_{c,i,t} + \beta 6 \ln \text{linkage\_f}_{c,i,t} + \partial + \delta + \phi + \varepsilon_{c,i,t} \end{aligned} \tag{9}$$

The variables in Eq. (9) are defined as follows. The explained variable $\text{RTA}_{c,i,t+1}$ takes the value of 1 if city c specializes in a technology field i at time $t+1$ and 0 otherwise. The main explanatory variable $\text{lnlinkage}_{c,i,t}$ takes the value of the natural logarithm of the total number of patents in the technology field i introduced from another region into the region. Each directed edge in the left figure of Fig. 1 constitutes a sample, and maximum flows in Table 2 can be seen in detail. Another variable $\text{Gap}_{c,i,t}$ is the difference value in complexity level between regions, that is, the complexity level of the technology outflow region subtracts the complexity level of the inflow region. By comparing the regional complexity of the source and destination regions of technology flows, three directions of trickle-down ($\text{Gap}_{c,i,t}>0$), proximity ($\text{Gap}_{c,i,t}=0$), and siphon ($\text{Gap}_{c,i,t}<0$) are distinguished. $\text{Density}_{c,i,t}$ indicates that the relatedness and $\text{Variety}_{c,i,t}$ reflects the intensity and diversity of relatedness between introduced technology field and the local knowledge portfolio. Furthermore, we control the region' s specialization in technology field i at year t, which reflects the local absorption capacity of this technology field. The variable of foreign technology inflow (lnlinkages_*f*) by using patent transaction data on foreign-to-Chinese from CIPO, which is the same source as China's intercity patent transfers. In this model, GDP and population density of the city, and year, region, technology field fixed effects are controlled.

To the best of our knowledge, this paper is one of the few to adopt the technology field level of geographical analysis in dealing with the role of technology flows in regional specialization. Previous work has used a larger scale, generally at region level. We consider the technology field as analytical level to be innovative for two main reasons. First, in EEG studies, when patent collaborations and citations are used to demonstrate the role of external linkages in local innovation, they are still mostly aggregated at the regional level (Santoalha 2019), which weakens the credibility of the conclusions and hinders further analysis. Second, the relatedness measure based on co-occurrence matrix was firstly put forward by Hidalgo et al. (2007), and Rigby (2013) applied it to analyze technologies by using patent data. To the level of industry or technology field has become the consensus of local diversification research. However, insufficient response from external linkage studies, e.g., Miguelez and Moreno (2017) constructed two measures of relatedness and similarity (discrete relatedness) to demonstrate the role of relatedness degree between external knowledge and local existing technologies in regional innovation. The model is also based on the regional level and differs from Hidalgo's relatedness (continuous relatedness).

4 Results

4.1 Baseline results

Based on the constructed econometric model, the panel multidimensional fixed effects regression is used to examine the influence of the introduction of technology on regional specialization. By calculating the variance inflation factor (VIF), it is determined that the model variables do not exist at multicollinearity (VIF is less than 10). Descriptive statistics and correlation analysis are shown in Tables 7 and 8 in the appendix. Table 3 presents the results of our empirical analysis starting with the baseline, more conservative model in column 1–3, and followed by three models with the interaction terms including *density, variety* and RTA_{t-1} separately in columns 4–6.

The regression coefficients and significance of both explanatory variables and control variables remain stable, indicating strong robustness in our results. First, in terms of the size and gap of technology flows, when the fixed effects of year, city and technology field are considered, *linkages* are significantly positive at the 1% level. For every 1% increase in the number of technologies traded from other cities, the probability of regional specialization in this technology field increases by about 0.12, indicating that regions are more inclined to specialize in technology fields with more external linkages, supporting previous work on this issue (Bathelt et al. 2004; Santoalha 2019). The variable measuring the gap between regions of technology flows is significantly negative, suggesting that the smaller

Table 3 Baseline models-all sample

	Baseline			Interaction term		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Linkages(log)	0.124***		0.128***	0.144***	0.142***	0.185***
	(0.028)		(0.028)	(0.028)	(0.029)	(0.029)
Gap		−0.029**	−0.032**	−0.032**	−0.031**	−0.064***
		(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
Density	0.111***	0.111***	0.111***	0.111***	0.111***	0.104***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Variety	0.578***	0.581***	0.573***	0.574***	0.581***	
	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	
RTA_{t-1}	2.260***	2.261***	2.259***	2.259***	2.259***	2.342***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Linkages_*f*(log)	0.528***	0.529***	0.529***	0.531***	0.530***	0.685***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
GDP(log)	0.028	0.028	0.029	0.027	0.029	0.026
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
POP(log)	0.059	0.060	0.060	0.061	0.059	0.114*
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)
Density × Linkages(log)				−0.019***		
				(0.004)		
Variety × Linkages(log)					−0.070***	
					(0.026)	
RTA_{t-1} × Linkages(log)						0.159***
						(0.056)
Constant	−9.903***	−9.867***	−9.950***	−6.270***	−5.871***	−4.936***
	(0.783)	(0.782)	(0.784)	(0.776)	(0.770)	(0.772)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes
N	55,384	55,384	55,384	55,384	55,384	55,384
R^2	0.331	0.331	0.331	0.331	0.331	0.321

Robust standard errors are shown in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

the technology gap, the more conducive to regional specialization. Furthermore, in terms of the technology field, a higher relatedness and a larger number of weak links of the transferred technologies with local knowledge base are positively correlated with the region's capacity to specialize in specific technologies. This capacity also appears to be path dependent, as the lag of the dependent variable

RTA is significant and positive, suggesting that the recombination innovation of existing knowledge that is related and diversified is key to establishing technology specialization advantage, depending on the local absorptive capacity and the capability to understand, process, absorb and internalize the knowledge, which is in line with the results of previous works on regional specialization (Miguelez and Moreno 2017; Zhu et al. 2021). Furthermore, foreign technology inflows also positively correlate with the regional specialization, suggesting that, consistent with cross-regional external linkages, knowledge spillovers from foreign firms contribute to the technological advantage of Chinese cities.

The results are shown in models 4–6 in Table 3. *Linkages* are significant but negatively correlated with both *Density* and *Variety* of interaction terms, suggesting that regions are more likely to specialize in technological activities that have more external linkages with relatively low relatedness and a small number of strong links. This resonates with the findings of other studies. The coefficient of the interaction term between FDI and density is also negative and significant in Zhu et al. (2017). The weak impact of relatedness indicates that external linkages are conducive to promoting local breakthrough regional specialization. In addition, linkages with relatively low relatedness benefit more from a lower level of variety. Knowledge spillovers via a small number of strong links reduce the uncertainty and risks of the external linkages (Zhu et al. 2021).

4.2 Technology flows and local breakthroughs

To further confirm that the different directions of technology flows play a differentiated role in regional specialization (hypothesis 1–3), we assessed the estimations by three directions including trickle-down, proximity and siphon. Relative complexity is compared with the average complexity of the local technology portfolio. The results in Table 4 clearly show that, first, the estimated parameters of all variables are mostly unaltered, except for significance changes in *linkages*. The coefficients of trickle-down and proximity direction of technology introduction on regional specialization are significantly positive, but the siphon direction is not significant. Furthermore, relatively high complexity technologies are more likely to outperform in the directions of trickle-down and proximity, suggesting that regions are more likely to specialize in relatively complex technological activities (higher than the local) that have more external linkages from regions with relatively strong innovation ability (higher than the local) or from regions with similar innovation ability, which verifies the role of technology flows on the latecomer advantage of relatively backward regions in studies. However, the siphon direction did not pass the significance test, and technologies from relatively backward regions did not bring relatively breakthrough knowledge to the innovation regions, which is consistent with the prior hypothesis.

To further demonstrate the robustness of the results, specific flow directions (as shown in Table 2) are evaluated separately, and the results are presented in the Table 5. Consistent with the above, the trickle-down and proximity directions are more likely to outperform. In the analysis of specific technology flow, the receiving

Table 4 Specialization models for three directions

	Trickle-down		Proximity		Siphon	
	Relatively low complexity	Relatively high complexity	Relatively low complexity	Relatively high complexity	Relatively low complexity	Relatively high complexity
	(1)	(2)	(3)	(4)	(5)	(6)
Linkages(log)	0.190***	0.344***	0.127**	0.423**	0.0305	−0.299
	(0.050)	(0.098)	(0.055)	(0.184)	(0.061)	(0.289)
Density	0.106***	0.094***	0.0899***	0.049***	0.134***	0.190***
	(0.008)	(0.015)	(0.007)	(0.016)	(0.010)	(0.051)
Variety	0.365***	0.339**	0.460***	0.472***	0.783***	1.589***
	(0.048)	(0.133)	(0.042)	(0.161)	(0.042)	(0.339)
RTA_{t-1}	2.214***	1.994***	2.408***	2.416***	2.624***	2.556***
	(0.049)	(0.121)	(0.049)	(0.172)	(0.062)	(0.448)
Linkages_*f*(log)	0.114	0.777*	0.456***	1.326***	0.794***	0.047
	(0.149)	(0.453)	(0.106)	(0.495)	(0.087)	(0.438)
GDP(log)	−0.007	−0.034	0.035	2.653**	−1.522**	−8.240**
	(0.052)	(0.159)	(0.031)	(1.196)	(0.678)	(3.563)
POP(log)	0.188*	−0.001	−0.018	−0.079	0.462*	0.948
	(0.107)	(0.221)	(0.119)	(0.419)	(0.240)	(1.940)
Constant	−7.825***	−3.949	−8.169***	−53.77**	12.96	123.0*
	(1.403)	(3.406)	(1.192)	(21.504)	(11.889)	(63.812)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,341	4024	14,960	2686	16,394	1226
Pseudo R^2	0.289	0.369	0.309	0.437	0.490	0.641

Relatively high complexity includes technology samples with higher than the average complexity of the local technology portfolio, while relatively low complexity is the opposite. Trickle-down involves external linkages from regions with relatively strong innovation ability (Gap > 0), proximity involves external linkages from regions with similar innovation ability (Gap = 0) and siphon involves external linkages from regions with relatively weak innovation capabilities (Gap < 0). Robust standard errors are shown in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$

Table 5 Specialization models for specific flow directions

Direction	Gap	Coefficient	R^2	Flows	Coefficient	R^2	Control	FE
Trickle-down	2	0.181**	0.301	level3 → level1	0.181**	0.301	Yes	Yes
	1	0.206***	0.316	level3 → level2	0.133	0.444	Yes	Yes
				level2 → level1	0.255***	0.294	Yes	Yes
Proximity	0	0.147***	0.303	level3 → level3	0.074	0.569	Yes	Yes
				level2 → level2	0.070	0.489	Yes	Yes
				level1 → level1	0.120**	0.252	Yes	Yes
Siphon	−1	−0.052	0.445	level1 → level2	−0.164*	0.395	Yes	Yes
				level2 → level3	0.114	0.568	Yes	Yes
	−2	0.107	0.579	level1 → level3	0.107	0.579	Yes	Yes

Robust standard errors are shown in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$

regions with weak innovation ability (level 1) are all significantly positive, which indicates that for less innovative regions, external linkages play an important role in regional specialization.

One possible reason is the heterogeneity between the capacities of knowledge-producing regions and receiving regions. Knowledge from the core to edge regions (trickle-down) always more complex than the receiving regions, and benefit for regional place-based diversification. As for absorption capacity of the receiving regions, the research suggests that complex technologies produced in innovative regions have become ubiquitous over a long period while reduce the complexity of technology flowing to edge regions (Hu et al. 2005). The above reflects the late advantages of the less innovative regions. Knowledge from regions with similar innovation ability are also benefit for receiving regions, which is in line with the previous works (Boschma 2005; Feldman et al. 2015). However, knowledge from edge regions are difficult to extend the technology space of innovation regions. In

Table 6 Growth models for three directions

	Trickle-down		Proximity		Siphon	
	Relatively low complexity	Relatively high complexity	Relatively low complexity	Relatively high complexity	Relatively low complexity	Relatively high complexity
	(1)	(2)	(3)	(4)	(5)	(6)
Linkages(log)	0.100***	0.102**	0.105***	0.212***	0.083***	0.082
	(0.025)	(0.045)	(0.025)	(0.052)	(0.019)	(0.059)
Density	0.027***	0.014**	0.024***	0.010*	0.022***	0.024**
	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)	(0.011)
Variety	0.259***	0.244***	0.288***	0.192***	0.388***	0.180**
	(0.025)	(0.056)	(0.020)	(0.063)	(0.014)	(0.076)
RTA_{t-1}	0.390***	0.416***	0.433***	0.442***	0.281***	0.175
	(0.025)	(0.054)	(0.023)	(0.068)	(0.025)	(0.122)
Linkages_*f*(log)	0.088	0.235**	0.183***	0.258***	0.084***	0.237***
	(0.066)	(0.114)	(0.053)	(0.063)	(0.031)	(0.049)
GDP(log)	0.003	−0.001	0.002	0.012	0.720***	−1.355
	(0.021)	(0.033)	(0.016)	(0.026)	(0.213)	(1.159)
POP(log)	−0.013	0.029	−0.201***	−0.069	−0.082	−0.741
	(0.049)	(0.074)	(0.056)	(0.121)	(0.093)	(0.477)
Constant	−0.203	−0.653	1.173**	0.266	−12.66***	32.42
	(0.520)	(0.764)	(0.504)	(0.947)	(3.920)	(21.806)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,513	3128	11,018	2269	13,104	1053
Adj. R^2	0.577	0.664	0.638	0.782	0.659	0.816

The dependent variable Growth corresponds to the increase in the number of patent applications of a technology i in a region r from period $t-1$ to period t Robust standard errors are shown in parentheses. *$p<0.10$, **$p<0.05$, ***$p<0.01$

contrast to the trickle-down direction, technology introduction in the siphon direction is more about quantitative growth for the receiving regions than about promoting local breakthroughs.

4.3 Technology flows and growth models

We further construct a growth model, taking the relative growth of the amount of local knowledge production in the introduced technology field as the dependent variable. The results in Table 6 clearly show that the coefficients of trickle-down and proximity direction of technology introduction on regional specialization are still significantly positive. The most interesting results is that the coefficient of siphon direction changes from insignificant to significant (in relatively low complex technology), which suggests that knowledge from regions with relatively weak innovation capabilities has a quantitative growth effect on innovative regions, but has no effect on local breakthroughs.

5 Conclusion and discussion

Recent studies emphasize less innovative regions are faced with the "diversification dilemma" based on relatedness rules and complex knowledge. On the one hand, relatedness restricts regions lacking long-term accumulation from jumping further, leading to a vicious outlook of "the rich get richer, the poor get poorer" (Hidalgo et al. 2007). On the other hand, Balland et al. (2019) think investment in innovation prompts regional actors' demand for complex knowledge. However, the lack of local diversification capabilities and the relative scarcity of complex knowledge, make it difficult for regions to obtain the innovation benefits of complex knowledge. In this context, technology flows are considered to be an important way for less innovative regions to achieve local breakthroughs through external linkages. While continuous research has been dedicated to local diversification, or more to discussing the role of external knowledge from the perspective of informal linkages.

This article has investigated the role of technology flows in regional specialization, with a particular focus on the effects of different directions, including trickle-down, proximity and siphon. Based on patent transactions between regions in China during the period 2005–2016, some interesting results are found in this study. First, regions are more likely to specialize in technological activities that have more external linkages with relatively low relatedness and a small number of strong links. Second, for less innovative regions, more technology inflows from regions with strong innovation capacities (trickle-down) can help the region to establish a comparative advantage in this technology field. Third, for innovative regions, more technologies inflow from regions relatively with weak innovation capabilities have no significant role in specializing or experiencing technological growth in complex technological activities, but has a promoting effect on local production of low complex technologies. These results are useful for relatively backward regions because they provide a reasonable way to link other regions to explore the establishment of local technology advantages, so that the implementation of cross-regional advantage assistance policies in China can appropriately stimulate the innovation sprout in backward regions. In addition, this study also further verify the framework of "dual-pipelines", which has been developed to elaborate the role of domestic and transnational introduced technology in promoting local innovation capacity based on "buzz-and-pipeline" theory (Wang et al. 2023; Bathelt et al. 2004). Research shows that "dual-pipelines" not only promote the growth of the number of local innovations, but also play an important role in regional specialization.

This conclusion is accompanied by some important policy implications. Boschma et al. (2017) distinguishes between path-based and place-based regional diversification. Innovation regions are more inclined to path-based (new to the world) diversification, while less innovative regions can obtain complex knowledge spillovers from innovation regions to achieve place-based (new to the region) diversification. We demonstrate a potential pathway for less innovative regions to achieve place-based diversification, that is, strive to acquire external technologies to bridge the technology gap and actively establish linkages with innovative regions. Although external forces cannot become the continuous driving force for regional development, they can jump further in technology space through the place breakthrough of external shocks, and then seek further regional development under the law of relatedness, which also provides referential value for EU or other developing countries.

The data limitation of patent transactions is the main problem of this study. First of all, this stems from the fact that in patent transactions, the recorded address belongs to the applicant, not the inventor. In cases where the applicant's address diverges from the inventor's address (such as when the corporate headquarters is the applicant, while the R&D facility serves as the actual inventor), this primarily reflects the transfer of patent ownership rather than the actual dissemination of knowledge. This nuance can impact the segmentation of samples in the context of certain technology flows. Second, as a formal market activity, patent transactions require a certain cost, and if a local entity is willing to buy patents from other regions but cannot afford it, the transaction will not occur, which may ignore other informal technology flows. In addition, while the volume of data in this article is large (more than 540,000 patent transactions), due to data access restrictions, we were unable to examine technology transactions in recent years from 2016 to 2023, which may affect whether the conclusions of this study are applicable to the present.

While technology flows represent a significant factor influencing regional specialization, it's essential to acknowledge that governments and informal institutions also wield substantial influence over cross-regional linkages in regional specialization (Cortinovis et al. 2017). Regrettably, this study lacks an in-depth exploration of the mechanisms through which entities depend on the role of technology flows from innovative regions to less innovative regions. Patent transactions are only one way to measure technology flows, so the direction of multidimensional knowledge flows in the form of scientific papers, project collaborations, talent migration, R&D investment, and commodity trading should also be explored. For example, collaboration between the first author of a paper or patent and other authors can

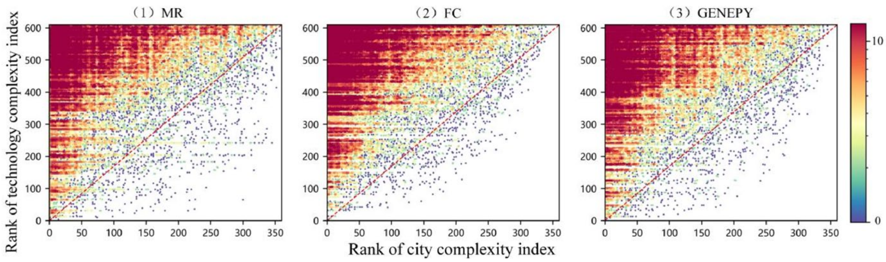

Fig. 2 Inverted triangle diagram of the three methods of MR, FC and GENEPY

roughly distinguish the main direction of knowledge flow. There is a need to further examine the impact of the direction of other forms of technology flows on regional specialization.

Appendix

In order to compare the pros and cons of the three methods, we use an inverted triangle diagram and statistics to compare the urban and technological complexity in 2001, 2005 and 2016.

First, comparing all results, Fig. 2 visualizes the results in 2016, where the abscissa represents the city complexity ranking and the ordinate represents the technology complexity ranking. Since the most complex cities have the most diverse technologies, the more similar the results are to the inverted triangle, the better robust the model has. It can be seen from the figure that the overflow points on the right side of the MR red line are the most scattered, so that the result of MR has the poorest robustness. In addition, the result of FC is the best, and

Table 7 Descriptive statistics

Variables	Observations	Maximum	Minimum	Mean	SD	VIF
RTA_t	55,384	1	0	0.477	0.499	–
Growth	55,384	5289	−2599	56.80	241.0	–
Linkages	55,384	265	1	1.855	3.646	1.02
Gap	55,384	2	−2	−0.01	1.218	1.69
RD	55,384	100	0	32.03	8.258	1.26
VR	55,384	10.61	0	6.918	0.925	1.69
RTA_{t-1}	55,384	1	0	0.465	0.499	1.18
Linkages_*f*	55,384	32	0	0.109	0.812	1.04
GDP	55,384	2.512 × 108	0	8.374 × 107	7.086 × 107	2.24
Pop	55,384	14,052	13.11	1306	851.9	1.10
Application	55,384	14,921	0	269.7	757.6	–

Table 8 Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
RTA_t	1										
Growth	0.159	1									
linkages	0.037	0.070	1								
Gap	−0.042	−0.18	0.014	1							
RD	0.282	0.094	0.039	0.036	1						
VR	0.159	0.375	0.097	−0.434	0.053	1					
RTA_{t-1}	0.599	0.106	0.040	−0.035	0.355	0.144	1				
Linkages_*f*	0.078	0.116	0.049	−0.097	0.091	0.167	0.072	1			
GDP	0.047	0.243	0.034	−0.619	0.131	0.603	0.045	0.149	1		
Pop	0.019	−0.012	−0.005	−0.123	0.223	0.012	0.023	0.036	0.188	1	
Application	0.219	0.677	0.105	−0.249	0.167	0.541	0.213	0.267	0.381	0.003	1

Table 9 The results of the top 10 cities of the three methods of MR, FC and GENEPY

Rank	Method of reflections Hidalgo and Hausmann (2009)			Fitness and Complexity Tacchella et al. (2012)			GENEPY (Sciarra et al 2020)		
	2001	2005	2016	2001	2005	2016	2001	2005	2016
1	Lingshui (5.939)	Shenzhen (4.377)	Shenzhen (4.597)	Shanghai (134.150)	Beijing (152.343)	Shanghai (5.469)	Beijing (1.390)	Beijing (1.823)	Shenzhen (0.462)
2	Pu'er (3.703)	Beijing (4.186)	Beijing (3.727)	Beijing (20.688)	Shanghai (46.493)	Shenzhen (5.445)	Shanghai (0.932)	Shanghai (1.404)	Shanghai (0.321)
3	Shanghai (3.382)	Shanghai (3.580)	Shanghai (3.659)	Shaoxing (15.675)	Tianjin (43.498)	Xi'an (4.288)	Shenzhen (0.759)	Shenzhen (1.109)	Beijing (0.228)
4	Beijing (3.354)	Tianjin (2.890)	Nanjing (3.217)	Shenzhen (11.119)	Shenzhen (8.954)	Beijing (4.013)	Tianjin (0.714)	Chengdu (0.589)	Chengdu (0.163)
5	Shenzhen (2.931)	Nanjing (2.853)	Xi'an (3.104)	Tianjin (11.108)	Hangzhou (5.228)	Wuxi (3.870)	Wuhan (0.426)	Hangzhou (0.537)	Nanjing (0.158)
6	Tianjin (2.459)	Hangzhou (2.798)	Chengdu (2.936)	Wuhan (8.191)	Chengdu (4.796)	Jinan (3.733)	Shenyang (0.317)	Guangzhou (0.456)	Xi'an (0.135)
7	Changjiang (2.396)	Chengdu (2.527)	Mianyang (2.859)	Hangzhou (7.997)	Xiamen (4.347)	Nanjing (3.732)	Chengdu (0.308)	Nanjing (0.453)	Guangzhou (0.114)
8	Nanjing (2.756)	Suzhou (2.306)	Zhuhai (2.830)	Changchun (6.979)	Guangzhou (4.240)	Chengdu (3.690)	Hangzhou (0.308)	Tianjin (0.440)	Wuxi (0.100)
9	Wuhan (2.237)	Xi'an (2.292)	Wuhan (2.706)	Shijiazhuang (6.587)	Shijiazhuang (4.136)	Tianjin (3.442)	Nanjing (0.297)	Shenyang (0.279)	Mianyang (0.099)
10	Hangzhou (2.103)	Guangzhou (2.207)	Guangzhou (2.680)	Xi'an (6.043)	Nanjing (3.475)	Dalian (3.109)	Guangzhou (0.223)	Suzhou (0.240)	Suzhou (0.097)

GENEPY is between the two. Therefore, from the perspective of all urban samples, FC ≈ GENEPY > MR.

Secondly, comparing the specific values of the top ten cities (Table 9), the FC coefficient fluctuates greatly, and the literature involving FC generally adopts standardized results to avoid the problem of excessive coefficient gaps in different years. MR and GENEPY results are relatively stable, but the MR in 2001 was inconsistent with the actual, including Lingshui, Pu'er, Changjiang and other less developed regions whose coefficients were too large. Due to the relatively small number of patent application data in 2001, the results are not robust, but the GENEPY results are relatively stable. As a consequence, from the specific value, GENEPY > MR >> FC.

Therefore, this paper adopts GENEPY. In fact, GENEPY is a compromise algorithm proposed for the shortcomings of MR and FC algorithms, see Sciarra et al. (2020), for details.

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Declarations

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References

Anton J, Yao D (1994) Expropriation and inventions: appropriable rents in the absence of property rights. Am Econ Rev 84(1):190–209
Audretsch DB, Feldman MP (1996) R&d spillovers and the geography of innovation and production. Am Econ Rev 86(3):630–640
Balland PA, Boschma R (2021) Complementary interregional linkages and Smart Specialisation: an empirical study on European regions. Reg Stud 55(6):1059–1070
Balland PA, Rigby D (2017) The geography of complex knowledge. Econ Geogr 93(1):1–23
Balland PA, Boschma R, Crespo J, Rigby D (2019) Smart specialization policy in the EU: relatedness knowledge complexity and regional diversification. Reg Stud 53(9):1252–1268
Balland PA, Jara-Figueroa C, Petralia SG, Steijn M, Hidalgo CA (2020) Complex economic activities concentrate in large cities. Nat Hum Behav 4(3):1–7
Bathelt H, Malmberg A, Maskell P (2004) Clusters and knowledge: local buzz global pipelines and the process of knowledge creation. Prog Hum Geog 28:31–56
Boschma R (2005) Proximity and innovation: a critical assessment. Reg Stud 39(1):61–74
Boschma R (2017) Relatedness as driver of regional diversification: a research agenda. Reg Stud 51(3):351–364
Boschma RA, Coenen L, Frenken K, Truffer B (2017) Towards a theory of regional diversification: combining insights from evolutionary economic geography and transition studies. Reg Stud 51(1):31–45
Boschma R, Heimeriks G, Balland PA (2014) Scientific knowledge dynamics and relatedness in biotech cities. Res Policy 43(1):107–114

Boschma R, Iammarino S (2009) Related variety trade linkages and regional growth in Italy. Econ Geogr 85:289–311
Boschma R, Lambooy JG (1999) Evolutionary economics and economic geography. J Evol Econ 9(4):411–429
Breschi S (2011) The geography of knowledge flows. Handbook of regional innovation and growth, pp 132–142
Breschi S, Lissoni F, Malerba F (2003) Knowledge-relatedness in firm technological diversification. Res Policy 32:69–87
Castaldi C, Frenken K, Los B (2015) Related variety unrelated variety and technological breakthroughs an analysis of US state-level patenting. Reg Stud 49:767–781
Choi J, Jang D, Jun S, Park S (2015) A predictive model of technology transfer using patent analysis. Sustainability 7(12):16175–16195
Cortinovis N, Xiao J, Boschma R, Oort F (2017) Quality of government and social capital as drivers of regional diversification in Europe. J Econ Geogr 17:1179–1208
Dosso M, Lebert D (2020) The centrality of regions in corporate knowledge flows and the implications for smart specialisation strategies. Reg Stud 54(10):1366–1376
Drivas K, Economidou C (2014) Is geographic nearness important for trading ideas? Evidence from the US. J Technol Transf 40(4):629–662
Feldman MP, Kogler DF, Rigby DL (2015) Rknowledge: the spatial diffusion and adoption of rDNA methods. Reg Stud 49(5):798–817
Findlay R (1978) Relative backwardness direct foreign investment and the transfer of technology: a simple model. Q J Econ 92(1):1–16
Frenken K, Van Oort F, Verburg T (2007) Related variety unrelated variety and regional economic growth. Reg Stud 41:685–697
Galetti J, Tessarin M, Morceiro CP (2021). Skill relatedness, structural change and heterogeneous regions: evidence from a developing country. Pap Reg Sci 100(6)
Griffith R, Redding S, Van Reenen J (2003) R&D and absorptive capacity: theory and empirical evidence. Scand J Econ 105:99–118
Grossman GM, Helpman E (1994) Technology and trade. NBER Working Paper 4926 Cambridge MA: NBER
Guevara MR, Hartmann D, Aristarán M, Mendoza M, Hidalgo CA (2016) The research space: using career pathsto predict the evolution of the research output of individuals institutions and nations. Scientometrics 109(3):1695–1709
Hall BH, Jaffe A, Trajtenberg M (2005) Market value and patent citations RAND. J Econ 36(1):16–38
Hidalgo CA, Balland PA, Boschma R, Delgado M, Feldman M, Frenken K, Glaeser E, He C, Kogler D, Morrison A, Neffke F, Rigby D, Stern S, Zheng S, Zhu S (2018) The principle of relatedness. In: Springer proceedings in complexity (pp 451–457) Springer Paper originally presented at the International Conference on Complex Systems (ICCS) Cambridge MA USA July 22–27
Hidalgo CA, Hausmann R (2009) The building blocks of economic complexity. Proc Natl A Sci 106:10570–10575
Hidalgo CA, Klinger B, Barabasi AL, Hausmann R (2007) The product space and its consequences for economic growth. Science 317:482–487
Hirschman A (1958) The strategy of economic development. Yale University Press, New Haven
Hu A, Jefferson G, Guan X, Jinchang Q (2005) R&D and technology transfer: firm-level evidence from Chinese industry. Rev Econ Stat 87(4):780–786
Jun B, Alshamsi A, Gao J, Hidalgo CA (2020) Bilateral relatedness: knowledge diffusion and the evolution of bilateral trade. J Evol Econ 30(2):247–277
Kemeny T (2011) Are international technology gaps growing or shrinking in the age of globalization? J Econ Geogr 11(1):1–35
Kogler DF, Rigby DL, Tucker I (2013) Mapping knowledge space and technological relatedness in US cities. Eur Plan Stud 21(9):1374–1391
Liu C, Niu C, Han J (2019) Spatial dynamics of intercity technology transfer networks in China's three urban agglomerations: a patent transaction perspective. Sustainability 11:1647
Liu W, Tao Y, Bi K (2022) Capturing information on global knowledge flows from patent transfers: an empirical study using USPTO patents. Res Policy 51(5):104–509
Lucas R (1988) On the mechanics of economic development. J Monet Econ 22(1):3–42

Marco AC, Myers A, Graham SJ, D' Agostino P, Apple K (2015) The USPTO patent assignment dataset: descriptions and analysis. USPTO Economic Working Paper No 2015-2 Available at SSRN: https://ssrn.com/abstract=2636461or102139/ssrn2636461

Mariani MS, Vidmer A, Medo M, Zhang YC (2015) Measuring economic complexity of countries and products: which metric to use? Condens Matter Phys 88(11):293

Miguelez E, Moreno R (2015) Knowledge flows and the absorptive capacity of regions. Res Policy 44

Miguelez E, Moreno R (2017) Relatedness external linkages and regional innovation in Europe. Reg Stud 52(5):688–701

Neffke F, Henning M, Boschma R (2011) How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. Econ Geogr 87:237–265

Pinheiro F, Balland PA, Boschma R, Hartmann D (2022) The dark side of the geography of innovation: relatedness complexity and regional inequality in Europe. Reg Stud 1–16

Rigby D (2013) Technological relatedness and knowledge space: entry and exit of US cities from patent classes. Reg Stud 49(11):1922–1937

Romer P (1986) Increasing returns and long-run growth. J Polit Econ 94(5):1000–1037

Santoalha A (2019) Technological diversification and smart specialization: the role of cooperation. Reg Stud 53(9):1269–1312

Sciarra C, Guido G, Ridolfi L, Francesco L (2020) Reconciling contrasting views on economic complexity. Nat Comm 11:3352

Sorenson O (2010) Complexity network and knowledge flows In: Boschma R Martin R et al (eds) The handbook of evolutionary economic geography. Edward Elgarm

Spulber FD (2008) Innovation and international trade in technology. J Econ Theory 138(1):1–20

Storper M (1997) The regional world: territorial development in a global economy. Guilford Press, New York

Tacchella A, Cristelli M, Caldarelli G, Gabrielli A, Pietronero L (2012) A new metrics for countries' fitness and products' complexity. Sci Rep-UK 2:723

Walsh JP, Lee YN, Nagaoka S (2016) Openness and innovation in the US: collaboration form idea generation and implementation. Res Policy 45(8):1660–1671

Wang B, Mao W, Piao J, Liu C (2023) Does external linkage stimulate innovation capacity? The analysis based on "dual-pipelines" framework. Pap Reg Sci 102(3):613–633

Whittle A, Kogler D (2019) Related to what? Reviewing the literature on technological relatedness: where we are now and where can we go? Pap Reg Sci 1–17

Young S, Lan P (1997) Technology transfer to china through foreign direct investment. Reg Stud 31(7):669–679

Zhang G, Duan H, Zhou J (2016) Investigating determinants of inter-regional technology transfer in China: a network analysis with provincial patent data. Rev Manag Sci 10:345–364

Zhu S, He C, Zhou Y (2017) How to jump further and catch up? Path-breaking in an uneven industry space. J Econ Geogr 17(3):521–545

Zhu S, Guo Q, He C (2021) Strong links and weak links: how do unrelated industries survive in an unfriendly environment? Econ Geogr 97(1):66–88