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Observing regional divergence of Chinese nanotechnology centers

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ABSTRACT

While China has emerged as one of the world's leading technological innovators, past studies have uncovered that technology centers have been overwhelmingly concentrated in Beijing and Shanghai. We take a step further to investigate whether this geographic concentration has persisted over time with nanotechnology-related patents. We apply the spatial analysis techniques and employ Gini's coefficient and global Moran's I. We additionally test the spatial patterns at four scales: the municipality, the county, the intra-metropolitan, and the distance-based.

We find that while Beijing and Shanghai have remained the two dominant nanotechnology clusters, the Shanghai region, together with Jiangsu and Zhejiang, surpassed the traditionally productive Beijing–Tianjin region by 2007. We did not identify spatial autocorrelation at the province level, but at the county level, and at the scale between 20 km and 75 km. The intra-metropolitan analysis in Beijing and Shanghai further confirmed that the geographic concentration of nanotechnology is small, around 20 km. These results support the regional divergence theory and a small scale of technology diffusion, as well as the possibility of continually increasing inequality in China and its technology development.

1. Introduction

In recent years, the People's Republic of China has emerged not only as a mass manufacturer, but also as one of the world's leading technology nations. Many semiconductor products come from China, approximately one in ten professionals in Silicon Valley's high-tech workforce is from mainland China [1], and China successfully became only the second country to launch the radar-evading stealth fighter jet [2]. In addition to anecdotal evidence, various bibliometric studies have suggested that China has made a major advancement in the fields of science and technology. China has surpassed Japan and now is ranked second in the production of academic journal articles in science and engineering fields [3]. In the nanotechnology field, often considered one of the cutting-edge areas in science and engineering, China has surfaced as one of the top players [4–6]. Indeed, while the journal *Nature Nanotechnology* [7], and Lenoir and Herron [8] predicted that China would surpass the United States by 2012, according to Kostoff et al. [9], China not only achieved this in 2009, but also produced 20% more academic journal articles in science and engineering fields than the United States by 2012. Additionally, China dominates in the nanotechnology area of most-cited academic articles: the top eighteen out of the twenty scholars are of Chinese origin [10].

However, such success may come at a cost. While China boasts world-class research institutes in nanotechnology such as the Chinese Academy of Sciences, Tsinghua University, and Peking University, to name a few [11], they are overwhelmingly concentrated in two regions: Beijing and Shanghai. This concentration of technology centers could become an important issue because it can bias the geographic locations of technology, knowledge, scientific workforce, and wealth, and eventually could enlarge inequality in China [12]. Rising inequality will explicitly contradict the goal of harmonious regional growth set by the Chinese government [13] and could obstruct long-term sustainable growth, especially in this enormous and demographically diverse country.

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Examining the Chinese case could reveal significant implications for technology development and geography. In contrast with the United States, the Chinese government has most aggressively invested in and prioritized nanotechnology development using the top-down approach [14]. Such an approach may be effective to create a selected number of research institutes, but technological diffusion and long-term sustainability of the technological, as well as economic development, may be questionable. Moreover, the Chinese case exhibits a different pattern from even other East Asian nations. For example, Japan, Taiwan, and South Korea managed equitable high growth through interregional distribution of resources [15] and regionally oriented technology programs [16]. The strong central government and vast scale of the country may create an entirely different development pattern for China.

This article applies bibliometric analysis to examine the geography of nanotechnology research centers in China. While several past studies analyzed the location and heavy geographic concentration of nanotechnology centers, we consider it more important to take a step further to investigate whether such concentration has persisted over time. Based on Chinese nanotechnology patents, our analysis identifies the leading regions and shifts among them, and employs Gini coefficients and local and Global Moran's I to test spatial concentration. Moreover, we critically examine the concentration by not relying on the conventional administrative unit, such as provinces and counties, but by employing distance-based measure and intra-metropolitan analysis. Although we do not detect a spatial clustering of nanotechnology centers at the large province level, there is a significant clustering at the small county level that has been persistent over time. Furthermore, our spatial analysis indicates that such clustering is most observable at the scale of 20 km. Thus, based on the technological clustering at this small scale, we support the regional divergence hypothesis and related concerns about the potential rise in inequality in China.

2. Literature review

There has been a long debate about regional convergence and divergence in technology, even before the emergence of information technology [17]. Studies about the convergence theory often were based on the neoclassical growth theory in which capital and labor were mobile and could relocate over space without friction [18]. Furthermore, imitation was conventionally less expensive than discovery [19], and thus poor regions could catch up with technologically advanced nations. This catch-up convergence could occur if government provided the infrastructure and legal framework to foster labor and capital productivity growth. It further assumed that technology was a public good and was available to every economic player.

Several empirical studies involving patent analysis supported this convergence thesis. Co [20] found that states whose patents per capita were higher than the U.S. average in 1963–69 experienced either slower or negative growth in the later years compared to lagging states. Johnson and Brown [21] echoed these findings by adding that formerly wealthy states were the slowest to convert from stagnating sectors because they tended to remain with traditional and even stagnating industries. Thus, the initial state of a region was important, but its overall innovativeness could change over time. Ó hUallicháin and Leslie [22] gave a nuanced conclusion, but still supported the convergence theory. Their study found spatial convergence among U.S. states between 1963 and 1993, while a modest level of divergence took place between 1993 and 2003.

Another set of studies indicated a regional and structural shift of innovation in the past few decades in the United States. The Sunbelt states, such as Florida, Texas, and California, were growing faster technologically than the traditional manufacturing region of the Northwest and Midwest [23–27]. However, these studies about the emergence of the "newcomers" did not necessarily support the convergence theory because the studies did not provide an analytical criterion about the most lagged regions, which often continued to be most lagging. Furthermore, it will be more important to consider the continuous trajectory between the new risers, the Sunbelt states, and the traditional Northeast and Midwest. If the Sunbelt states continue to grow faster than the traditional centers, that would bring divergence.

In contrast, we would expect the divergence of regions by incorporating theories of evolutionary economics, such as the increasing returns to scale and endogeneity of growth and technological development [28,29]. In other words, regions with certain economic and geographic endowments would bring positive feedbacks of agglomeration and concentration, while the initial location of firms and industries might happen by historical accident [30]. A handful of empirical regional studies supported such theory. Ó hUallicháin [31] discovered that the largest U.S. metropolitan areas predominated the patent activities, and such advantages arose from the concentrations of technologically intensive manufacturing and well-educated workforce. Bettencourt and others [32] found a super-linear effect with U.S. metropolitan areas between 1980 and 2001, indicating that larger metropolitan areas were becoming even more productive. Sonn and Park [17] dissected the analysis between cities with similar size (horizontal convergence) and between larger and smaller cities (vertical divergence). They concluded that horizontal convergence dominated over vertical divergence, leading to a net effect of overall convergence.

We identify four major limitations of the past studies. First, these apparently mixed results indicate that variations may come from differences over time, by geographic regions, by industry or technology types. Thus, it will be critical to test the phenomenon of convergence and divergence in a specific context. As mentioned before, Ó hUallicháin and Leslie found convergence before 1993 but divergence after 1993. Moreover, the difference potentially coming from industry or technology can be critical, and we have to consider two related empirical studies. Varga [25,27] disaggregated patent technology types by IT, drugs, chemicals, high-tech machinery, defense and aerospace, and professional and scientific instruments, and found substantially different patterns of specialization and emergence/decline of U.S. metropolitan regions between 1970 and 1992. Johnson et al. [33] found that different technology types showed significant differences in the distance of patent citation, though the pattern of patent citation was different from the geographic clustering of patents. More specifically, in computers and biotech, particularly affecting California and Texas, the citation distance has shortened, while in other industries citation distance has increased over time.

Second, the past patent studies overwhelmingly were concentrated on the U.S. case. There have been few studies examining the non-U.S. context. So far, only one European case has been identified: Carrincazeaux and others [34] demonstrated a significantly high concentration in France where almost half of the entire country's R&D activities are carried out in the Paris region. We can expect substantially different outcomes for East Asia given the differences in land use, government policy regarding regional development, transportation and other infrastructure, and stages of overall economic development.

With regard to China, we have identified only two studies about patents and geographic analysis[1] despite the attention the country has received in recent years. Yifei Sun [36] concluded that between 1985 and 1995, traditional innovative centers, such as Beijing, Shanghai, Tianjin, and Jiangsu, have declined, while new areas, such as Guangdong, Shandong, Zhejiang, and Fujian emerged. In contrast, Liu and Yuntao Sun [13] observed a shift of innovation activities from the inland to the eastern coastal areas. Beijing remained a strong region, but Shanghai and Guangdong have emerged as new innovative centers. In short, these two past studies also have provided mixed results and limited understanding about patents and their geographic distributions in China. This prompts three rationales for our research approach: First, we examine the case of China, one of the major nanotechnology players in the world. Second, our case, specifically focusing on China and nanotechnology, can control for the technology-specific condition mentioned above. Third, nanotechnology is newly emerging technology, so we can test the geographic distribution of this technology in the early stage of its development. The previous studies with sectoral analysis have examined relatively new industrial sectors, such as IT and biotech, but have not paid any attention to the stage of development at which new types of technologies or industries are emerging.

We further point out two other limitations of the past research. Third, the past studies relied on a single indicator to test the divergence. In contrast, this article investigates the state of divergence by employing three different indicators: (1) identifying the leading regions and shifts among them, (2) calculating the regional inequality measure using the Gini coefficient, and (3) analyzing the spatial cluster with different geographic weights. This method of using multiple indicators is critically important because we do not consider relying on one indicator to be sufficient. De Michelis and Monfort [37] provided a notable caution about this approach. They investigated the income inequality in the European Union and obtained different results with different indicators. “Indeed, a closer examination of the distribution dynamics reveals that convergence may take place, even within groups of regions for which such movement would remain undetected by an aggregate inequality measure” (p.19). Although their mixed result came from different threshold levels within the same indicator, we will take a cautious approach and employ several indicators to analyze.

It is one thing to analyze the general patterns of highly innovative places, such as the U.S. northeastern vs. southern states. Such analysis can reveal a structural shift among the leading regions; the top one became one of the top five and vice versa. However, we should continue testing the overall state of divergence through other indicators that cover places besides the leading ones. The standard measure of divergence is to calculate the share by an identified number of top regions, the score in Theil's index, or the Gini coefficient. These share-based indicators are useful if the unit of analysis is relatively homogeneous, such as individuals or households. A geographical unit, most commonly an aggregate measure of individual actors such as individuals or firms, may experience a shift within its basic constitution over time. Therefore, we will employ this second indicator, aware of its limitations.

These concerns over measuring indicators lead to the fourth and perhaps most critical limitation of the past studies: a lack of debate over the unit of analysis, the distance, and geographic weights to measure the divergence. In other words, past studies discussed regions and states, but failed to account for the scale of spillover and possible neighboring spatial effects, or the methods and rationale used to define neighbors. The common unit of analysis was either the states [20,38] or metropolitan areas [17,31,32]. A few other studies have examined both the state and metropolitan levels [24,27,39]. However, debate over the utility of using distance as the unit of analysis is surprisingly scarce, often indicated by a sentence or two, such as “states are the most relevant policy making units” for economic development and science and technology (Audretsch and Feldman 1996, 631)[2] or “cities or counties rather than states may be the more appropriate unit of analysis for asking whether diversity or specialization promotes innovation” [20, p. 418]. The rationale for the selected unit was barely explained. In fact, most studies seemed to select a spatial unit based on methodological convenience rather than on a specific theoretical framework.

We modify this approach by employing different spatial units and weights. Although we initially conduct our analysis at the Chinese province level, somewhat an equivalent of the U.S. state level, we do not consider testing only at the state level to be optimal for the following two reasons. First, distance between states varies substantially. The closest centroid-based distance in Chinese province and special city units is 79 km, the median is 380 km, and the maximum is 1110 km.[3] We should not expect comparable spillover or clustering effects between provinces due to this variance. Secondly, we hypothesize that knowledge spillover takes place in regions smaller than province/state, such as the local or metropolitan levels, as indicated by a handful of literature. Anselin et al. [40] found a 50-mile (80-km) radius spillover effect, and their subsequent study [41] found a 75-mile (120-km) radius. At the same time, they acknowledged that only weak evidence had connected knowledge spillovers and defined distance (p.417). Cohen et al. [42] demonstrated that firms could manage a 200 km distance if the transaction was clearly defined between different divisions of development centers, but that closer proximity was necessary for tight and uncertain coordination. Lastly, Zucker, Darby, and their colleagues demonstrated that scholars

[1] Yifei Sun [35] found overconcentration of foreign R&D investment in Beijing and Shanghai, but we excluded it in this debate because it did not investigate patents. Tang and Shapira [37] conducted an analysis similar to this article, but their analysis was based on academic journal publications and their unit of analysis was only at the provincial level, the limitations of which we discuss later in Section 2.

[2] However, this only tells that policy intervention takes place at the state level, and does not necessarily determine the process or geographic dimension of technology development taking place at the state level.

[3] As a reference, the mean distance in the lower forty-eight U.S. states and Washington, DC is 33.2 km (approximately 20 miles), the distance between Maryland and Washington, DC. The median is 394.0 km and the maximum is 541.4 km. The variation is substantially large.

cited more often if they were located within a specific metropolitan level rather than at the larger state level [43,44]. Thus, while there is some evidence to suggest that the smaller scale closer to the metropolitan areas may be more appropriate than U.S. states or Chinese provinces in knowledge spillover, we do not believe that there is sufficient evidence yet to conclude this definitively. We will follow the caution from Anselin et al. [40] and test at both province and county levels in China. In addition to these polygons, or contiguity-based geographic weights, we further will employ distance-based weights to test the spatial clustering of nanotechnology patents. Moreover, we will visually analyze the diffusion patterns at two highly concentrated regions: Beijing and Shanghai. Section 3 will discuss our method in more detail.

3. Method and analysis

We used Chinese patents to analyze the state of divergence in patent production. Although patents have been probably the most widely used indicators of innovation [20,45,46], we should address their limitations before using them. First, there are many commercial innovations that are not patented. Second, many patents have never been developed into commercially valuable forms [27,47]. However, there have been plenty of studies that demonstrated high correlations between patents and various indicators of innovation, such as the Small Business Administration Innovation Database and corporate R&D activities [48–50]. Statistical correlations were significantly high in those studies, which concluded that counts of innovations and patents practically provided identical regression results in knowledge production [27,51]. We should note two other advantages of using patent data. Griliches [52] pointed out that a granted patent clears a minimum scrutiny of the patent office as to its novelty, and its value is tested as the inventor files with fees: if the patent has absolutely no commercial value, the inventor would not even file it. Additionally, patent data has the widest spatial and temporal coverage [20].

We obtained data of nanotechnology-related patents from the Chinese State Intellectual Property Office (SIPO) by using sixteen nanotechnology-related keywords in Chinese to extract the data, listed in the Appendix A. The coverage of the period was from 1986 to May 2008. The initial search yielded 20,273 patents, of which we focused on 18,225 invention patents (89.9%), an equivalent of the U.S. utility patents, and excluded 2048 Chinese utility and design patents (10.1%). We further excluded patents filed by 3218 foreign entities (including Taiwan, Hong Kong, and Macao), 941 patents filed by one individual, Yang Mengjun,[4] and 347 patents without geospatial information. Our final database contained 13,719 patents.

We geocoded the data based on its postal code. Like the five-digit zip code in the United States, Mainland China has six-digit codes that are attached to specific areas. We used Google API to identify longitude and latitude of a centroid location of each postal area.[5] For the analysis at the province and county levels, we joined polygons and the centroid location of postal areas.

There are at least three ways to analyze geographic patterns of knowledge spillovers with patents: 1) to analyze the location of where patents are filed, 2) to analyze the citation patterns of patents, and 3) to analyze co-inventors and diffusion of them. In this article, and with patent analysis in China, we unfortunately have to rely on the first method, to analyze the location of filed patents. At this moment, the Chinese patent system does not list any citation information. Furthermore, we considered that identifying unique individual inventors for co-inventor network is nearly impossible given the limited number of common last names among Chinese and that our scale of patents is as large as five figures.

At the provincial level, we analyzed twenty-five provinces (sheng), five autonomous regions (zizhiqu), and four special cities (zhixiashi), totaling thirty-four units. Hereafter, we refer this to level of analysis as provinces. While Beijing has been the most prolific region for a long time, Shanghai took over the position in 2004 and has continued to produce more patents since then (Fig. 1). We observed a decline of patent applications between 2006 and 2007, which was more dramatic for Beijing than Shanghai, and this partly could be a time lag between the applications and data input into the database. Thus, we consider 2007 as a reference point, but do not conclude that patent production in China has declined since 2006.

We then analyzed the leading regions and found a rise in neighboring regions, such as Shanghai, Jiangsu, and Zhejiang for one group, and Beijing and Tianjin for another group (Fig. 2). This indicates a potential spatial autocorrelation, which we will revisit later in this section.

At the county level, there are 2975 counties, and we found clusters of nanotechnology centers most visibly on the Eastern coastline: Beijing, Shanghai, and areas in-between (Fig. 3). However, we are aware of the limitations of the visual interpretation of ratios through maps due to standard errors and differences in area size [53], and we will leave this evaluation of clustering by calculating Global Moran's I in the next section.

Next, we employed Gini coefficients to test the state of inequality among regions and analyzed both at the province/city and county scales. Fig. 4 demonstrates that the inequality level has not changed significantly over time at either the province/city or county scales. The figure additionally shows that the state of inequality is substantially higher (over 0.98) at a smaller, county scale because many counties have not filed nanotechnology patents.

To consider spatial effects, we employ Global Moran's I to test the state of divergence. Moran's I measures the degree of spatial autocorrelation, and a statistical significance of Moran's I over time could suggest that nanotechnology centers cluster more geographically, thus leading to the divergence. We started with the queen contiguity, which is most commonly used in the polygon-based analysis. We first tested at the province level and used the contiguity from the first to the third order, keeping in mind that the mean distance varies from 394 km for the first order to 501 km for the third order. While there was no spatial autocorrelation before 2006, there was a statistically significant and increasing level of clustering for 2006–7 in the second and

[4] Patents filed by this individual were all based on traditional Chinese medicine and had no relevance to nanotechnology. None of his patents was granted.

[5] About 1% of the data showed postal codes that differed from the province name provided by the patent filers. Many were jointly filed by inventors based at differing locations. In these instances, we used the locations as identified by the postal codes.

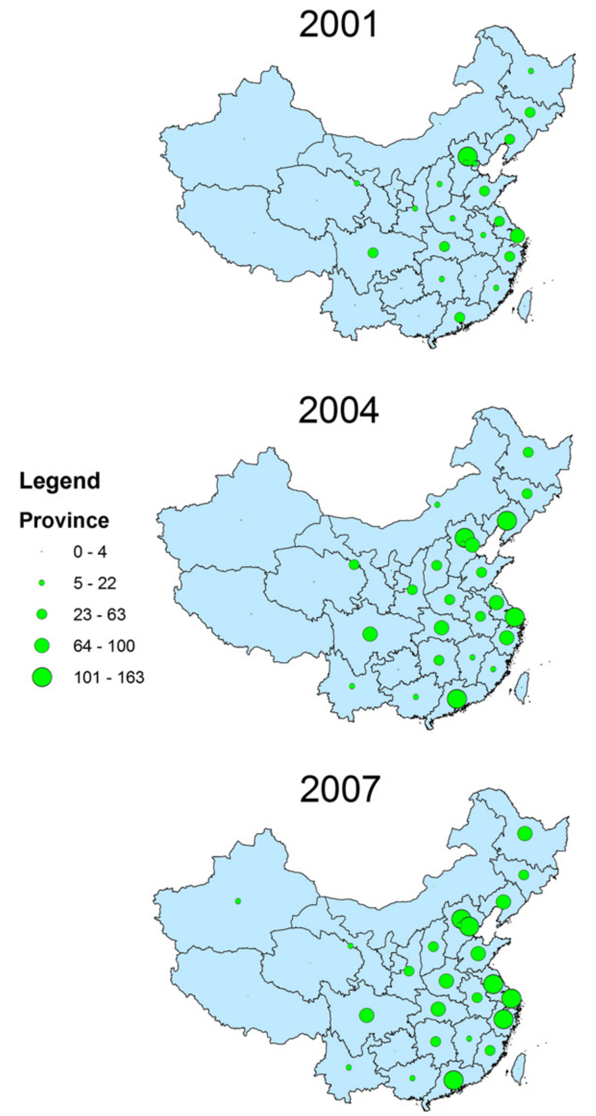

Fig. 1. Nanotechnology patent applications at the province level (2000, 2004, 2007).

the third orders. However, since this applies only to the last two years, including a reference year, 2007, we do not consider this a conclusive evidence of the regional divergence yet. If we normalize patents by population, we see further weak evidence of spatial clustering (Table 1).

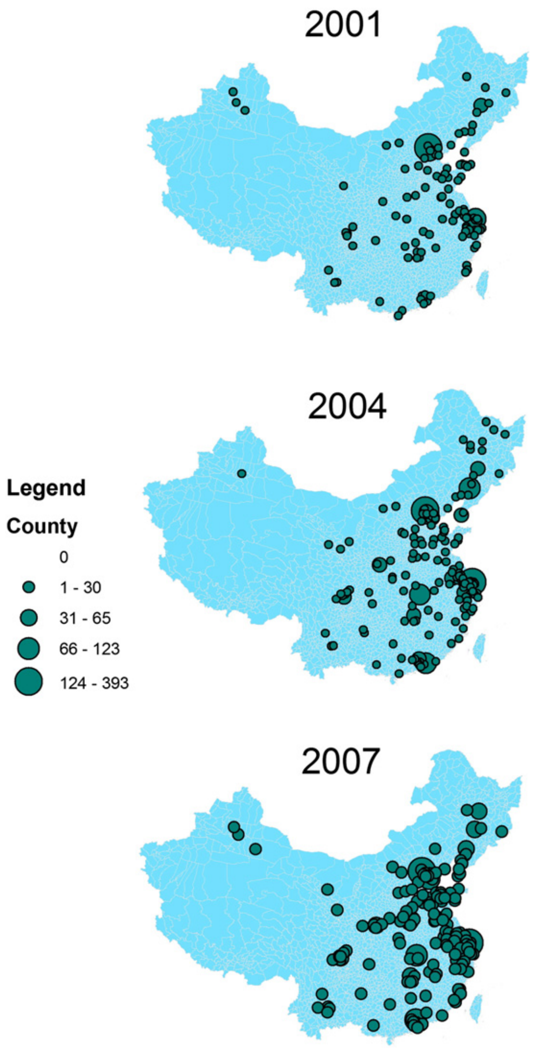

Fig. 3. Nanotechnology patent applications at the county level (2000, 2004, 2007).

We then tested at the county level. The mean distance varies from 34.7 km for the first order to 43.1 km for the third

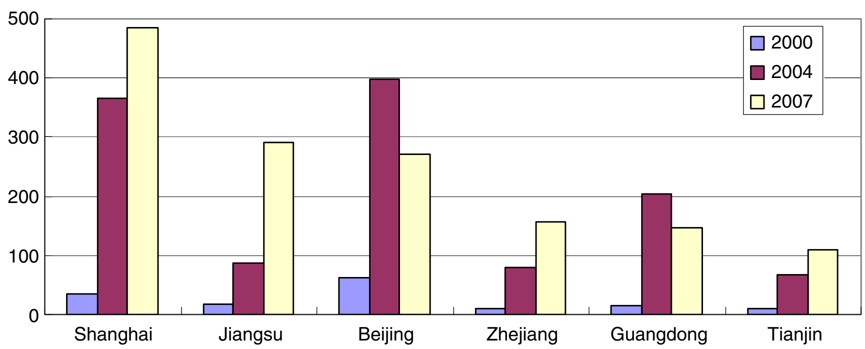

Fig. 2. Top seven city-provinces.

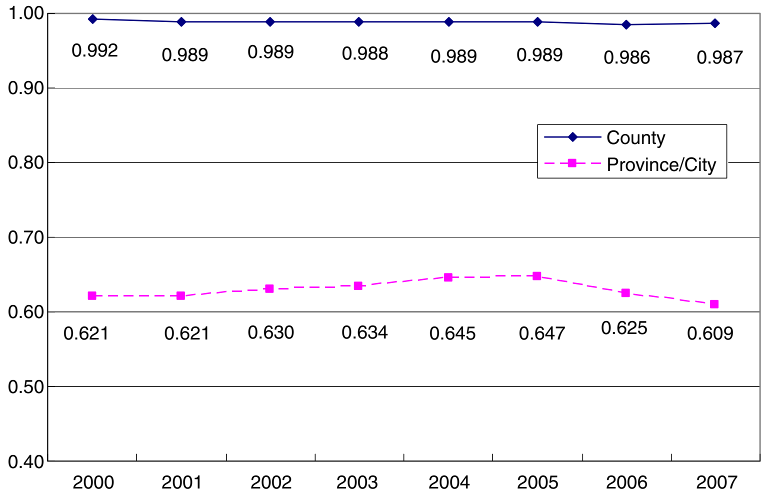

Fig. 4. Gini coefficient at county and province/city levels.

Table 1
Moran's I at the province level.

	2000	2001	2002	2003	2004	2005	2006	2007
Without normalization by population								
1st order	0.051	−0.025	−0.041	0.086	−0.058	0.075	0.075	0.1670
2nd Order	0.119	−0.013	−0.024	0.054	0.001	0.126	0.244**	0.3864***
3rd order	0.132**	0.038	0.001	0.047	−0.004	0.054	0.137*	0.2288***
With normalization by population								
1st order	−0.1035	−0.1057	−0.1099	−0.0629	−0.1173	−0.0661	−0.0876	−0.0275
2nd order	0.1002	0.0254	0.0253	0.0110	0.0262	0.0561	0.1527*	0.1085*
3rd order	0.0571	0.0118	0.0041	−0.0130	−0.0052	0.0056	0.0601	0.0358

Note: *** Significant at 99% level, ** significant at 95% level, * significant at 90% level.

order contiguity. Moran's I in the first order contiguity is somewhat sporadically significant, and we cannot conclude with this result yet (Table 2). In contrast, Moran's I from the second and the third contiguities was significant in all years between 2000 and 2007. The expected value is $-1 / (n - 1) = -1 / (2975 - 1) = -0.000336$. Since all Moran's I results were larger than this figure, we can conclude that spatial autocorrelation exists [54]. Unfortunately, we could not test this figure at the county level with normalization. The Chinese Census at the county level has many missing data as they tend to reclassify rural counties into arbitrarily aggregated units from time to time.

The variance of Moran's I's significance between the first, second, and third order contiguities, along with the variance of distance between these contiguities, cautions us that the polygon-based units may not be the most appropriate ones to capture spatial clustering. Thus, we analyzed Moran's I with inversely weighted distance-based measures from 10 km to 75 km (Fig. 5). Moran's I was not statistically significant with less than 20 km distance, but was significant between 20 km and 75 km, except in 2007, in which it was significant between 40 km and 75 km. In each year, Moran's I was higher in 20–25 km, but declined with distances over 30 km. This suggests that the spatial autocorrelation, and hence knowledge spillover, may take place most effectively in the 20–25 km distance range.

While we have found consistent results from various analyses based on Moran's I, such analysis comes with one technical limitation: we are unable to normalize the patent production, due to the limited data availability at the county level in China. To compensate for this limitation, we conducted our last test, a visual analysis of selected nanotechnology subfields in Beijing and Shanghai, the two largest concentrations of nanotechnology patents.[6] This visual analysis does not completely remove the normalization issue. However, since we can identify the precise location of patent applicants at the postal code level, this exercise helps us to identify which institution at what location filed patent applications, including specific universities and companies. Thus, we can semi-normalize patent applications by institutions. Furthermore, we can test whether knowledge spillover takes place between universities and corporations.

At the nationwide scale, universities and various branches of the Chinese Academy of Sciences (CAS) have become the dominant applicants of nanotechnology patents throughout the 2000s. In 2000, universities and CAS filed 28.6% of patents, while they expanded this share to almost half by 2007. In the

[6] We obtained the centroid of postal code areas through Google API and mapped on Google Map using RGoogleMap package in R.

Table 2
Moran's I at the county level.

	2000	2001	2002	2003	2004	2005	2006	2007
1st order	0.0311**	0.0117	0.0523***	0.0314**	0.0325**	0.0265*	0.0430**	0.0192
2nd order	0.0425***	0.0621***	0.0708***	0.0686***	0.0799***	0.0609***	0.0612***	0.0363***
3rd order	0.0367***	0.0451***	0.0634***	0.0515***	0.0584***	0.0441***	0.0477***	0.0276***

Note: *** Significant at 99% level, ** significant at 95% level, * significant at 90% level.

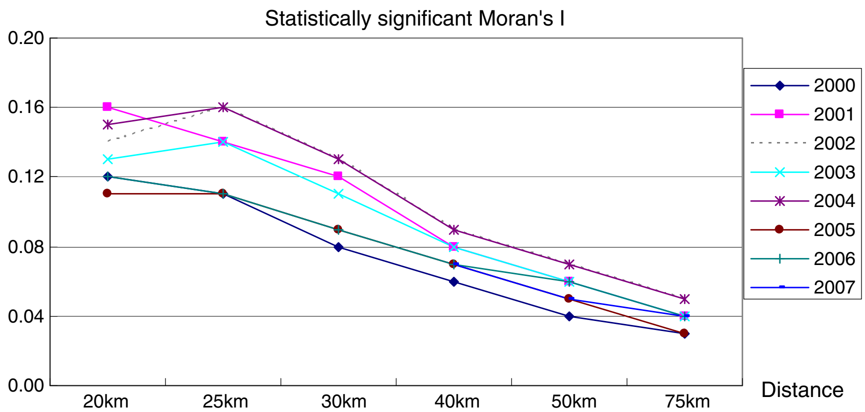

Fig. 5. Moran's I based on distance (statistically significant at 99.9% level).

meantime, the share filed by individuals has decreased steadily, and the share filed by corporations has been stagnant over the years. These figures suggest that universities are the predominant players in the creation of nanotechnology in China, and the commercialization of nanotechnology by industry has been in the premature stage thus far (Table 3).

Nanotechnology is an umbrella term for small-scale technologies. The method to control atoms or molecules can range from physics and chemistry to engineering disciplines. Thus, to focus on knowledge spillover of a specific type of nanotechnology, we select three sub-fields based on the International Patent Classification System: C08 — organic macromolecular compounds, A61 — hygiene-based medical and veterinary science, and H01 — basic electric elements. These sub-fields are the three largest sub-fields of nanotechnology patent applications received by China's patent office, and represent 13.1%, 12.4%, and 12.4% of the total patent applications, respectively. They cover chemistry, medical, and engineering disciplines, thus giving us some breadth of understanding, if not complete. Given the large variation, we analyzed by geography (two), by sub-fields (three), and by years (2000–7 = eight), which totaled 48 (forty-eight) maps. Due to the large number, we present limited maps in this section.

Shanghai: In the cases of both A61 and C08, the largest concentration is represented by two large circles at north of Yangpu, a county level district, where Fudan University is located. The circle northeast of Minhang, a district in Shanghai, is East China University of Science and Technology, and another circle between Minhang and Fengxian is Shanghai University. Patent applications by corporations (triangle) and individuals (cross) are almost negligible, except in the case of C08 where two triangles are present between Minhang and Fengxian exist. The overall concentration is in the central area of Shanghai, and the geographic scale is 20–30 km (Fig. 6).

Beijing: There is a clear concentration in the northwest side, more specifically north of Haidian, where all the major institutes are located: Tsinghua University, Peking University, several institutes of the Chinese Academy of Sciences, the National Center of Nanoscience and Nanotechnology, and Beijing

Table 3
Types of nanotechnology applicants in China.

	University/CAS	Corporations	Individuals	Government/PLA	Joint	Other
2000	28.6%	23.9%	43.6%	0.0%	0.0%	3.9%
2001	26.3%	21.4%	41.8%	2.1%	0.4%	8.1%
2002	30.3%	20.0%	40.4%	2.2%	0.0%	7.1%
2003	34.3%	20.5%	34.8%	1.3%	0.0%	9.1%
2004	36.6%	20.9%	32.4%	0.6%	0.0%	9.5%
2005	44.1%	22.1%	25.0%	1.8%	0.1%	6.9%
2006	42.5%	21.7%	23.3%	2.1%	0.9%	9.6%
2007	49.4%	18.3%	18.5%	0.8%	0.6%	12.4%

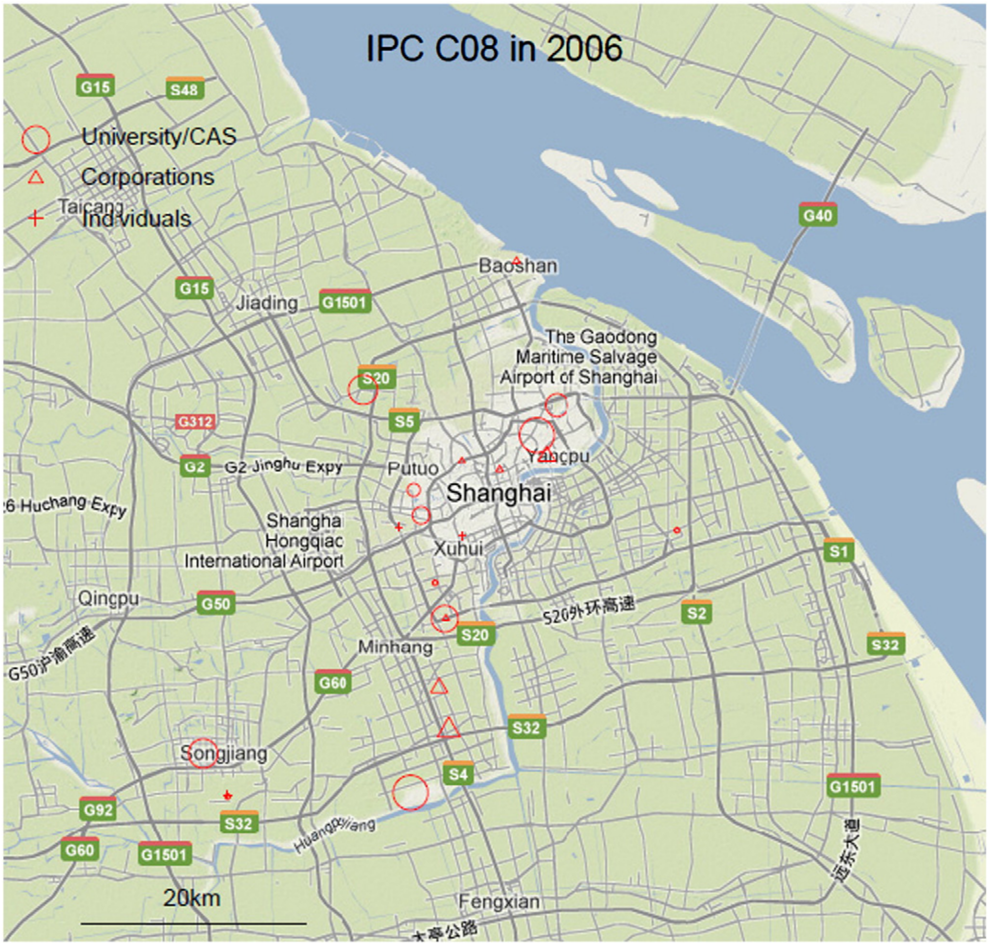

Fig. 6. Map of Shanghai with IPC sub-field C08 by types of applicants (2006).

University of Aeronautics and Astronautics. Non-university applicants are smaller and more geographically sporadic and scattered than around Shanghai. This scale of concentration is around 20 km (Fig. 7).

These findings from the visual analysis suggest that the geography of nanotechnology is substantially small, at the scale of around 20 km, consistent with the result from distance-based Moran's I. Furthermore, the geographic spillover seems to be concentrated among key research institutes within such a small scale of geographic area, and there is little evidence to suggest knowledge spillover between universities and corporations.

4. Discussion

It is important to summarize the major findings, consistencies, and inconsistencies from our series of analyses: (1) a visual analysis at the province and county levels, (2) shifts between the leading regions, (3) Gini coefficient analysis, (4) Global Moran's I at the province and county levels, (5) Global Moran's I with the inverse distance weight, and (6) a visual analysis in Beijing and Shanghai. First, the visual analysis at the province and county levels demonstrated that the geography of nanotechnology patent production was highly uneven and concentrated on the East Coast. Second, even among places on the East Coast, two leading regions dominated nanotechnology patent production: Beijing and Shanghai. Additionally, the greater Shanghai region, including Jiangsu and Zhejiang, experienced faster growth than the traditionally productive Beijing region.

Third, the Gini coefficient indicated high geographic concentration, particularly at the county level. However, because the coefficient was relatively stable over time, this analysis could not answer the question of whether the spatial clustering increased over time. An analysis solely using this indicator would be inconclusive.

Fourth, we additionally employed Global Moran's I. While the spatial autocorrelation was not most significantly present at the province level, it was critical to extend the analysis to the county level. We then observed statistically significant spatial autocorrelation at the scale of the second and third order contiguities. While the polygon-based contiguity measure could have a large variance between units, the inversely weighted distance-based measure confirmed the spatial autocorrelation at the scale between 20 km and 75 km. Furthermore, the distance of 20–25 km seemed to capture the autocorrelation most effectively.

Fifth, we came back to a visual analysis at the intra-metropolitan level in Beijing and Shanghai. Regardless of three

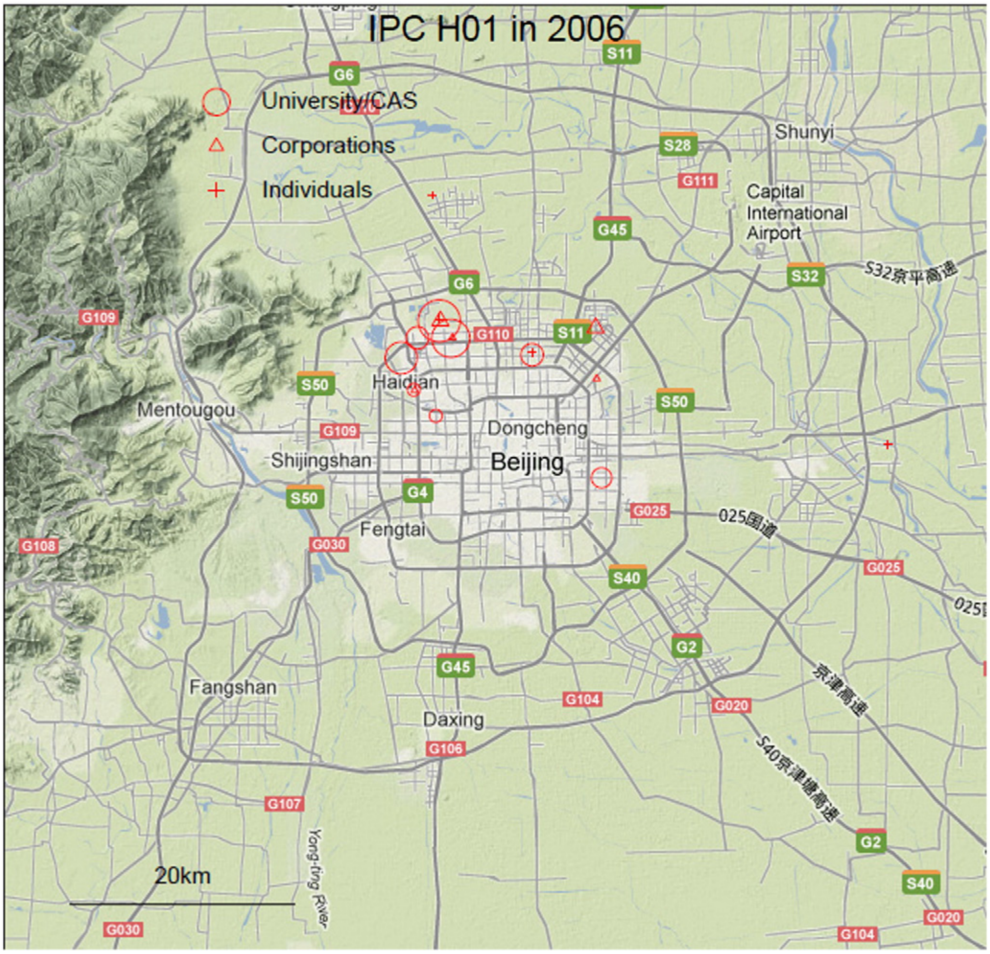

Fig. 7. Map of Beijing with IPC sub-field H01 by types of applicants (2006).

sub-fields, both the Beijing and Shanghai cases demonstrated that institutions of learning, such as universities and CAS, are the dominant nanotechnology patent applicants, and the scale of spillover was highly concentrated and small, around 20 km. This is a consistent finding with the distance-based measure of Global Moran's I.

With these findings, we draw three major conclusions. First, the geography of nanotechnology patent production is highly uneven, and the degree of such unevenness was persistent throughout the observed years. This supports the regional divergence theory, and technologically productive regions may prosper more, while technologically lagging regions may stagnate. The geography of technology was considerably small, around 20 km in the intra-metro visual analysis, particularly for emerging technology, like nanotechnology. Our concern becomes even more serious if we consider that technology is not only an end to be used once it is created, but also a means to create more advanced technology [55]. In other words, a productive region can create more advanced nano-based technologies, while lagging regions cannot. Furthermore, we find little evidence that nanotechnology is diffusing from university to industry because universities have continuously expanded patent applications, while that of applications by corporations seems to have stagnated. Thus, this phenomenon increases the inequality in China, which has a clear policy implication. While China seems successful in advancing its technology levels by distributing large-scale government research funds to key technology institutes, the government should consider the next step of technology advancement: how to geographically disperse such advanced technology. The government must consider spillovers of technology at two levels: from advanced to lagging regions and from university to industry. In either case, the current top-down approach by the Chinese central government does not seem to solve this inequality and limited spillover issue. Even in areas such as Zhongguancun in Beijing, and Yangpu and Minhang in Shanghai where high-tech zones have been established with universities and research institutes as the centers of gravity, we have not found sufficient evidence that nanotechnology-related patenting activities have flourished at among corporations at arm's length. There also seems to be a lack of industry spin-off from institutions of learning. Given that nanotechnology's similarity to science-based technologies such as IT and biotechnology, the lack of technology diffusion also suggests an overall low level of nanotechnology-related entrepreneurial activities.

Second, we would not support a super-linear effect of the divergence theory, which argued that the initial innovation capacity determined the later growth [31,32]. We observed a dynamically evolving pattern in which the regional productivity level shifted within the most productive regions. It was a semi-linear effect in which more productive regions got even more productive, but this rule was not rigid. Within more productive regions, there were some shifts. In this sense, this Chinese nanotechnology case presented a pattern close to the horizontal convergence (within a similar group) observed by Sonn and Park [17]. Our finding contrasted with that of Tang and Shapira [56], who found the super-linear dominance of Beijing in all the years they tested, between 1991 and 2006, in the case of nanotechnology publication. However, we would not call it a convergence, but rather a dynamic shift that can enlarge the divergence within the similar group, particularly if the Shanghai region continues to grow faster in the future. Furthermore, we did not find any evidence to suggest the net effect of the horizontal convergence dominating the vertical convergence.

Third, the use of various units of analysis and various indicators for spatial analysis was critical. It was a lengthy analysis. However, findings in this article suggest that analyzing a spatial pattern by employing one indicator, one unit of analysis, and one type of geographic weight seems to be insufficient. A naïve selection of the unit of analysis, either by states or metropolitan areas, could yield a biased result. A methodological convenience should not drive this aspect of research design, and a thorough analysis is required. This is a crucial point for geographers and regional scientists, particularly because there is only a limited body of literature discussing the scale of knowledge spillovers. We found that the concentration happens at the scale of around 20 km. This was smaller than the scale Anselin and his colleagues found in the case of the United States — 80 km or 120 km. Their analysis was based on spatial regression and a statistically significant independent variable at 50 km (or 75 km in their later study), but it was not clear if they tested at different scales and if they had a theoretical and empirical rationale for that unit. On the other hand, we obtained our results based on testing at different scales. Additionally, it is likely that the Chinese case, with larger population and extremely high density, could bring an entirely different scale of spillovers than that of the United States. China's knowledge production centers may be more concentrated given their historical legacy in the development of science and higher education [57]. This was the first study to investigate the unit of analysis more systematically, and we need further empirical testing and theoretical debates about this issue.

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Appendix A. Sixteen keywords to extract nanotechnology

Nano, quantum dot, quantum well, self-assembly, fullerene, PDMS, quasicrystal, molecular motor, soft lithographic, mesoporous material, coulomb blockade, molecular wire, molecular device, molecular ruler, NEMS, or Langmuir–Blodgett.

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