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Exploring the spatial dimensions of nanotechnology development in China: the effects of funding and spillovers

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ABSTRACT

This paper investigates the factors driving nanotechnology development in Chinese regions. Advanced regions of China have spearheaded the country's rapid growth in nanotechnology, aided by substantial support from the government. While this head start could potentially perpetuate regional inequalities through agglomeration economies, the results suggest that knowledge spillovers exert a substantially greater impact in peripheral regions compared with the advanced ones, and may thus be compensating for the limited institutional support they receive and their weak technological capabilities. This research contributes to the regional innovation literature by highlighting that a formal scientific network can counteract the forces of agglomeration economies and spur innovation in peripheral regions.

KEYWORDS

nanotechnology; geographical proximity; collaboration; knowledge spillovers; agglomeration; Chinese regions; publications and patents

JEL O30, O33, R12

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INTRODUCTION

In the economic geography literature, the issue of balanced regional development has revolved around the degree to which agglomeration economies increase the concentration of economic activities in advanced regions, and hence perpetuate regional economic disparities (Ottaviano & Thisse, 2004; Scott & Storper, 2003). Agglomeration economies refer to the beneficial effects for firms stemming from the concentration of economic activities in a region (Caniëls & Verspagen, 2001). They arise, in particular, from the vast opportunities for the exchange and spillovers of information and expertise among organizations in a region. Geographical proximity facilitates spillovers of knowledge because, as knowledge is intrinsically sticky (Winter, 1987), it permits close and repeated interactions between actors, allowing them to understand, identify and integrate relevant knowledge (Antonelli, 2001; Arundel & Guena, 2004; Boschma, 2005; Breschi & Lissoni, 2009; Jaffe, 1989; Ponds, Van Oort, & Frenken, 2010; Verspagen & Schoenmakers, 2004). Confirming this, a vast body of empirical research finds that geographical distance is a barrier to knowledge spillovers (Breschi & Lissoni, 2009; Verspagen & Schoenmakers, 2004; Wang, Meijers, & Szirmai, 2017). From the point of view of peripheral regions, particularly those located very far from centres of excellence, a greater degree of agglomeration economies implies lower prospects of benefitting from the technological advancements of core regions, causing them potentially to fall behind on the technological ladder.

In spite of the advantages of geographical proximity, however, innovation process is displaying a growing trend of cooperation between innovators in different geographical locations (Autant-Bernard, Billand, Frachisse, & Massard, 2007; Waltman, Tijssen, & Eck, 2011). The propensity to collaborate even grows with greater distance (Letaifa & Rabeau, 2013). Accessing expertise from different geographical settings with non-overlapping knowledge bases can facilitate greater possibilities for knowledge combination and create more radical and valuable innovations (Cockburn & Henderson, 1997; Petruzzelli, 2011). More distant collaborations are also believed to lead to higher social impact

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(Frenken, Ponds, & Van Oort, 2010; Nomaler, Frenken, & Heimeriks, 2013). In the specific context of regional technological development, long-distance cooperation among innovators assumes a singular importance as it can contribute to the technological catching up of regions lagging behind in technological capabilities.

Collaboration network of scientists reflects the cognitive proximity and social connectedness between them (Autant-Bernard et al., 2007; Boschma, 2005; Breschi & Lissoni, 2003). This is because joint research is often developed by co-authors who share the same or related knowledge, but it may also represent certain underlying social connections in that many collaborations stem from familiarity between scientists. Autant-Bernard et al. (2007) suggest that the probability of collaboration is more influenced by social distance than by geographical distance. A collaboration network can, therefore, be a substitute for geographical proximity in facilitating interpersonal interactions and therefore knowledge spillovers. In this vein, Breschi and Lissoni (2003, p. 6) point out that a 'community of scientists or practitioners exchange "tacit" knowledge even from a long spatial distance'. That is, knowledge spillovers may not necessarily be bound in space and, therefore, need not be a consequence of agglomeration. Waltman et al. (2011) show that the average collaboration distance per joint publication has increased dramatically over the years, partly because technological advancements made it possible to 'codify and share knowledge across large distances' (Morescalchi, Pammolli, Penner, Petersen, & Riccaboni, 2015, p. 652).

While recent research has shown that long-distance collaborations improve innovation outcomes (Frenken et al., 2010; Nomaler et al., 2013; Petruzzelli, 2011), there is still only a limited understanding of the extent to which they facilitate technological progress in peripheral regions. This paper seeks to fill this gap in the context of nanotechnology development in China – a country that has been striving to transform itself from an investment-driven to an innovation-driven economy. We focus on the significance of formal collaboration ties in nanotechnology research among scientists based in different Chinese regions for generating spillovers in, in particular, technologically lagging Chinese regions. China presents an interesting context in which to explore the questions addressed in this paper because of its vast regional imbalances, with knowledge creation and innovation activities highly concentrated in the coastal regions.[1] As for the focus on nanotechnology, which represents a set of science-based-enabling technologies that are still in the early stages of their technological life cycles, it is widely seen to create significant long-term pay offs to countries engaging in its development and commercialization and one in which China has made dramatic progress (Niosi & Reid, 2007). Although state support has been an essential feature of nanotechnology development in China, with the bulk of state funding targeting advanced regions, the present data reveal that peripheral regions of China have been making rapid progress in nanotechnology innovations in recent years. We further observe from the data that scientific publications from the latter regions increasingly involve collaborators from other regions, lending weight to the prediction that such collaborations might be a major potential contributor to the dynamism of these regions.

The empirical analysis is carried out on a panel data set of Chinese regions over a 10-year period. The results indicate that collaboration-driven spillovers were a significant contributor to nanotechnology patenting in peripheral regions. The effect of geographical proximity, as well as funding, was limited mainly to core regions that lie along the eastern cost of China.

The paper is structured as follows. The following section provides the theoretical and empirical background of the study and raises the specific questions for empirical scrutiny. The third section presents the data and explains the methods. The fourth section discusses the trends in and patterns of nanotechnology development in China with a regional focus. The results of the econometric analysis are discussed in the fifth section. The final section summarizes the paper's contribution to the economic geography and catch-up literatures, discusses some policy implications and identifies some avenues for future research.

BACKGROUND AND RESEARCH QUESTIONS

Regional imbalances and the importance of knowledge spillovers

The economic geography literature highlights that innovation activities are typically geographically concentrated (Geppert & Stephan, 2008; Henderson, 2003; Scott & Storper, 2003). This phenomenon is particularly observed in less developed countries (Crescenzi, Rodríguez-Pose, & Storper, 2012) and with regard to emerging technologies whose development is often spearheaded by leading companies that tend to be located in core regions characterized by what Kuznets (1960, p. 329) calls their 'dense intellectual atmosphere'. These core regions can leverage their advantages to grow faster because new innovations emerge from the existing knowledge elements of a region (Malerba & Orsenigo, 1995).

With regard to the question of whether inequalities between core and peripheral regions persist, widen or narrow, a factor whose role has received much attention is knowledge spillovers (Caniëls & Verspagen, 2001; Ottaviano & Thisse, 2004). A fairly large body of research has highlighted the fact that knowledge spillovers are spatially bound, which makes it harder for backward regions to benefit from the technological advancements of more developed regions (Antonelli, 2001; Arundel & Guena, 2004; Jaffe, 1989; Verspagen & Schoenmakers, 2004). Fundamental to this conclusion is the tacit nature of knowledge, as it embodies idiosyncrasies and traditions of the locations in which they are developed. The acquisition of tacit knowledge, therefore, calls for interpersonal interactions that typically occur more frequently between actors who are in close geographical proximity to each other (Breschi & Lissoni, 2001; Saxenian, 1994; Von Hippel, 1994). Research suggests that interactions between innovators through dense social networks (e.g., of former students, teachers and colleagues) is key to the exchange of ideas and knowledge development in such geographically bound knowledge hubs (Zucker, Darby, & Armstrong, 1998). The notion that spillovers require geographical proximity implies that peripheral regions in large less-developed countries, with vast geographical distances separating regions, can potentially fall further behind core regions because they may be unable to benefit from the technological developments taking place in the latter regions.

More recently, however, researchers have found that formal linkages, in particular, co-authorship ties between scientists in different locations, can be an important channel of long-distance knowledge flows (Cockburn & Henderson, 1997; Frenken et al., 2010). While these studies suggest that collaborations with geographically distant partners may help access unique, location-specific idiosyncratic knowledge and competencies, little research exists on the effect of region-spanning scientific networks in creating positive knowledge flows to peripheral regions, especially in less developed countries. In this respect, nanotechnology development in China presents a particularly relevant context for examining the role of scientific networks in generating potentially important knowledge spillovers from core to peripheral regions.

Research context: nanotechnology development in China

Nanotechnology has applications in a wide spectrum of economic activities and, hence, represents what evolutionary scholars call a 'new technology system' (Perez & Soete, 1988) that can potentially play a decisive role in shaping a country's competitive advantage. A dominant position in nanotechnology implies a significant 'window of opportunity' for a less developed country to move closer to the global techno-economic frontier. This is because such a system not only allows for the creation of first-mover advantages in new, potentially fast-growing sectors, but also helps spur technological progress in a broad range of sectors (Niosi & Reid, 2007; Perez & Soete, 1988). Realizing this, China has been adopting an ambitious nanotechnology development strategy.

As is well known, innovation activities in China are spatially concentrated, reflecting an unbalanced distribution of institutions engaged in research and development (R&D) and in R&D resources (Fujita & Hu, 2001; Lin, Cai, & Li, 2003; Wang & Szirmai, 2013). This pattern is manifested, as the data show (see the fourth section), also with regard to nanotechnology which took off in a small number of leading regions. Nevertheless, we observe that lagging regions are catching up rapidly in nanotechnology output. While this raises the potential role played by spillovers from leading regions to lagging regions in China, a recent study on the growth of nanotechnology in China points to very little proximity-driven spillovers of nanotechnological knowledge (Motoyama, Cao, & Appelbaum, 2014). This is, of course, not a surprising result given the vast distances separating China's peripheral regions from its leading regions along the East coast. A more pertinent mechanism of spillovers could be collaboration ties particularly since, as the data reveal, peripheral regions are increasingly relying on collaborations with other regions in generating scientific output. This makes it salient to explore the question: to what extent have collaboration networks generated interregional spillovers of nanotechnology knowledge in China? We expect that spillovers would be particularly important for technological advancements in peripheral regions, allowing them to compensate for their limited resources and competences. Conversely, the benefits for advanced regions through these collaborations are likely minimal as their superior internal capabilities may continue to be the prime driver of their innovation.

DATA AND VARIABLES

For the econometric analysis, this study uses a panel data set of 30 Chinese regions spanning 11 years (2000–10).[2] The dependent variable is measured as the count of patent applications (e.g., Basberg, 1987; Griliches, 1990) filed by inventors from a Chinese region at China's State Intellectual Property Office (SIPO); it is meant to capture a region's nanotechnology output. The SIPO has three types of patent categories: utility models, industrial design and invention patents. As noted by Li and Pai (2010), the technical threshold for utility models and industrial design is very low and patent filings in these two types do not necessarily represent innovation capacity. Hence, we exclude these two patent categories and consider only invention patent in calculating regional patent output in nanotechnology.

We gathered over 30,000 nano-patent applications from the China Patents Full-text Database.[3] In deriving the number of patent applications by a region, we adopted the full counting method. Each patent is counted as 1 for a region if there is any organization from this region appearing in the inventor address of this patent. Accordingly, for example, a patent involving co-inventors from two different regions will be counted as one patent in each region. Data on nano-funding at regional level are collected from the National Natural Science Foundation of China (*Statistical Report*, various years); expenditure on general R&D is derived from *China Statistical Yearbook on Science and Technology* (various issues); and data on gross domestic product (GDP) and GDP per capita are collected from *China Statistical Yearbook* (various issues).

In our framework, interregional spillovers can stem from two sources: nanotechnology-related knowledge of regions measured by patents in this technological area; and the funding for nanotechnology research received by regions. Prior research has shown that R&D expenditure, used as a proxy for innovation activities, carried out in one location can generate spillovers in others through a variety of channels, such as proximity (Funke & Niebuhr, 2005; Wang, Meijers, et al., 2017) and collaboration networks (Fritsch & Franke, 2004; Jaffe, 1989). From this perspective, we suggest that funding, which represents subsidies provided for augmenting R&D expenditure on nanotechnology, can generate spillovers of knowledge to other locations.

We focus on spillovers via both geographical proximity and formal collaboration networks. To capture the former, this study uses the geographical proximity between regions to construct a set of spillover variables. The spatial proximity weight to capture spillovers from region j to region i can be expressed in three different ways depending on the different underlying assumptions (see also Ertur, Le Gallo, & Baumont, 2006; Ponds et al., 2010; Vinciguerra, Frenken, Hoekman, & Van Oort, 2011; Wang, Meijers, et al., 2017). Compared with the two other types of proximity weights (see Note A1 in Appendix A in the supplemental data online), the column standardization of the weight matrixes is considered more appropriate (Ponds et al., 2010). Following the existing literature (e.g., Ertur et al., 2006; Vinciguerra et al., 2011; Wang, Meijers, et al., 2017), this study adopts spatial proximity weights constructed through column standardization:

$$w_{ji} = \frac{w^*_{ji}}{\sum_{j=1}^{30} w^*_{ji}} \quad (i, j = \text{region } 1, \text{region } 2, \ldots, \text{region } 30, \ i \neq j) \tag{1}$$

$$w^*_{ji} = \frac{1}{d^2_{ji}}$$

where d_{ji} is the geographical distance between regions i and j. Equation (1) captures knowledge flows from region j to region i with the assumption that spillovers from j to i may be affected by spillovers from j to regions other than i. In particular, if region j is geographically closer to the average region than to region i, there will be fewer spillovers flowing to region i compared with that to the average region.

The knowledge spillovers and funding spillovers that region i receives from other regions through the effect of geographical proximity can be defined respectively as:

$$\text{TECHSPILL}^{\text{spatial}}_{it} = w_{ji} * \text{PAT}_{jt} \quad (i, j = \text{region } 1, \text{region } 2, \ldots, \text{region } 30, \ i \neq j) \tag{2}$$

$$\text{FUNDSPILL}^{\text{spatial}}_{it} = w_{ji} * \text{FUND}_{jt} \quad (i, j = \text{region1}, \text{region } 2, \ldots, \text{region } 30, \ i \neq j) \tag{3}$$

where PAT_{jt} is the number of nanotechnology-related patents in region j in year t; and FUND_{jt} is the nano-funding received by region j in year t.

In addition to the distance weight above, we also construct weights based on a dynamic interregional collaboration matrix as follows:[4]

$$\begin{bmatrix} P_{1,1,t} & P_{1,2,t} & \cdots & \cdots & \cdots & \cdots & P_{1,30,t} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ P_{30,1,t} & \cdots & \cdots & \cdots & \cdots & \cdots & P_{30,30,t} \end{bmatrix}$$

where an element P_{jit} is the number of co-authored nano-publications involving regions j and i in year t. The knowledge spillovers (TECHSPILL_{it}) and nano-funding spillovers (FUNDSPILL_{it}) that region i receives from all other regions are defined respectively as:

$$\text{TECHSPILL}^{\text{collab}}_{it} = \frac{\text{PUB}_{jit}}{\text{PUB}_{jt}} * \text{PAT}_{jt} \quad (i, j = \text{region } 1, \text{region } 2, \ldots, \text{region } 30, \ i \neq j) \tag{4}$$

$$\text{FUNDSPILL}^{\text{collab}}_{it} = \frac{\text{PUB}_{jit}}{\text{PUB}_{jt}} * \text{FUND}_{jt} \quad (i, j = \text{region } 1, \text{region } 2, \ldots, \text{region } 30, \ i \neq j) \tag{5}$$

where PUB_{jit} is an element of the collaboration matrix defined above and is the number of publications involving scientists from both regions i and j in year t; and PUB_{jt} is the total number of publications of region j in year t (the column sum in the matrix above).[5] The scientific collaboration weight is meant to capture the extent to which scientists of a region are engaged with those from other regions. It suggests that when a certain region accounts for a higher proportion of co-authors in the publications of another region, its scientists are engaged in more intense interactions with those from the latter compared with scientists from other regions. A higher degree of interaction with a region in turn implies access to a larger pool of knowledge elements, as well as increased familiarity between scientists that smoothes the process of knowledge exchange (Cohen & Levinthal, 1989, 1990), thereby raising the chances of benefitting more from knowledge spillovers. A collaboration network is particularly salient as a mechanism of knowledge flows in the context of nanotechnology as it is a science-based technology whose diffusion is known to be less constrained by geographical distance (Herstad, Aslesen, & Ebersberger, 2014).

Towards constructing the publication weights (PUB_{jit}, PUB_{jt}) in the above two equations, over 164,000 nanotechnology-related publications from Thomson Reuters' Web of Science (WoS) were collected. The database is constructed based on an evolutionary lexical query searching and defining strategy developed by the Georgia Institute of Technology (for more details, see Porter, Youtie, Shapira, & Schoeneck, 2008; Wang & Notten, 2010). Next, an international collaboration intensity variable is constructed. This variable captures the effect of potential knowledge spillovers resulting from collaboration with foreign countries, which the literature highlights as an important channel of spillovers (e.g., Lee & Lim, 2001; Wang & Wang, 2017; Wang, Wang, & Philipsen, 2017):

$$\text{CI}_{it\_\text{int}} = \frac{\sum \text{PUB}_{ikt}}{\text{PUB}_{it}} \ (k = \text{country } 1, \text{country } 2, \ldots, \text{country } 27) \tag{6}$$[6]

where $\text{CI}_{it\_\text{int}}$ represents the international collaboration intensity in nanotechnology-related publications of region i in year t; PUB_{ikt} is the number of co-authored nanotechnology-related publications involving region i and the foreign country k in year t; and PUB_{it} is the total number of nanotechnology-related publications stemming from region i. Each of the 27 foreign countries has had at least 10 papers co-authored with an author based in China during the period of analysis.

As control variables we include regional high-tech R&D personnel (*RDH*, the number of R&D personnel in a high-tech sector in a region) and graduate share (*GRAD*) in all models. We use high-tech R&D personnel (Guan & Yam, 2015) as a proxy for the innovation input of a region, given that no precise measure of R&D activities specific to nanotechnology is available. As nanotechnology is a cross-cutting technology that spans a variety of high-tech industries, this measure can be considered as a good proxy for R&D capabilities of a region in nanotechnology research. Nevertheless, the fact that this variable is an imperfect measure, as it may encompass R&D inputs of other sectors, suggests the need for caution when interpreting the results. Graduate share refers to the share of postgraduates (with a master's degree or a doctorate) in the population in a region, and has often been employed in prior research to capture the endowment of a region's human capital (Frenz & Ietto-Gillies, 2009; Lau & Lo, 2015; Wang & Yao, 2003). This variable is highly correlated with regional per capita income, pointing to its strong association with regional economic prosperity.

The empirical model is defined as follows:

$$\begin{aligned} T_{it} = {} & \alpha_1 \ln \text{FUND}_{it-1} + \alpha_2 \ln \text{TECHSPILL}^{\text{collab}}_{it-1} \\ & + \alpha_3 \ln \text{TECHSPILL}^{\text{spatial}}_{it-1} + \alpha_4 \ln \text{FUNDSPILL}^{\text{collab}}_{it-1} \\ & + \alpha_5 \ln \text{FUNDSPILL}^{\text{spatial}}_{it-1} + \alpha_6 \text{CI}_{it_{int-1}} \\ & + \alpha_7 \text{RDH}_{it-1} + \alpha_8 \text{GRAD}_{it-1} + \varepsilon_{it} \end{aligned} \tag{7}$$

where T_{it} is the patent applications filed by inventors of region i at the SIPO in time t. In the regression analysis, we sequentially include the key variables and avoid including correlated variables in the same model.

The extent of government funding and interregional collaborations are likely to be influenced by the pattern of innovative capabilities across regions, so the spillover and funding variables may display a certain degree of endogeneity. To tackle this, we lag these variables by one year in the estimation models. In the robustness section, we discuss the results based on more elaborate models that further address concerns of potential endogeneity problems in the model.

TRENDS IN AND PATTERNS OF NANOTECHNOLOGY DEVELOPMENT IN CHINA

This section sets the stage for the econometric analysis conducted below in the fifth section. It discusses the growth in nanotechnology and nanoscience in China, highlighting the major differences between core and peripheral regions with respect to capabilities, state funding for nanotechnology research, publication and patent output, and the extent of collaboration with scientists in other regions and other countries.

In identifying core and peripheral regions, one key consideration is local capabilities that are regarded as an important factor in absorbing knowledge spillovers. As absorptive capacity is 'largely a function of the level of prior related knowledge' (Cohen & Levinthal, 1990, p. 128) and as nanotechnology is well recognized as a science-based technology, this study uses the nanotechnology-related scientific knowledge to capture local absorptive capacity. In particular, it conceptualizes the number of nano-publications of a region as representing the basic nanotechnology-related knowledge of that region. Owing to China's well-recognized interregional economic and technological disparities (Lin et al., 2003; Wang & Szirmai, 2013), Chinese regions are often classified into different groups. Most earlier studies tend to have taken a dichotomous approach, distinguishing between high- and low-capability regions, as respectively those located along the East coast and the rest. While it is well accepted that the high-capability regions indeed tend to form a strong core group along the eastern coast (e.g., Crescenzi et al., 2012), to categorize the rest of the regions as one group is arguable, given that the far-western regions possess very different economic characteristics than those located in the middle. Therefore, to capture better the heterogeneity among Chinese regions, we classify the 30 Chinese regions into three groups: high-, medium- and low-capability regions (see Note A2 in Appendix A in the supplemental data online), based on the level of their nano-related scientific knowledge measured in terms of the total number of scientific publications during the period of study.[7]

Changing trends in regional knowledge disparity

The period 2000–10 witnessed the number of nanotechnology patents with Chinese addresses growing at an annual rate of 37%, from 275 to 6333. Nanotechnology-related publications have also been skyrocketing in China, from 3169 in 2000 to over 23,000 in 2010. However, as noted above, any discussion of the overall growth of nanotechnology in China masks wide differences in scientific capabilities across Chinese regions. Figure A1 in Appendix A in the supplemental data online illustrates the strong regional disparities in nano-funding, nano-patenting and general R&D expenditure in China over the period 2000–10. The average nano-funding received by eight leading regions is over 13 billion yuan per year compared with just 2.4 billion yuan on average received by the remaining 22 regions. With their very high R&D expenditures, coastal regions in Eastern China, and a few inland regions close to them, stand out compared with the rest of China. It is also of interest to note that the regional disparity of nano-funding is more pronounced than that of general R&D expenditure. While R&D expenditures in some central regions have been reasonably high (see the light blue areas in Figure A1 in Appendix A in the supplemental data online), nano-funding (green circles) and nano-patent applications (red triangles) have been concentrated in coastal regions. In fact, in nano-patent applications, four regions (Beijing, Shanghai, Jiangsu and Guangdong) accounted for more than 50% of the national total. Compared with Eastern and Central regions, other regions of China lag far behind in all these indicators. Regions in white in Figure 1A online are relatively economically weak. The five main provinces without much R&D input as well as scientific or technological output are Inner Mongolia, Xinjiang, Gansu, Qinghai and Tibet.

A look at the trend in patent applications in the three categories of regions suggests an increasing dynamism in lagging regions in recent years (see Table A1 in Appendix A in the supplemental data online). While high- and medium-capability regions witnessed a higher growth in nano-patent applications during the first half of the period under study (1999–2004), the low-capability regions experienced the fastest growth during the second half (2005–10). In line with these findings, we note a sharp decline in the coefficient of variation in nanotechnology-related publications and patents between 1999 and 2010 respectively, from 1.71 to 1.14 and from 1.95 to 1.34 (see Figure A2 in Appendix A in the supplemental data online).

Table 1. Collaboration intensity in nano-science (%).

	12-year average (1)	1999–2004 (2)	2005–10 (3)	Comparison (4) = (3) – (2)
International collaboration				
All regions	15.4	19.5	15.9	–3.6
High capability	19.4	21.2	18.7	–2.5
Medium capability	14.1	14.7	13.5	–1.2
Low capability	12.8	23.1	15.5	–7.6
National collaboration				
All regions	45.9	41.3	47.3	6.1
High capability	32.5	31.7	34.1	2.4
Medium capability	39.1	44.8	39.6	–5.2
Low capability	66.0	51.3	68.3	17.0

Notes: (1) Based on the number of scientific publications, the 30 Chinese regions studied are classified into three categories: high-capability regions (10), medium-capability regions (10) and low-capability regions (10).
(2) International collaboration intensity is calculated based on equation (6).
(3) National collaboration intensity is calculated as:

$$CI_{it\_nl} = (\sum^{PU} B_{ijt}/PUB_{it}),$$

where j = region 1, region 2, … , region 30, $i \neq j$).
Source: Authors' own calculations based on data collected from Web of Science.

Collaboration patterns among Chinese regions

Interregional collaboration intensity in scientific publications not only was much higher than that of international collaborations but also registered an increase between the two periods; it was about 41% during the first period and increased by about 6 percentage points during the second period (Table 1). In contrast, international collaboration intensity in scientific publications for an average Chinese region dropped from about 20% in earlier years to 16% in recent years, with both the high- and low-capability regions exhibiting a higher collaboration intensity than medium-capability regions.

Interestingly, interregional collaboration intensity was on average the highest in low-capability regions, followed by medium- and high-capability regions. In fact, a majority of scientific publications originating in lagging regions were the result of collaborations with scientists from other regions. Also, the interregional collaboration intensity of low-capability regions increased substantially in recent years, reaching about 68% in the latest period of the analysis (2005–10) compared with only 34% in the case of regions with the highest scientific capability during the same period.

These observations, in particular the growing nanotechnology output and increasing reliance on interregional collaborations of lagging regions, lend credence to our above suggestions that collaboration networks may be an important source of catching up in lagging regions, especially in low-capability regions; forging links with scientific communities in other Chinese regions could help these regions compensate for their weak scientific capabilities. In order to verify these conjectures and, more broadly, to understand if different forces are at work in the development of nanotechnology in the three sets of regions, the following section carries out separate econometric analyses for each regional category.

RESULTS OF THE ECONOMETRIC ANALYSIS

Summary statistics and correlation matrices for the total sample and the samples for the high-, medium- and low-capability regions are reported in Table A2 in Appendix A in the supplemental data online. The averages of key variables display substantial differences across regions. The average nano-funding in high-capability regions was three times as high as in medium-capability regions, and almost 28 times as high as in low-capability regions (13.08 million yuan for high-capability regions versus 3.68 million yuan for medium-capability regions and 0.48 million yuan for low-capability regions).[8] Similarly, average R&D personnel in high-capability regions was close to 17 and four times that in low- and medium-capability regions respectively. Differences in the share of graduates in the total population between the three sets of regions also display a similar pattern; however, the extent of regional differences is slightly lower with high-capability regions having about 10 and three times as high the share of graduates compared with low- and medium-capability regions respectively.

As the dependent variable is the number of nanotechnology patents, a count data model such as negative binomial or Poisson is more appropriate than ordinary least squares (OLS). As to the choice between these two models, as Chinese regions exhibit wide variations in patenting, the critical assumption of the equality of mean and variance of the Poisson model does not hold, leading to a preference for the negative binomial model. Given the somewhat short-panel nature of the data set, fixed effects may not produce consistent estimates, so we adopt the population-averaged (PA) model with semi-robust standard errors (Cameron & Trivedi, 2010). As a robustness check, the random effect (RE) model is also employed; the results are similar to those from the PA model and are available in Tables B1 and B2 in Appendix B in the supplemental data online.

Regression results are documented in Tables 2 and 3. All models include the full set of control variables, as well as year dummies to account for unobserved annual events that may affect patenting in all regions. The correlation coefficient between *Nanotech spillovers* and *Funding spillovers* (via both collaboration and proximity) is rather high, so these two variables are employed in separate regression models. Furthermore, to illustrate the consistency of the results on spillovers to the exclusion of funding, and vice versa, separate equations – that include only spillovers, only funding and both – are estimated.

Two sets of analysis are carried out: for the full sample and for the three regional samples. Table 2 presents results based on the full sample with different combinations of the key explanatory variables. Table 3 provides separate results for each of the three regional categories (high-, medium- and low-capability regions).

In order to examine the statistical fit of models with the full set of variables compared with the more parsimonious models, we carried out likelihood ratio (LR) tests. These tests show that combining funding and nanotechnology collaboration spillover variables (model 4, Table 2) improves model fit compared with models with only one of the two variables included (models 1 and 2, Table 2) at a significance level of 1%. Similarly, the model that combines funding with collaboration spillovers resulting from funding (model 8, Table 2) also improves the model fit at a 1% level compared with models with only one of these variables included (models 1 and 6, Table 2). However, adding spatial spillover variables to funding does not statistically improve model fit at the 5% level (model 9 compared with model 1, Table 2), in partial agreement with the suggestion that physical proximity between regions is perhaps of lower importance in effecting interregional knowledge flows in a large country such as China. We provide a more nuanced interpretation of the effect of spatial proximity below in the discussion of the results.

Effect of funding

As China's nanotechnology development programme provides the context for this study, we begin by discussing the results of the funding variable (Table 2). In model 1, we include nano-funding with only control variables, yielding a positive and significant coefficient for this variable. This variable continues to show a significant positive coefficient in more elaborate models where we add the two nanotechnology spillover variables (models 4 and 5) and the nano-funding spillover variables (models 8 and 9). Results show that public nano-funding has been significantly contributing to improving nanotechnological output. Although it is uncertain whether financial support from government can compensate for the absence of private capital and viable markets, these results fit with the general view that Chinese policies on nanotechnology development follow a top-down approach (Motoyama et al., 2014).

Next, Table 3 compares the results for the three categories of regions (high-, medium-, and low-capability regions). Estimates for the three categories are made using Stata's split-coefficient routine that estimates a separate coefficient for each regional group. This allows for a direct comparison to be made of the effect of a variable across the three categories than the traditional interaction models. Results indicate that direct funding has the highest positive effect on patenting in high-capability regions and the lowest effect on low-capability regions (model 1, Table 3). A chi-squared test further confirmed that the regression coefficients of nano-funding significantly differ across the three groups (at the 1% significance level). The magnitude effects indicate substantial differences in the impact of funding across the three regional categories: an increase in nano-funding from the sample average of 5.3 (logarithm of average funding) to 7.7 (mean + 1 SD (standard deviation)) results in an increase in patenting of 129%, 61% and 27% in high-, medium- and low-capability regions respectively. These findings are consistent with the discussions made below in the fourth section that advanced regions lead in both nano-funding and nano-patenting, and shed more light on the highly unbalanced nature of nanotechnology development in China (Motoyama et al., 2014).

Effect of spillovers – collaboration versus spatial effects

This section discuss the results of the key explanatory variables. In models 2 and 3 in Table 2, the nano-funding variable is replaced respectively with the collaboration- and proximity-based nanotechnology spillover variables. In line with expectations, the results seem to indicate that while both formal collaborations and proximity generate significantly positive knowledge spillovers, the effect of the former is stronger. The pattern seems similar in models 4 and 5 where we combine these two spillover variables with nano-funding variable. In models 6–9, nanotechnology spillover variables (both collaboration and proximity induced) are replaced with nano-funding spillover variables. The results show a similar pattern, with funding generating interregional spillovers through both collaboration networks and through proximity. Results for the three subsamples (Table 3) point out that, in some contrast to the effect of nano-funding, nanotechnology spillovers from

Table 2. Results of negative binomial analysis of nanotechnology patent applications: full sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nano-funding	0.152***			0.137***	0.142***			0.120**	0.136***
	(0.057)			(0.051)	(0.048)			(0.060)	(0.046)
Nanotech spillovers – collaboration		0.462***		0.459***					
		(0.101)		(0.126)					
Nanotech spillovers – proximity			0.333***		0.287**				
			(0.115)		(0.116)				
Funding spillovers – collaboration						0.417***		0.351***	
						(0.062)		(0.098)	
Funding spillovers – proximity							0.430***		0.366***
							(0.115)		(0.113)
International collaboration intensity	0.008***	0.006**	0.007***	0.008***	0.009***	0.006	0.006**	0.008*	0.008***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
High-tech R&D personnel	0.233***	0.159***	0.178***	0.156***	0.182***	0.209***	0.158***	0.202***	0.162***
	(0.038)	(0.038)	(0.046)	(0.040)	(0.049)	(0.047)	(0.045)	(0.046)	(0.048)
Graduates to population	0.667***	0.448**	0.421*	0.413**	0.540***	0.564***	0.429*	0.517***	0.525***
	(0.177)	(0.225)	(0.237)	(0.173)	(0.175)	(0.165)	(0.239)	(0.142)	(0.180)
Constant	–0.197	0.636**	1.105*	–0.015	–0.009	–0.608	–0.212	–0.817**	–1.009
	(0.391)	(0.281)	(0.618)	(0.370)	(0.535)	(0.383)	(0.798)	(0.407)	(0.741)
Observations	330	330	330	330	330	330	330	330	330
Regions	30	30	30	30	30	30	30	30	30
Wald chi^2	1449.22	996.29	1013.89	2288.99	1766.14	1789.51	1026.16	3110.74	1934.89
Prob. > chi^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: (1) Dependent variable = nano-patent applications.
(2) Explanatory variables are lagged by one year.
(3) Semi-robust standard errors are shown in parentheses.
(4) Year dummies are not reported.
(5) ***1% significance level; **5% significance level; and *10% significance level.

Table 3. Results of negative binomial analysis of nanotechnology patent applications: by regional category.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Nano-funding (high)	0.379***			0.374***	0.383***			0.345***	0.355***
	(0.053)			(0.070)	(0.062)			(0.081)	(0.066)
Nano-funding (med)	0.312***			0.250***	0.285***			0.199**	0.220***
	(0.079)			(0.070)	(0.076)			(0.083)	(0.079)
Nano-funding (low)	0.098**			0.091*	0.099**			0.100**	0.104**
	(0.046)			(0.051)	(0.048)			(0.050)	(0.050)
Nanotech spill – collaboration (high)		0.341**		0.103					
		(0.158)		(0.147)					
Nanotech spill – collaboration (med)		0.436**		0.348*					
		(0.180)		(0.195)					
Nanotech spill – collaboration (low)		0.538***		0.488***					
		(0.093)		(0.161)					
Nanotech spill – proximity (high)			0.316***		0.074				
			(0.114)		(0.080)				
Nanotech spill – proximity (med)			0.250*		0.170				
			(0.151)		(0.136)				
Nanotech spill – proximity (low)			0.166		0.158				
			(0.134)		(0.138)				
Funding spill – collaboration (high)						0.530***		0.169	
						(0.094)		(0.142)	
Funding spill – collaboration (med)						0.507***		0.358***	
						(0.103)		(0.139)	
Funding spill – collaboration (low)						0.351***		0.312***	
						(0.076)		(0.104)	
Funding spill – proximity (high)							0.492***		0.208**
							(0.119)		(0.084)
Funding spill – proximity (med)							0.376***		0.313***
							(0.124)		(0.113)
Funding spill – proximity (low)							0.135		0.184
							(0.135)		(0.141)

(*Continued*)

Table 3. Continued.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
International collaboration (high)	0.004	0.015	0.016	0.002	0.006	0.008	0.009	0.002	0.006
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)	(0.010)
International collaboration (med)	–0.014	–0.004	–0.007	–0.006	–0.011	–0.009	–0.007	–0.012	–0.011
	(0.016)	(0.010)	(0.011)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)	(0.014)
International collaboration (low)	0.012***	0.006**	0.008***	0.011***	0.013***	0.008**	0.009***	0.012***	0.013***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
High-tech R&D personnel (high)	0.109**	0.154***	0.134***	0.118**	0.107**	0.126**	0.071	0.127**	0.078*
	(0.044)	(0.047)	(0.044)	(0.049)	(0.049)	(0.050)	(0.045)	(0.050)	(0.047)
High-tech R&D personnel (med)	0.129**	0.164***	0.177***	0.104*	0.113*	0.135***	0.102**	0.114**	0.081
	(0.052)	(0.046)	(0.043)	(0.055)	(0.059)	(0.051)	(0.042)	(0.054)	(0.055)
High-tech R&D personnel (low)	0.161***	0.120***	0.141***	0.132***	0.136***	0.143***	0.137***	0.146***	0.123**
	(0.046)	(0.037)	(0.036)	(0.050)	(0.051)	(0.049)	(0.047)	(0.053)	(0.057)
Graduates to population (high)	0.316**	0.589**	0.392	0.373**	0.321**	0.393**	0.224	0.340**	0.252*
	(0.151)	(0.250)	(0.245)	(0.154)	(0.133)	(0.184)	(0.254)	(0.160)	(0.148)
Graduates to population (med)	0.335	0.201	0.323	0.157	0.248	0.262	0.262	0.223	0.204
	(0.335)	(0.377)	(0.354)	(0.401)	(0.339)	(0.290)	(0.309)	(0.321)	(0.269)
Graduates to population (low)	0.374	–0.301	0.306	–0.295	0.263	0.231	0.585	–0.112	0.319
	(0.329)	(0.317)	(0.371)	(0.308)	(0.296)	(0.304)	(0.430)	(0.313)	(0.340)
Constant	1.117**	1.355***	1.695***	0.532	0.676	0.469	1.216	0.182	0.298
	(0.469)	(0.391)	(0.633)	(0.421)	(0.588)	(0.455)	(0.749)	(0.446)	(0.663)
Observations	330	330	330	330	330	330	330	330	330
Regions	30	30	30	30	30	30	30	30	30
Wald chi^2	3312.97	2753.49	2411.67	4567.90	4540.64	1703.22	3875.57	3116.52	29112.65
Prob. > chi^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: (1) Dependent variable = nano-patent applications.
(2) Explanatory variables are lagged by one year.
(3) Semi-robust standard errors are shown in parentheses.
(4) Year dummies are not reported.
(5) ***1% significance level; **5% significance level; and *10% significance level.

other regions through collaborations exerted a higher impact in low-capability regions than in medium- or high-capability regions (models 2 and 4). A chi-squared test confirms that the coefficients are significantly different between low- and high-capability regions ($p = 0.0373$). The magnitude effects demonstrate that an increase in interregional nanotechnology spillover through collaborations from the sample average of 2.4–3.8 (mean + 1 SD) results in an increase in patenting of 16%, 63% and 98% respectively in high-, medium- and low-capability regions. These results are in line with the above suggestions that collaboration linkages with other regions may compensate for lagging regions' weak capabilities and the low degree of governmental support they receive. Nano-funding spillovers through collaborations, too, exert significant positive effects in all regions. While high-capability regions seem to benefit more from these spillovers in a parsimonious model (model 6), in the full model with nano-funding included (model 8) the differential effect across regions slightly reverses with only medium- and low-capability regions experiencing statistically significant impact.

In contrast to spillovers via formal collaborations, those through spatial proximity exhibit the highest effect in high-capability regions. In fact, nanotechnology knowledge spillovers via proximity exerted a significantly positive effect (at the 5% level) only in high-capability regions (model 3). This appears to suggest that informal networks, created, for example, through localized labour turnover, generate knowledge spillovers only among the leading regions which are clustered along the eastern coast of China. To reconcile the findings for lagging regions with the existing literature that has found positive localized knowledge spillovers (Breschi & Lissoni, 2009; Ponds et al., 2010), one may contend that the majority of the lagging regions, especially the low-capability ones, are too far away from the leading regions to stimulate informal interactions between the scientific communities of leading regions. The average geographical distance between Chinese regions – measured by the distance between capital cities – is around 2000 km, which is far beyond the informal spillover distance threshold suggested in the literature (e.g., Bottazzi & Peri, 2003; Moreno, Paci, & Usai, 2005).[9] The results on nano-funding spillovers via proximity, however, point to significant positive effects not only in high-capability regions but also in medium-capability regions (models 7 and 9). This shows that spatial-proximity-driven spillovers (Antonelli, 2001; Arundel & Guena, 2004; Jaffe, 1989; Verspagen & Schoenmakers, 2004) also exist in China in the context of nanotechnology development, but only in the high- and medium-capability Chinese regions. Peripheral regions (with low capacity), which are mostly located in the west of China, seem unable to gain spillovers via proximity, which is in line with prior findings (Motoyama et al., 2014).

In summary, the results on spillovers indicate that in the development of nanotechnology in China, scientific networks spanning regions have been playing an important role in generating spillovers from core to peripheral regions in the country. These spillovers may have been compensating for the absence of proximity-driven spillovers in the periphery and, in the process, helping mitigate regional imbalances in the progress of nanotechnology development.

Effect of control variables

Among the remaining variables that may affect nanotechnology development, the international collaboration intensity variable has a positive coefficient, albeit not consistently significant across all specifications in the full sample (Table 2). However, this variable tends to have a uniquely significant and positive effect for low-capability regions, underscoring the importance of external resources for knowledge development in these regions (Table 3). As discussed above, the international collaboration intensity on average is around 15% for China as a whole, about 20% for high-capability regions and between 13% and 14% for medium- and low-capability regions. These figures seem low compared with those for other countries. For example, Ozcan and Islam (2014) note, with regard to collaboration pattern in nanowire technology, that China has a relatively lower degree of international collaborative involvement compared with four other countries they studied: the United States, Japan, South Korea and France. The lack of any significant impact of international collaboration especially in leading regions, which are the central sources of growth in nanotechnology, supports the view that the surge of nano-patent applications in China, in particular in its high-capability regions, was driven by China's indigenous capability rather than by international collaborations. More broadly, these results are in agreement with the notion that in the development of new technologies intra-national linkages are likely to be more effective than international ones (Metcalfe & Ramlogan, 2008).

Finally, turning to the remaining control variables, R&D personnel in high-tech sectors is statistically significant in all models in the full sample (Table 2) and in almost all models for all three regional groups (Table 3). This suggests the key role played by R&D inputs for the growth of nanotechnologies. Graduates share in population is significant in the full sample (Table 2). Yet, the significant effect is limited only to high-capability regions (Table 3), indicating the dearth of highly educated human capital in low-capability regions.

Robustness analyses

While we have used lagged values of explanatory variables, this may not have been enough to rule out completely any potential endogeneity of the key variables: spillovers, and funding. This section describes the approaches adopted for ensuring that not only endogeneity but also spatial dependence have not biased the estimated effects of these variables.[10]

A first concern is that higher spillovers in a region through collaborations with other regions may be the result of, rather than the cause of, higher innovativeness. This has parallels in the international trade literature where higher trade openness is considered to be influenced by higher income levels, creating a bias in the estimated effect of the former on the latter. To address this problem, scholars have focused on the role of geographical factors that may shape trade openness and through it affect income levels. For instance, Ortega and Peri (2014) estimated a gravity model that predicts bilateral trade flows as stemming from geographical factors such as partner countries' size, distance with each other, colonial history etc. These variables are argued not to influence income except through trade and, therefore, represent good instruments to predict trade openness. This approach has substantial salience in the context of the present study because interregional collaborations are well known to be affected by geography-related factors such as distance and the presence or absence of legal borders (e.g., Breschi & Lissoni, 2009; Verspagen & Schoenmakers, 2004). Considering these differences, as well as those related to regional innovation patterns, we estimate a gravity model that predicts joint academic research between regions as follows.

$$\begin{aligned} \ln \mathrm{JP}_{ijt} = {} & \beta_1 \ln \mathrm{Dis}_{ij} + \beta_2 \ln \mathrm{RD}_{it} + \beta_3 \ln \mathrm{RD}_{jt} \\ & + \beta_4 \ln \mathrm{Grad}_{it} + \beta_5 \ln \mathrm{Grad}_{jt} \\ & + \beta_6 \ln(\mathrm{Dis}_{ij} \cdot \mathrm{Border}_{ij}) + \beta_7 \ln(RD_{it} \cdot Border_{ij}) \\ & + \beta_8 \ln(RD_{jt} \cdot \mathrm{Border}_{ij}) + \beta_9 \ln(\mathrm{Grad}_{it} \cdot \mathrm{Border}_{ij}) \\ & + \beta_{10} \ln(\mathrm{Grad}_{jt} \cdot \mathrm{Border}_{ij}) + \varepsilon_{ijt} \end{aligned} \tag{8}$$

where $\ln \mathrm{JP}_{ijt}$ is the log of the number of joint publications between region i and region j in year t; Dis_{ij} is the geographical distance between region i and j; Border_{ij} is a dummy variable that takes the value 1 if regions i and j share a border, and 0 otherwise; RD_{it} and RD_{jt} refer to the R&D expenditure in regions i and j in year t respectively; and Grad_{it} and Grad_{jt} refer to the number of graduates of regions i and j in t respectively.

Subsequently, we derive a measure of knowledge flows as predicted by the gravity equation for each region i as follows:

$$\mathrm{Collab\_pred}_{it} = \sum_{j=1}^{30} \exp(\beta_t . Z_{ijt}) \quad (j \neq i) \tag{9}$$

where β_t is the vector of coefficients; and Z_{ijt} is the vector of explanatory variables in equation (8). We use this variable to replace the collaboration spillover variable and re-estimate the main equation (7).

A second, related concern might be that nano-funding could be targeted more towards advanced regions, also creating potential endogeneity problems. To address this, we adopt a two-stage instrumental variables model (Cameron & Trivedi, 2010) in which we first predict nano-funding using the instruments the number of trade unions and the past value of nano-funding:

$$\begin{aligned} \ln \mathrm{FUND}_{it} = {} & \gamma_1 \ln \mathrm{FUND}_{it-1} + \gamma_2 \mathrm{CI}_{it-1} + \gamma_3 \mathrm{RDH}_{it-1} \\ & + \gamma_4 \mathrm{GRAD}_{it-1} + \gamma_5 \ln \mathrm{TU}_{it-1} \\ & + \gamma_6 X_{it-1} + v_{it} \end{aligned} \tag{10}$$

where $\ln \mathrm{FUND}_{it}$ is the logarithm of nano-funding received by region i at year t; $\ln \mathrm{FUND}_{it-1}$ is the logarithm of nano-funding received by region i in the previous period $(t-1)$; $\ln \mathrm{TU}_{it-1}$ is the logarithm of the number of trade unions in region i at year $t-1$; and X_{it-1} represents the vector of the key explanatory variables in the original equation (7). While it is not easy to find good instruments for funding, we believe that trade union presence is a reasonably good instrument as it might represent the extent of policy influence a region might have that could affect funding; at the same time, it is unlikely to have direct effects on innovation performance of a region.[11]

We re-estimate the main equation (7) after replacing actual funding with its predicted value derived from the above equation and the actual knowledge spillovers with predicted knowledge spillovers derived from equation (9). The estimation results are reported in Table A3 in Appendix A in the supplemental data online. These results are in line with the original results, indicating in general a positive and significant effect of both funding and spillovers.

Finally, spatial dependence, in particular, of knowledge spillovers can bias the estimates of the key variables. It is, therefore, important to ensure that the effect of the key variables, in particular, collaboration-driven spillovers, is unaffected by the effect of spatial-proximity driven spillovers. For this we run estimations by including the variable 'Nanotech spillovers – proximity', derived in equation (2), that capture proximity-driven spillovers in all specifications. The results remain similar and are reported in Tables B3 and B5 in Appendix B in the supplemental data online for the full sample and the three regional categories respectively. As a further robustness check, we construct a second proximity-driven spillover variable replacing patents in equation (2) with publications. These results, too, confirm the robustness of the findings and are reported in Tables B4 and B6 in Appendix B online.

DISCUSSION AND CONCLUSIONS

Employing nanotechnology development in China as the research setting, this paper examined the importance of knowledge spillovers for innovation, particularly for peripheral regions. While prior research extensively examined interregional spillovers resulting from geographical proximity, we focused also on spillovers emanating from collaboration network of scientists spanning regions.

The evidence presented in this paper suggests that China's success in nanotechnology development in general owes in large part the fostering of indigenous scientific capabilities through strong financial support from the state. As to be expected, the bulk of the governmental support targeted the advanced regions of China and the effect of funding had a greater impact in these regions given their ability to 'generate greater bang for the buck'.

Geographical proximity with other similarly advanced regions tended to display some significant positive spillover effects in high-capability regions which are concentrated along China's eastern coast, and to a lower extent in medium-capability regions that occupy the East–Central part of China. This confirms the general understanding in the economic geography literature (e.g., Caniëls & Verspagen, 2001) that proximity among advanced regions might generate agglomeration economies in these regions, which, while they help perpetuate their success, may leave peripheral regions behind. Specific to the Chinese context, the limited proximity spillovers received by medium- or low-capability regions may also be seen in the light of the fact that these regions are mostly inland, western regions far from the advanced coastal regions. This finding may have implications beyond the development process associated with a science-based enabling technology such as nanotechnology. Technological context is a critical factor in generating proximity-driven spillovers (Frenken et al., 2010), with studies suggesting that spillovers tend to occur more easily in high-tech sectors (Autant-Bernard, Fadairo, & Massard, 2013). This may suggest that proximity might induce even more limited spillovers of other, less cutting-edge technologies associated, for example, with the low- and medium-technology industries that dominate Chinese manufacturing.

While the above finding may point to a less-than-optimistic prospect for the catching up of lagging regions, a more reassuring picture emerges from the findings on the role of spillovers via the collaboration networks of scientists. Spillovers transmitted through such networks turn out to be the key source of nanotechnology innovation in peripheral regions. Combined with the evidence that direct R&D funding from the state contributed very little in these regions of China, we can conclude that spillovers via collaborations may have been the single most important factor in the rapid progress made in nanotechnology development by peripheral regions in recent years.

The findings of the study have several theoretical implications. First, the economic geography literature recognizes that owing to the presence of formal long-distance channels of knowledge such as collaborations, geographical proximity is not a necessary condition for knowledge spillovers (e.g., Boschma, 2005); the present study contributes to this literature by demonstrating that such formal collaboration linkages can be more salient for lagging regions with limited own capabilities. Second, this study, with its focus on an emerging-economy setting, also contributes to the catch-up literature: it highlights that, on the one hand, targeted technology development programmes may indeed help spur the development of a new technology system in leading regions; and, on the other hand, scientific linkages with these regions can help peripheral regions make rapid technological progress, compensating for their limited scientific capabilities.

This study raises some policy implications as well, particularly in the context of technology development in China and other similar emerging economies. Unlike in Europe, where the European Union's research funding is geared to promote collaboration between European countries (Hoekman, Scherngell, Frenken, & Tijssen, 2013), the Chinese government's funding strategy is devoid of any serious measures to stimulate interregional collaborations. So far, the emphasis in the government's funding guidelines has been limited to either international collaborations or industry–university collaborations. It may very well be the case that funding also continues to flow in the near future more into leading regions where scientific capabilities are stronger. While this is unavoidable on efficiency grounds, it appears imperative that peripheral regions can leverage and expand their scientists' ties in the broader scientific network within China and benefit from knowledge spillovers. Therefore, the Chinese government's funding strategy may need to incorporate measures to ensure scientific cooperation that spans regions. Such a strategy would be a natural extension to the current emphasis on university–industry collaboration, which, although it has not been explicitly examined in this paper, is well known to generate knowledge spillovers. As evidenced by this study, cooperation among scientists and technologists can potentially substitute for the relatively weak capabilities of some regions. Nurturing and expanding such networks through the right policies and incentives can play a vital role in helping today's technologically lagging regions catch up in the production and use of new technologies, thereby ensuring a more even pattern of regional development.

Given the heterogeneity between regions and countries in their propensity to collaborate, future research may explore these questions in other geographical contexts, such as Europe where the geographical, institutional and social conditions are more variegated than in China. This can help answer, in particular, whether the limited impact of geographical proximity in generating spillovers in peripheral regions is due to the peculiar geography of China. In addition, it would be important to understand the extent to which different types of networks act as a mechanism of long-distance knowledge spillovers to peripheral regions in the context of other technologies. This is because for a science-based technology such as nanotechnology, the fairly developed scientific collaboration networks present in China, as well as in other similar emerging economies, are particularly suitable for effecting knowledge flows. However, in the context of other technologies, such as biotechnology, that are characterized by a more complex innovation process with a varied set of actors, such as start-ups, university research laboratories and established pharmaceutical companies, the forces of agglomeration (Zucker et al., 1998) are likely to be harder to overcome. This presents policy-makers in peripheral regions with potentially daunting challenges, such as helping heterogeneous sets of actors build and strengthen linkages with actors in more advanced regions. Understanding this process, particularly in emerging economy settings, presents an important opportunity for future research in economic geography.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES

1. As pointed out by a reviewer, the concentration of nanotechnology in certain regions is partly due to the nature of this technology, whose development is perhaps characterized as Schumpeter Mark II innovation in which high initial R&D investments offer more advanced regions a head start (Breschi et al. 2000).
2. Mainland China has a total of 31 provincial regions. Tibet is not included in the analysis owing to lack of data.
3. 'Nano-patent' is defined as a patent with a 'nano' word in the title filed between 1995 and 2010. The search string used was '发明名称= (纳米) AND 申请日=19950101 :20101231 AND 申请人地址= (i)', in which 'i' was replaced by the name of each of the 31 Chinese regions. The data contain only 'invention patents', not 'utility models' or 'industrial design'.
4. Given that collaboration networks evolve over time, we treat collaboration as a dynamic construct; the existing literature has paid only scant attention to the dynamic aspect of collaboration due primarily to the use of cross-sectional data.
5. The nano-patent collaboration data are not available; hence, this study uses the collaboration extracted from nano-publication to create the interregional as well as the international collaboration variable that is defined below.
6. This variable takes into consideration the number of foreign countries involved in each publication. For instance, if region i collaborates in a publication with foreign countries A and B, this will be counted twice.
7. We refer interchangeably to high-capability regions as leading regions and to medium- and low-capability regions as lagging regions.
8. The values for nano-funding, R&D and GDP are in current prices.
9. Bottazzi and Peri (2003) find that spillovers are greatly localized and exist only within a distance of 300 km; Moreno et al. (2005) state that significant R&D spillovers take place in the range between 0 and 500 km.
10. The authors thank the associate editor and an anonymous reviewer for their suggestions on the approaches adopted here.
11. To testthe quality of instruments, we used Hansen's J test of over-identifying restrictions. Given that we could apply this test only after estimating a 'built in' instrumental variable model in Stata, we estimated an instrumental variable Poisson model (using the 'ivpoisson' command in Stata). We estimated the model with robust standards errors clustered on regions in order to take into account the panel nature of the data. In none of the model specifications reported in Table A3 in Appendix A in the supplemental data online is the test statistic significant at the 5% level. The models were run without year dummies lest the models would not converge.

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