

Inter-regional Scientific Collaboration in China

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ABSTRACT

Chinese scientific output has increased dramatically in recent years, but its internal spatial structure has received scant attention. Estimated gravity models of intercity scientific co-authorships show that there are two types of spatial political bias in China, apart from the expected mass and distance effects. Intercity co-authorships involving Beijing are more common than Beijing's output volume and location would imply, and this Beijing bias is increasing over time. The second type of spatial political bias is greater intra-provincial collaboration than is accounted for by size and distance. The geography of Chinese science is thus not only monocentric as regards overall scientific output, but also exhibits unusually hierarchical collaboration patterns. Unlike in Europe and North America, national and regional capitals are becoming ever more important as scientific coordination centers.

Keywords: scientific collaboration, network, China, spatial political bias

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1. Introduction

The recent rise of Chinese science has attracted considerable attention (Nature, 2013; Royal Society, 2011; Zhou and Leydesdorff, 2006). While China's annual economic growth amounted to about ten percent in the first decade of the twenty-first century, its scientific growth averaged 18 percent per year between 1996 and 2008 (Royal Society, 2011, p. 20). China's scientific growth is thus even more dramatic than its economic growth.

While this rise has resulted in a number of scholarly articles (Liefner and Hennemann, 2011; Zhou and Leydesdorff, 2006; Zhou et al, 2009), we still know little about the *internal spatial structure* of Chinese science. In particular, previous studies do not address the role that geography has played in scientific interaction *among cities* in China.¹ Most such studies are descriptive and take a national or, at best, a provincial perspective².

The aim of this paper is to understand the spatial structure of Chinese science, using an econometric application of the well-known gravity model of interacting nodes. It is widely known that Beijing has greater science output than can be accounted for by the size of its population or economy, even when compared with Chinese cities of otherwise similar size and sophistication such as Shanghai or Shenzhen. What is less well known is whether size and distance are the only important factors that explain the *interactivity* of Chinese science, which is what one would expect in purely market-driven spatial structures, or whether political prioritization of national and/or regional capitals introduces a *political spatial bias*. Statistical testing of potential spatial bias is the primary aim of this study. A second question, which is conditional on the potential existence of political spatial bias, revolves around

¹ It is scientists within cities that collaborate and not cities per se, but cities function as nodes that host scientists.

² This relates to two aspects: the geographical scope (e.g. world, continent or nation) and the spatial unit (e.g. country, sub-national region or city region). Most studies, not only China-related ones, focus on other scope-unit combinations than a nation and its city regions. Some studies partially overlap with this study by focusing on either city regions *or* on a single nation. For example, Matthiessen et al. (2002; 2010) provide a global network analysis of city regions whereas Havemann et al. (2006) use trend analysis to study collaboration between German immunological institutes. The closest analogy to this study is Ponds et al. (2007), which focuses on collaboration between Dutch NUTS3 regions. See Frenken et al. (2009) for a summary of this literature and the observation that "studies on collaboration patterns among regions or cities are rare."

whether such biases increase over time or not. This question relates to recent European findings, which show that national border effects are decreasing over time. A supplementary question is to compare the efficacy of different measures of mass. The most common measure is the research output quantity, which is easily observed but may be affected by endogeneity problems. As alternative measures, we compare exogenous approximations of market or political input volumes such as city region GDP and the number of national research universities in a city. Such comparisons may offer pointers that help us understand spatial allocation principles with Chinese characteristics.

The paper proceeds as follows. Section 2 summarizes the recent growth of Chinese science, while section 3 introduces the application of gravity models and similar approaches to the analysis of scientific cooperation. The following section presents methods and a descriptive overview of the dataset. Section 5 presents the empirical results, whereas the penultimate section amounts to an exploratory extension of the analysis that attempts to “read between the lines” of the econometric estimates. Section 7 concludes.

2. The rise of Chinese science

Table 1 shows the world’s top 12 science city regions in three distinct periods. While Europe and North America dominate global rankings of science cities, these rankings are not entirely static. The two most conspicuous changes after 2000 have been the rise of three East Asian cities—Beijing, Shanghai, and Seoul—and the decline of Moscow. In 1996-98 there were no Chinese cities among the top-12 city regions, while by 2010 Beijing and Shanghai had joined this group, with Beijing ranked first.

Table 1: The world's top-12 science city regions

Rank	1996-1998		2002-2004		2008-2010	
	City region	SCI papers	City region	SCI papers	City region	SCI papers
1	London	69,303	Tokyo-Yokohama	81,798	Beijing	100,835
2	Tokyo-Yokohama	67,628	London	73,403	London	96,856
3	San Francisco Bay Area	50,212	San Francisco Bay Area	56,916	Tokyo-Yokohama	94,043
4	Paris	49,438	Osaka-Kobe	54,300	Paris	77,007
5	Osaka-Kobe	48,272	Paris	53,005	San Francisco Bay Area	75,669
6	Moscow	45,579	New York	51,047	New York	70,323
7	Boston	42,454	Boston	49,265	Boston	69,250
8	New York	41,566	Los Angeles	44,401	Seoul	67,292
9	Randstad (Amsterdam)	37,654	Randstad (Amsterdam)	44,094	Randstad (Amsterdam)	65,527
10	Los Angeles	37,437	Beijing	42,007	Osaka-Kobe	60,615
11	Philadelphia	29,376	Moscow	41,001	Los Angeles	58,176
12	Berlin	24,514	Seoul	33,083	Shanghai	50,597

Note: Calculated by the authors on the basis of data from Thomson Reuters' Science Citation Index (SCI)

Table 2: The 31^a leading science cities in China (*global top-75 cities in bold*)

Rank	City (province)	SCI publications (2008-2010)	City (province)	SCI growth (1996-98-2008-10)
1	Beijing (Beijing)	100,835	Shenzhen (Guangdong)	+46.3%
2	Shanghai (Shanghai)	50,597	Ningbo (Zhejiang)	+31.7%
3	Nanjing (Jiangsu)	27,647	Qingdao (Shandong)	+27.9%
4	Wuhan (Hubei)	21,752	Nanchang (Jiangxi)	+26.6%
5	Guangzhou (Guangdong)	20,987	Chongqing (Chongqing)	+26.1%
6	Hangzhou (Zhejiang)	19,597	Harbin (Heilongjiang)	+25.2%
7	Xi'an (Shaanxi)	17,545	Nanning (Guangxi)	+24.4%
8	Chengdu (Sichuan)	14,716	Zhengzhou (Henan)	+23.4%
9	Tianjin (Tianjin)	12,950	Suzhou (Jiangsu)	+23.0%
10	Changchun (Jilin)	11,824	Guangzhou (Guangdong)	+22.8%
11	Changsha (Hunan)	11,345	Shijiazhuang (Hebei)	+21.9%
12	Hefei (Anhui)	11,289	Dalian (Liaoning)	+21.4%
13	Harbin (Heilongjiang)	11,217	Hangzhou (Zhejiang)	+21.3%
14	Jinan (Shandong)	10,710	Changsha (Hunan)	+21.1%
15	Shenyang (Liaoning)	9,904	Guiyang (Guizhou)	+20.8%
16	Dalian (Liaoning)	9,658	Xi'an (Shaanxi)	+20.7%
17	Lanzhou (Gansu)	8,585	Fuzhou (Fujian)	+20.5%
18	Chongqing (Chongqing)	7,865	Chengdu (Sichuan)	+20.2%
19	Qingdao (Shandong)	6,693	Wuhan (Hubei)	+20.0%
20	Kunming (Yunnan)	4,948	Taiyuan (Shanxi)	+19.9%
21	Fuzhou (Fujian)	4,356	Jinan (Shandong)	+19.9%
22	Xiamen (Fujian)	4,295	Kunming (Yunnan)	+19.8%
23	Zhengzhou (Henan)	4,122	Shanghai (Shanghai)	+18.1%
24	Suzhou (Jiangsu)	3,825	Xiamen (Fujian)	+16.3%
25	Taiyuan (Shanxi)	3,416	Shenyang (Liaoning)	+16.3%
26	Nanchang (Jiangxi)	3,229	Nanjing (Jiangsu)	+16.2%
27	Shenzhen (Guangdong)	3,082	Tianjin (Tianjin)	+16.2%
28	Shijiazhuang (Hebei)	2,645	Beijing (Beijing)	+16.0%
29	Nanning (Guangxi)	1,886	Hefei (Anhui)	+14.7%
30	Ningbo (Zhejiang)	1,768	Lanzhou (Gansu)	+13.8%
31	Guiyang (Guizhou)	1,542	Changchun (Jilin)	+13.3%
China (31 cities)		424,830	China (31 cities)	+18.2%

^a: Chinese cities with more than 1,500 papers in 2008-2010.

Table 2 lists 31 leading Chinese science cities in 2008-2010 and their growth rates from 1996-1998 to 2008-2010. Beijing and Shanghai are not the only notable Chinese centers. Among the world's 75 largest science cities in 2008 to 2010, nine were in mainland China. These nine Chinese cities exhibited the nine highest SCI growth rates among the 75 cities between 1996 and 2010.

In fact all 31 cities had high growth rates, not only the top nine. If we compare their growth with the top 66 cities outside of mainland China, only two cities (Lanzhou and Changchun) had lower growth rates than the fastest-growing city among the 66, which was Seoul. Even so, these two lagging Chinese cities expanded faster than São Paulo, which ranked second among the non-Chinese cities. Remarkably, Beijing is one of the slowest-growing cities in China. In a nutshell, the stylized facts suggest that something is evidently happening in China, where there is thus an on-going process of new science cities emerging, seemingly out of nowhere.

3. Theoretical background

When thinking about scientific collaboration in space, the gravity model is appropriate as it is one of the key models of spatial interaction. It has not only enjoyed considerable success in various empirical applications, but also rests on sound theoretical micro-foundations. In what follows we provide a brief overview of the theoretical underpinnings of the gravity model of scientific knowledge flows, as well as an even briefer outline of the most popular alternative, which is the network approach, which is promising but remains underdeveloped as regards its application to spatial interaction in science.

3.1. The gravity approach

Theory. Building on earlier literature in the social sciences³, Beckmann (1993; 1994; 1999) provides a foundational gravity model of scientific knowledge flows. He adopts a probabilistic micro-level approach where two rational agents (scientists) supply inputs into joint scientific production. The production function exhibits the properties of positive marginal products, diminishing returns to substitution and constant returns to scale. The agents maximize collaborative scientific production net of costs when choosing their labor effort; costs include the time- and distance-dependent costs of achieving effective interaction. Through a series of substitutions and extensions, Beckmann obtains a gravity equation with scientific knowledge flows between two locations i and j :

$$C_{ij} = N_i \cdot N_j \cdot e^{-d_{ij}} \quad (1)$$

where N is the number of researchers in each location (i and j), and d is the distance between the two locations.

Andersson and Persson (1993) offer a deterministic alternative to Beckmann's model. Economic optimization of net deterministic benefits yields a gravity formulation that is closer to what is common in the empirical literature:

$$C_{ij} = M_i^{\lambda_1} \cdot M_j^{\lambda_2} \cdot d_{ij}^{-\beta} \quad (2)$$

M is scientific output (mass) in locations i and j , while λ and β are parameters that may be estimated empirically.

³ Isard (1960) documents early gravity applications in the social sciences, which served as precursors of later models and applications. Wilson (1970) as well as Sen and Smith (1994) provide the theoretical underpinnings for modeling spatial interaction behavior. Their models have been applied to the study of traffic flows, interregional trade and migration flows.

The gravity model thus implies that scientific collaboration between two locations increases proportionally with the product of the mass variables but declines with distance. Although both theoretical endeavors arrive at gravity formulations that conform to feasible empirical analyses, only Beckmann's model uses inputs as mass variables. Thus, a closer link to Beckmann's model would imply the use of input variables such as the number of scientists rather than scientists' output. As far as we know, all published gravity-type estimations of scientific interactivity use output volumes, and thus conform to Andersson and Persson (1993).

Comparable studies. The gravity approach suggests that one should account for geographic proximity, since spatial distance is often the best explanation of interaction quantities involving urban regions. Spatial proximity facilitates face-to-face communication, which in turn facilitates the transmission of tacit knowledge as well as serendipitous discoveries, both of which stimulate the production of creative outputs such as scientific publications (Andersson and Persson, 1993). Moreover, face-to-face interaction may increase interpersonal trust, making it easier for people to collaborate (Ponds et al, 2007).

Gravity models allow researchers to study how the effects of various factors *change over time*. Most studies that have examined distance effects in science have however tended to adopt a static framework, by analyzing collaboration at one point in time or by using pooled observations from several years (Hansen, 2013). There are a few exceptions, but Hoekman et al. (2010) is the only gravity-type analysis that explicitly addresses how effects change over time. Other things being equal, we would expect a decreasing effect of distance over time, since transportation and communication costs have been decreasing as a result of investments in relevant network infrastructures.

There are in fact only a few studies that analyze scientific collaboration with the help of gravity models (Acosta et al, 2011; Andersson and Persson, 1993; Hoekman et al, 2010;

Hoekman et al, 2009; Ponds et al, 2007; Scherngell and Hu, 2011)⁴. The distance effect is uniformly negative but the estimated magnitudes depend on the chosen measurement technique⁵. The distance effects in studies that resemble the present study range from -.23 to -.70. Hoekman et al. (2010) show that the distance effect increased in importance between 2000 and 2007 as regards European co-authorships. They explain this measured effect as reflecting the increasing emergence of collaboration involving researchers in peripheral European regions, which would imply a greater measured distance effect than if collaboration had remained confined to regions closer to the European center of gravity. Given the geographic size of China, we expect distance to be as important as it is in Europe. Still, the relevant question is not whether distance matters but *how much* it matters; how does it compare to distance frictions elsewhere and how does such friction evolve over time?

Political spatial bias. It is well known that a substantial share of Chinese science funding is attributable to governmental decision-makers. In spite of recent globalizing tendencies, Jonkers (2010) contends that the Chinese system of scientific research is still a top-down system with little bottom-up investigator-driven research. Moreover, leading research universities are with few exceptions located in Beijing or in provincial capital cities. As a consequence, it is likely that scientific collaboration patterns reflect political resource allocation decisions. Jonkers (ibid., p. 36) claims that this political influence manifests itself as a preference for funding large-scale team projects in areas that policy-makers deem

⁴ There are a few Chinese studies that analyze scientific collaboration. Only six of them address collaboration between spatially delimited areas and only one (Scherngell and Hu, 2011) uses a gravity estimation. Our gravity-type model differs from Scherngell and Hu in three important ways. First, our empirical observations use the global SCI database rather than a domestic Chinese database. This makes it possible to compare Chinese output and interactivity with cities outside China. Second, our spatial unit of analysis is a functional urban region rather than a province. The only provinces that approximate functional urban regions are Beijing, Shanghai and Tianjin. Thirdly, they analyze scientific collaboration for one single point in time (i.e. 2007) and thus they neither can exploit any panel techniques nor can they study any dynamics.

⁵ Some studies use alternative methods when examining the influence of distance (Katz, 1994; Liang and Zhu, 2002). Overall, comparable studies support the hypothesis that geographical proximity matters.

important. He also claims (ibid., pp. 148-49) that there is a network of Chinese scientists who jointly decide on the allocation of research funds.

One would thus expect political priorities to matter more than economic factors in science-related location choices. One illustration is the priority given to national or provincial capitals as the preferred locations for national universities. The booming centers for foreign direct investment and exports—primarily Ningbo, Shenzhen and Suzhou—account for tiny shares of China’s scientific publications, in spite of their high growth rates and per-capita incomes (see Table 2).

A hypothesis that conforms to the notion of political spatial bias is that we should expect the funding of scientific activities—including collaborative research projects—to prioritize Beijing on the one hand and provincial capitals on the other. The implication is an expected over-representation of linkages involving Beijing as well as provincial capital cities.

The dynamics of spatial political bias. The distance effect is just one facet of what a gravity model can measure. Though the theoretical gravity models do not include political biases such as capital-city over-representation or various effects of political borders, it is common to extend the basic model to account for such effects. Empirical studies of international science networks provide estimates of how international border crossings reduce interactivity between two localities (Hoekman et al, 2010; Okubo and Zitt, 2004)⁶. While linguistic or cultural barriers are less likely in China than in Europe, political barriers between provinces cannot be ruled out in light of the practice of Chinese science policy, which includes of division of labor between different levels of the spatial political hierarchy, such as nation, province and city.

⁶ There is a literature that looks at how national political or linguistic biases where favor national over international collaboration. For example, Okubo and Zitt (2004) show that French border regions cooperate little with regions on the other side of the border, with only the Paris region exhibiting strong international linkages in science.

Indeed, Scherngell and Hu (2011) contend that regional protectionism as a manifestation of political spatial bias is pervasive in both science and industry (Scherngell and Hu, 2011). Others have argued that provincial governments are inward-oriented in their science policies, protecting local institutes and universities with the aim of maximizing intra-provincial benefits (Chen and Wang, 2003; Yoon, 2011). However, assertions of provincial protectionism in science have so far relied on anecdotal evidence rather than on econometric estimates.

In their study of Europe, Hoekman et al. (2010) estimate not only the effects of national barriers, but also that such barriers became less important in the first decade of the 21st century. There is thus some empirical support for the idea that European science is becoming more integrated over time. The Chinese analogy to national border effects in Europe is what we call the “same-province effect,” which refers to the hypothesis that provincial funding organizations prefer to keep their funds within the same province.

3.2. Other theoretical approaches

The most common non-gravity approaches for analyzing interregional scientific collaboration are various adaptations of network theory⁷. The network approach provides a different way of examining scientific co-authorship, with the aim of identifying sub-networks or clusters of cities with stronger-than-average inter-linkages⁸.

An approach that focuses on “the world network of science cities” has probably been most influential in generating empirical studies. This approach takes its cue from Taylor

⁷ The “scientific collaboration in space” literature is mostly data-driven and devoid of a clear theoretical framework. Most studies offer descriptive analyses of research collaboration, which in some cases involve using trend analysis, matrix-based approaches or indices to measure various aspects of scientific collaboration, including geographical proximity as one such aspect (see Havemann et al, 2006; Katz, 1994; Liang and Zhu, 2002).

⁸ Most network studies do not use the city region as the analyzed spatial unit due to limited data availability (Frenken et al., 2009; White, 2011). Studies of interregional networks tend to infer connectivity from metrics of network centralization and clustering (Oner et al., 2010). Most network studies lack theoretical micro-foundations. Liefner and Hennemann (2011) is probably the best attempt to provide a theoretical framework to connect network theory to regional spatial phenomena.

(2004) and his notion of “world city networks.” Matthiessen et al. (2002; 2010; 2011) uses Science Citation Index (SCI) data to classify city regions as belonging to different hierarchical “levels” and “bands” on the basis of the volume and interactivity of their scientific activity. These attempts make use of a direct analogy of Taylor’s (2004) classification of world cities according to the location patterns of headquarters and offices of multinational corporations. While existing network approaches to science cities help provide a summary of the relative importance of different city regions, it remains the case that Taylor and his followers do not provide any theoretical foundation that is grounded in individual behavior, in contrast with the gravity model. There are thus strong theoretical reasons for giving priority to the gravity model as the preferred starting point for quantitative analyses of inter-city links.

4. Data and Methods

4.1. Data

Scientific co-authorships remain the main form of scientific collaborative output (Ponds et al, 2007). SCI-indexed co-authorships consist of all published articles in about 6,650 journals in science and engineering⁹. The co-authorship counts make use of the street address associated with the institutional affiliation of each author of an article.

The spatial delimitation of each city approximates labor market areas, thus including both a central city and its outlying suburbs. Comparable studies combine neighboring cities if the center-to-center time distance is less than 45 minutes (Matthiessen et al, 2002). In the

⁹ We recognize that the Science Citation Index is just one way of measuring scientific collaboration and output. It is also possible to use citation or patents data, although the latter involves a different literature and a different set of challenges (see Hu, 2010). We believe that both citation and, especially, patent data are associated with serious problems as regards the identification of *actual* spatial locations of the relevant inputs. Nevertheless, we acknowledge that the use of the SCI index comes with all the biases and problems inherent in this type of data. For instance, Hennemann et al. (2011) points out that there can be differences when using domestic bibliographic databases as opposed to international ones. However, given that science policy-makers attach increasing value to the *international* visibility of research, we believe that our focus on the rise of Chinese science as measured by SCI publication counts is justified (Jonkers, 2010, p.13). An additional advantage is that an international analysis allows for direct comparisons between cities and networks in different parts of the world.

Chinese case, the labor market areas in practice correspond to the urban districts of each included city, since the administrative delimitations of Chinese cities tend to encompass extensive rural hinterlands. China's universities and research institutes tend to have central urban locations, although suburban "university districts" are becoming more common. In any case, there are no specialized Chinese college towns that are as remote as College Station (Texas), Ithaca (New York) or State College (Pennsylvania).

The 31 included cities account for almost all SCI-indexed publications from mainland China (see Table 2). The covered time periods are 1996-1998, 2002-2004 and 2008-2010. These three-year periods are consistent with the approach of Matthiessen et al. (2010) in their network analyses of world science cities, and were chosen to facilitate international comparisons.

There was very little Chinese scientific output and few co-authored papers in the first of the three periods. We may therefore refer to the 1996-to-1998 period as an "embryonic" period, followed by a period of middling scientific growth between 2002 and 2004. The final period—from 2008 to 2010—represents full-fledged growth involving much larger output quantities than in the earlier periods. These contrasts should in turn enable us to capture the various spatial changes occurring within the Chinese system of scientific research.

4.2. Why use cities as the unit of analysis?

This study is part of the "scientific collaboration in space" literature (see Frenken et al, 2009). What makes our work distinct is its focus on scientific collaboration *between cities*. There are a few reasons for this. First, scientific research clusters in places such as large cities or university towns. In fact science tends to be more spatially concentrated than most types of production (Liefner and Hennemann, 2011; Matthiessen et al, 2002). Second, decreasing communication costs have not caused the obsolescence of cities. Instead, cities have

reinforced their importance as coordination centers of spatially dispersed activities (Sassen, 1991; Florida, 2002). Third, cities do not exist in isolation. Cities are always nodes in systems of interconnected cities (Taylor, 2004). The fourth and perhaps most important reason is that it is better suited for the questions at hand—such as spatial political bias. For example, a “same-province effect” necessitates a separation between intra-province and inter-province links between localities smaller than provinces. Fifth, functional urban regions correspond to highly integrated labor markets, including markets for scientific labor.

4.3. Gravity estimation

Scientific interaction is bidirectional in science as it is in trade. Unlike in trade, there is no obvious source or destination region when two or more scientists co-author a paper. Adaptations of the basic gravity model for the purpose of analyzing scientific cooperation should therefore include only one volume or mass variable, typically the product of the total publication volumes of two regions. Additionally, co-authorships consist of non-negative integer values (count data), which render ordinary least squares estimation inappropriate (Hilbe, 2011). Gravity models of co-authorships such as equation (2) thus tend to be based on a Poisson process:

$$\Pr[C_{ij}] = \frac{\exp(-\mu_{ij})\mu_{ij}^{C_{ij}}}{C_{ij}!}, \quad \mu_{ij} = \exp(\alpha + \lambda \ln M_i M_j + \beta \ln D_{ij}) \quad (3)$$

where scientific collaboration (C_{ij}) between cities i and j follows a Poisson distribution with conditional mean μ . The mass variable ($M_i M_j$) and distance variable (D_{ij}) are dependent on this conditional mean.

An alternative count model is the negative binomial model. The key difference concerns the conditional variance. The Poisson regression model assumes a Poisson distribution, where the conditional mean of the dependent variable equals the conditional variance. It is however common for the conditional variance to exceed the conditional mean, especially when the count variable has more zeroes than a Poisson-distributed data-generating process would yield. The resulting over-dispersion can be accounted for in the negative binomial model via an extra parameter denoted as α (Hilbe, 2011). In the case of Chinese co-authorships, an over-dispersion test consistently rejected the null hypothesis that the conditional variance of the dependent variable equals its conditional mean. Thus, the gravity-type regressions employ the negative binomial regression model.

Table 3 describes and lists the sources of the dependent and independent variables in the gravity-type models. Our main mass variable (**PUBSMASS**) follows the empirical literature and is the product of the SCI publication counts of two cities. As robustness checks we also consider alternative proxies for the mass variable: city publication products two years before the start of the observed co-authorship period (**PUBMASS2**); the product of the cities' GDP (**GDPMASS**); the product of the cities' volumes of tertiary teachers (**TEACHMASS**); and the product of the number of national universities in each of the two cities (**UNIMASS**). **GDPMASS** is often included in trade models, and is an attempt to proxy for overall agglomeration economies. **TEACHMASS** and **UNIMASS** are possible proxies for investments in scientific research.

The motivation behind these variables is threefold. First, the alternative measures address potential endogeneity problems associated with using **PUBMASS**¹⁰. In addition, we adopt lagged values to address potential simultaneity problems, while random effects and time dummies control for omitted variables that may be important. Second, **TEACHMASS** and

¹⁰ Acosta et al. (2011) is the only study to address this problem apart from the present study.

UNIMASS are potential input variables in line with Beckmann's formulation of the gravity model. Third, to examine the question as to which of the institutionally-driven or market-driven explanation predict scientific interaction better we have UNIMASS vs. GDPMASS. The former measures size effect as scientific size (based on national universities) and the latter as economic size.

Table 3. Variable descriptions and data sources

Variable Name	Description	Source
<i>Dependent variable</i>		
CO-AUTHORED PAPERS	Number of co-authored papers by city pair for three 3-year periods	Thomson-Reuters SCI database
<i>Independent variables</i>		
<i>Mass variables</i>		
PUBMASS	Log of (product of total number of SCI publications in city i and city j)	Thomson-Reuters SCI database
PUBMASS2	Log of (product of total number of SCI publications at provincial level); the city-specific number is imputed from the city's share of provincial GDP	China Statistical Yearbook on Science and Technology
GDPMASS	Log of (product of gross regional product in city i and city j)	China City Statistical Yearbook
TEACHMASS	Log of (product of higher education teachers in city i and city j)	China City Statistical Yearbook
UNIMASS	Log of [(product of number of national universities funded by Project 211 in city i and city j) + 1]	Ministry of Education and other sources
<i>Spatial friction</i>		
DISTANCE	Log of (geographic distance in kilometres between city i and city j)	Various sources
<i>Other variables</i>		
BELJING	1 = Link connects Beijing; 0 = Link does not connect Beijing	-
SAME-PROVINCE	1 = city i and j in same province; 0 = city i and j in different provinces	-

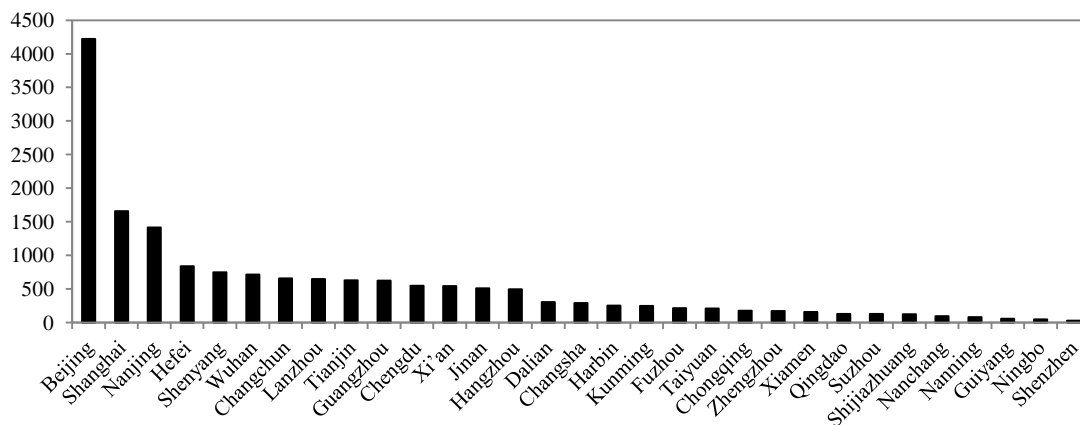
Note: Except for **PUBMASS**, where we conform to comparable studies by using the current year, all explanatory variables refer to observations two years before the beginning of the studied time period, i.e. 1994, 2000, and 2006, if observations are available for these years. In some cases, we use the closest available year.

5. Results

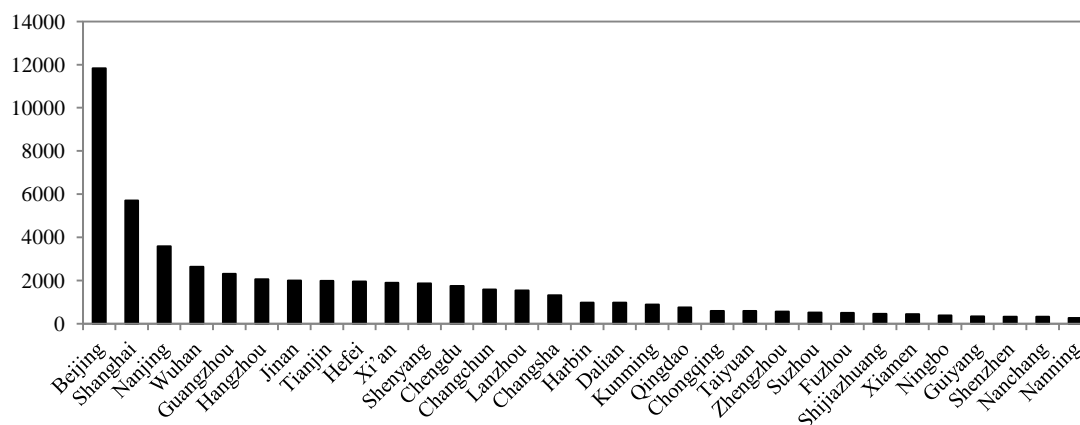
5.1. Descriptive analysis

We present co-authorship of each city with all other cities in Figure 1. Beijing, Shanghai and Nanjing are the major centers of cooperation with other cities across all periods. Guangzhou, Wuhan and Hangzhou also form part of this upper-level group with Guangzhou and Hangzhou replacing Hefei and Shenyang from the earlier period. While the bottom across the periods is made up roughly of the same cities such as Guiyang, Nanchang, Nanning, Ningbo, Shijiazhuang and Xiamen, one notable change is that of Shenzhen which has seen a dramatic increase from the second period to the third.

Co-authorship with other cities, 1996-98



Co-authorship with other cities, 2002-04



Co-authorship with other cities, 2008-10

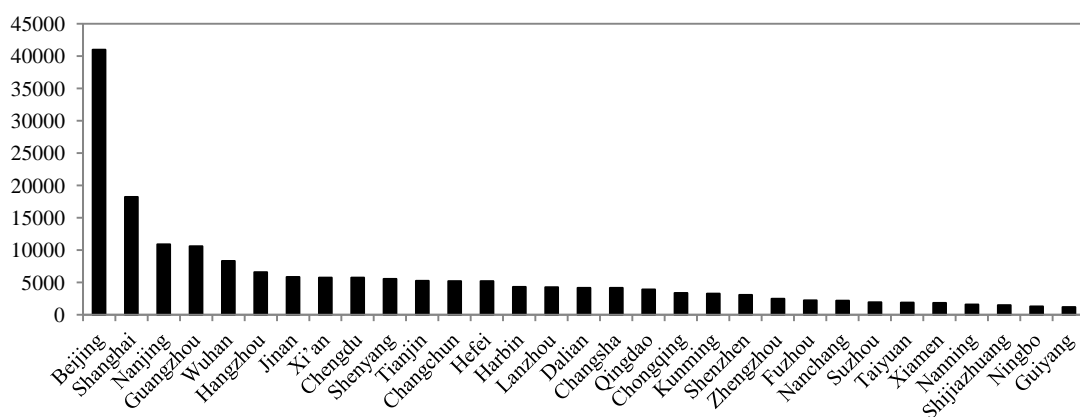


Figure 1. Total number of co-authored papers with other cities in three periods

One way of looking at China's network structure is to identify the most intensive co-authorship links. Figures 2 and 3 show all links involving .25 percent or more of the total

paper output of the 31 cities in 1996-1998 and 2008-2010, respectively. In the earlier period, this implies at least 150 co-authored papers, while in the later period the cut-off point is 1,000 papers. The increase in required papers reflects the rapid growth in China's scientific output.

What emerges is a Chinese science network that is decidedly Beijing-centric. In the earlier period, there are a total of twelve high-frequency links, eleven of which involve Beijing. In the later period, the total number of links has increased to 21 links, with 18 Beijing links. Since the identification of links is in relation to the total production of scientific papers in the relevant time period, the results show that intercity co-authorships have increased in relative as well as absolute importance. China's science network is becoming more interactive.

Figures 2 and 3 also help us identify the hierarchical levels in the Chinese science network. The relevant criterion is whether a city has one or more high-frequency links to other cities. In the earlier period, Beijing had high-intensity links with 11 cities. These 11 cities are all among the top 17 in total science output, and all are provincial capitals. In the second period, the second level encompassed 18 of the 19 largest Chinese science cities after Beijing in SCI output terms. The second period also exhibits changing tendencies, such as two non-Beijing links in the Yangtze River Delta region as well as two links between Beijing and cities that are not provincial capitals (Dalian and Qingdao).

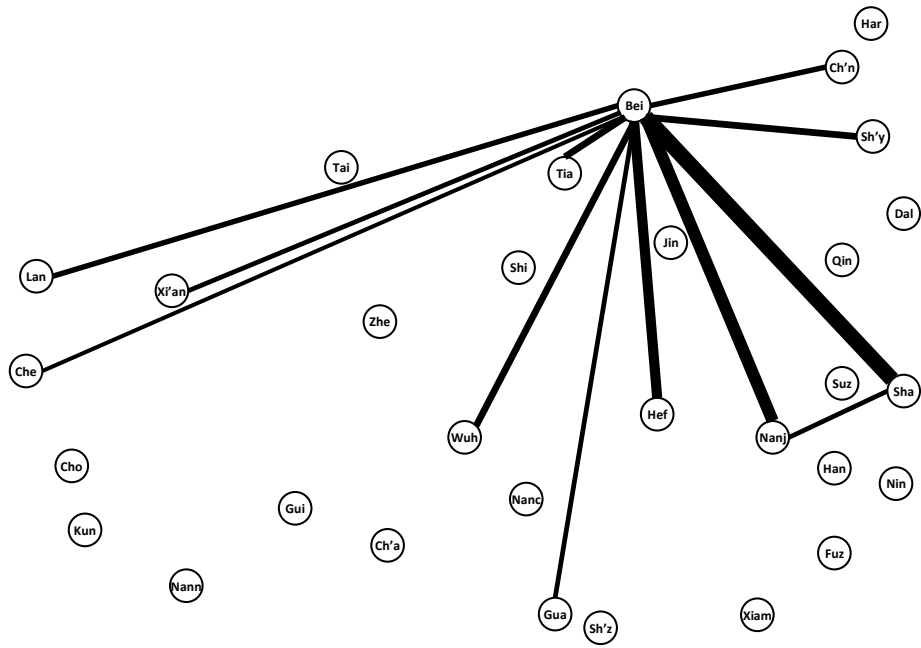


Figure 2. Intercity co-authorship links of 150 papers or more, 1996-1998

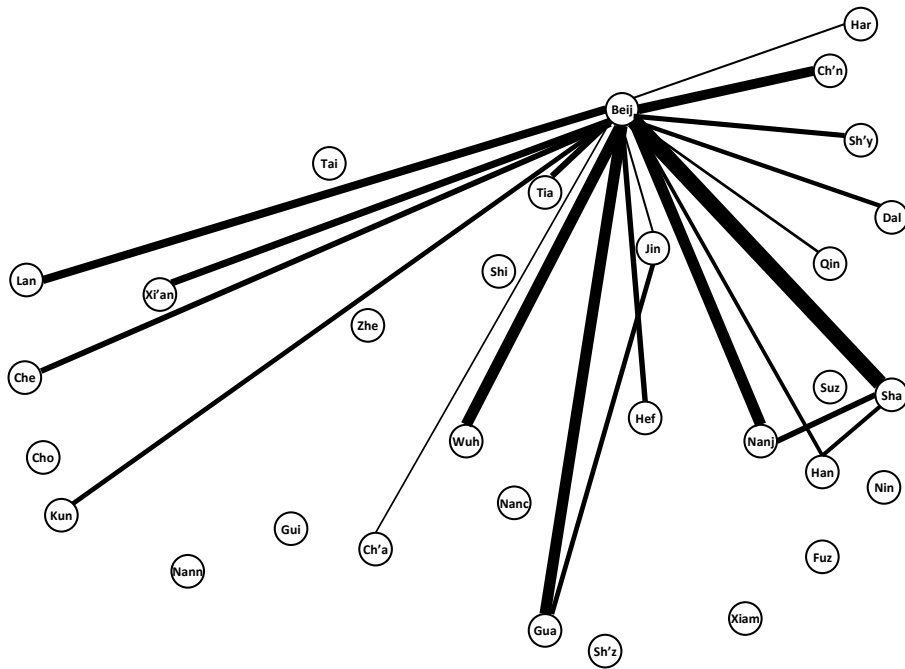


Figure 3. Intercity co-authorship links of 1,000 papers or more, 2008-2010

5.2. Gravity results

Table 4 gives the results of estimated pooled negative binomial regressions with five different specifications. The five regressions cover all three time periods and include the logarithm of the product of the SCI publication volumes in cities i and j as well as the logarithm of the distance in kilometers between i and j .

Table 4. Pooled negative binomial results

Dependent Variable: CO-AUTHORED PAPERS					
	(1) No Fixed Effects	(2) Fixed Effects	(3) Fixed Effects & Time Dummies	(4) Beijing, Same- province & Time Dummies	(5) City and Time Fixed Effects
PUBMASS	0.717*** (0.011)	0.632*** (0.011)	0.760*** (0.020)	0.837*** (0.019)	0.757*** (0.023)
DISTANCE	-0.319*** (0.032)	-0.335*** (0.031)	-0.310*** (0.034)	-0.226*** (0.033)	-0.309*** (0.034)
BEIJING	-	-	-	0.527*** (0.061)	-
SAME-PROVINCE	-	-	-	1.102*** (0.131)	-
City Fixed Effects	No	Yes	Yes	No	No
Beijing Effect	No	No	No	Yes	No
Same-province Effect	No	No	No	Yes	No
Time Dummies	No	No	Yes	Yes	No
City-Time Fixed Effects	No	No	No	No	Yes
<i>Dispersion parameter (α)</i>	0.583*** (0.029)	0.373*** (0.028)	0.355*** (0.029)	0.414*** (0.031)	0.334*** (0.026)
<i>Number of observations</i>	1395	1395	1395	1395	1395
<i>Log likelihood</i>	-5706.73	-5476.58	-5445.29	-5527.06	-5410.47
<i>Pseudo R²</i>	0.177	0.210	0.215	0.203	0.220

Note: ***, **, *: $p < .01, .05, .10$, respectively. Bootstrap-robust standard errors in parentheses.

Model (1) is the basic model with only mass and distance, while models (2) through (5) introduce various refinements. Models (2) and (3) introduce city fixed effects, while model (4) employs Beijing and same-province dummies instead of 30 fixed effects. Models (3) and (4) use time dummies to account for time trends. Model (5), finally, uses combined *city-and-time* fixed effects.

As expected, an increase in the product of the total number of publications is associated with an increase in the number of co-authored papers. The coefficient estimates range from .63 to .84, which is in line with comparable prior studies (Ponds et al, 2007; Scherngell and Hu, 2011). The distance effects have the expected negative sign and are highly significant. The estimated magnitudes are all in the vicinity of -.30. Most comparable studies report distance effects between -.23 and -.70, implying that spatial friction is not a greater impediment to interaction in China than it is in the West (see Hoekman et al, 2009; Scherngell and Hu, 2011). In fact this means distance friction though comparable to elsewhere is still smaller for a large country. We may interpret this result as indirect evidence that China's transport and communication infrastructures are unusually advanced for a middle-income country.

Model [4] shows that there are more interactions with Beijing than the output volume of the city *and* its geographic location vis-à-vis other Chinese cities can account for. This result corroborates Beijing's role as a top-level coordination center in the network. That a Beijing link should be attractive to scientists in other localities is unsurprising; the Chinese Academy of Sciences is in Beijing as are China's two global top-100 universities (Peking University and Tsinghua University). Consequently, Beijing-based scientists receive a disproportionate share of science funding (Feng and Pei, 2011). As such this is the consequence of Chinese science policy bearing on scientific interaction.

There is also a significant same-province effect, implying more intra-provincial collaboration than volume and spatial proximity considerations would lead us to expect. This echoes the presence of a spatial provincial bias as hypothesized, quite possibly politically driven.

Likelihood ratio tests indicate that models (1), (2) and (4) are nested in models (3) and (5), whereas (3) is not nested in (5). In other words, models with city fixed effects and time

dummies—entered either separately or jointly—outperform simpler regressions. These models are similar in spirit to Hoekman et al.’s (2010) models of inter-regional scientific interaction in Europe. Their estimated distance coefficient for aggregate science equaled $-.57$ for 2000 to 2007, after controlling for regional, national and linguistic border effects. There is thus some evidence that spatial friction may have a *greater* inhibitory effect in Europe than in China. This might suggest that national boundaries affect cross-border scientific cooperation in ways that are not easy to control for in formal models (Okubo and Zitt, 2004).

Table 5. Cross-sectional negative binomial results

	Dependent Variable: CO-AUTHORED PAPERS					
	(1)	(2)	(3)	(4)	(5)	(6)
	1996-1998: Fixed Effects	1996-1998: Beijing & Same-province Dummies	2002-2004: Fixed Effects	2002-2004: Beijing & Same-province Dummies	2008-2010: Fixed Effects	2008-2010: Beijing & Same-province Dummies
PUBMASS	0.811*** (0.040)	0.853*** (0.035)	0.768*** (0.041)	0.844*** (0.037)	0.695*** (0.040)	0.816*** (0.029)
DISTANCE	-0.271*** (0.066)	-0.200*** (0.067)	-0.339*** (0.068)	-0.284*** (0.061)	-0.312*** (0.052)	-0.200*** (0.051)
BELJING	-	0.420*** (0.110)	-	0.474*** (0.113)	-	0.678*** (0.104)
SAME-PROVINCE	-	0.882*** (0.271)	-	1.094*** (0.285)	-	1.282*** (0.144)
City Fixed Effects	Yes	No	Yes	No	Yes	No
Beijing Effect	No	Yes	No	Yes	No	Yes
Same-province Effect	No	Yes	No	Yes	No	Yes
<i>Dispersion parameter (α)</i>	0.422*** (0.056)	0.537*** (0.067)	0.414*** (0.048)	0.508*** (0.054)	0.251*** (0.036)	0.305*** (0.039)
<i>Number of observations</i>	465	465	465	465	465	465
<i>Log-likelihood</i>	-1250.37	-1281.19	-1788.86	-1828.07	-2354.50	-2398.87
<i>Pseudo R²</i>	0.225	0.206	0.188	0.170	0.179	0.163

Notes: ***, **, *: $p < .01, .05, .10$, respectively. Bootstrap-robust standard errors in parentheses.

Table 6. Results of negative binomial panels with random effects

Dependent Variable: CO-AUTHORED PAPERS					
	(1)	(2)	(3)	(4)	(5)
	PUBMASS	PUBMASS2	GDPMASS	TEACHMASS	UNIMASS
PUBMASS	0.822*** (0.022)	-	-	-	-
PUBMASS2	-	0.393*** (0.023)	-	-	-
GDPMASS	-	-	0.539*** (0.050)	-	-
TEACHMASS	-	-	-	0.554*** (0.020)	-
UNIMASS	-	-	-	-	0.713*** (0.045)
DISTANCE	-0.286*** (0.045)	-0.238*** (0.061)	-0.237*** (0.066)	-0.428*** (0.060)	-0.376*** (0.067)
Time Dummies	Yes	Yes	Yes	Yes	Yes
<i>Dispersion parameter (α)</i>	0.355*** (0.024)	0.934*** (0.058)	1.286*** (0.761)	0.355*** (0.029)	0.502*** (0.030)
<i>Number of observations</i>	1395	1395	1395	1395	1395
<i>Log-likelihood</i>	-5303.78	-5733.38	-5834.81	-5762.63	-5760.59
<i>Pseudo R²</i>	0.213	0.149	0.134	0.145	0.145

Notes: ***, **, *: $p < .01, .05, .10$, respectively. Bootstrap-robust standard errors in parentheses.

Table 5 decomposes the analysis into the three time periods, using cross-sectional models. The estimated variable coefficients show a great deal of consistency from one period to the next, with significant mass and distance effects. The distance effect seems to increase and decrease over this time period. One possible explanation could be that there are two opposing effects at work: one where scientists in periphery cities seek out long-distance cooperation especially with the core; and regional cooperation. The increased effect in early period is explained by greater weight placed in long-distance cooperation with the core, though not unimportant later on, still it declines in weight relative to regional scientific links.

The functions with Beijing and same-province dummies show that these Beijing effect tend to increase over time. Though other cities are increasing their contributions to China's total science output, there is also an increasing tendency—in relative terms—for co-authored papers to involve Beijing-based scientists. This is borne out by our earlier descriptive analysis and thus in line with what we expected: a Beijing dominance. This could epitomize the

institutional nature of science policy in China as scientists from smaller cities seek out collaboration from the core to gain resource access (Acosta et al, 2011).

Intra-provincial collaboration is also on the rise as indicated by the same-province dummy. This is in stark contrast to Hoekman et al (2010) who find a decline of a regional border effect over time and even more surprising that national boundaries in Europe may be less relevant as opposed to provincial boundaries that seem to be increasing impediment. This seems to suggest that the ‘spatial provincial bias’ is growing over time. Coupled with the fact that the Chinese research system is top-down institutionally driven (Jonkers, 2010), this could be dubbed as a ‘spatial *provincial* political bias’ or regional protectionism in science. It exists and is increasing over time. In turn this can be seen as a major impediment to the integration of Chinese science (Yoon, 2011).

The final set of regressions consists of negative binomial panels with random effects. The panels introduce four new specifications of the mass variable along with the original one: with all four regressions acting as robustness checks in the form of exogenous measures, and the last two being closer to the theoretical foundations of input-driven gravity and a GDPMASS vs UNIMASS comparison informative about the market-driven and institutional-driven debate.

Table 6 presents the results. The results suggest that there are many ways of approximating mass and, more importantly, though the exogenous measures are robust predictors of scientific interaction the more endogenous measure PUBMASS seems to overestimate the size effect. A comparison GDPMASS vs. UNIMASS reveals that UNIMASS is a more significant predictor of scientific collaboration than GDPMASS. This is suggestive that politics is a better predictor of scientific interaction than market- and economic-based explanation. Additionally, the distance effect is relatively robust across all

17 estimated models. The distance coefficient ranges from -.20 to -.43, which is similar—although slightly lower—than the “normal” range of -.23 to -.70.

6. Understanding the gravity results: an exploratory analysis

As an exploratory analysis we use a simple network analysis to garner further understanding as to the distance effect, the Beijing effect and the same-province effect (i.e. a ‘spatial provincial political bias’) found in our gravity estimation. As opposed to the descriptive analysis in sub-section 5.1, another way of revealing strong links is to identify whether links are stronger or weaker than expected in a relative sense. In turn this can reveal over-represented links and how much they are distance-sensitive. The expected number of co-authorships involving city i and city j should equal the product of the number of co-authored articles (with all cities in the network) in the two cities divided by the total number of co-authorships in the network. Figure 4 shows those links where the observed number of co-authorships equals or exceeds 150 percent of the expected number. Lines of medium thickness imply between two and three times as many observed as expected co-authorships, while the thickest lines imply observed frequencies that are more than three times greater than the expected ones. Table 7 shows the ten links with the highest ratios between observed and expected co-authorships. It is the identification of disproportionately strong links that makes it possible to construct proximity clusters such as “bands.”

Figure 4 reveals two tendencies. First, Beijing tends to have stronger than expected links to cities with *small* SCI publication volumes. Its six disproportionately strong links are with cities that are ranked 10th, 17th, 20th, 25th, 28th, and 31st in output (see Table 2). Another aspect of this tendency is that the smallest science cities tend to have numerous strong links. For instance, cities such as Guiyang, Kunming, Nanchang, Nanning, Ningbo, Shijiazhuang, Suzhou, and Taiyuan have three or four strong links. It is likely that this reflects intercity cooperation strategies among universities in cities with small local knowledge stocks. This

strategy should be especially attractive in China, since scientists working at top-ranked national universities have better access to national research funds.

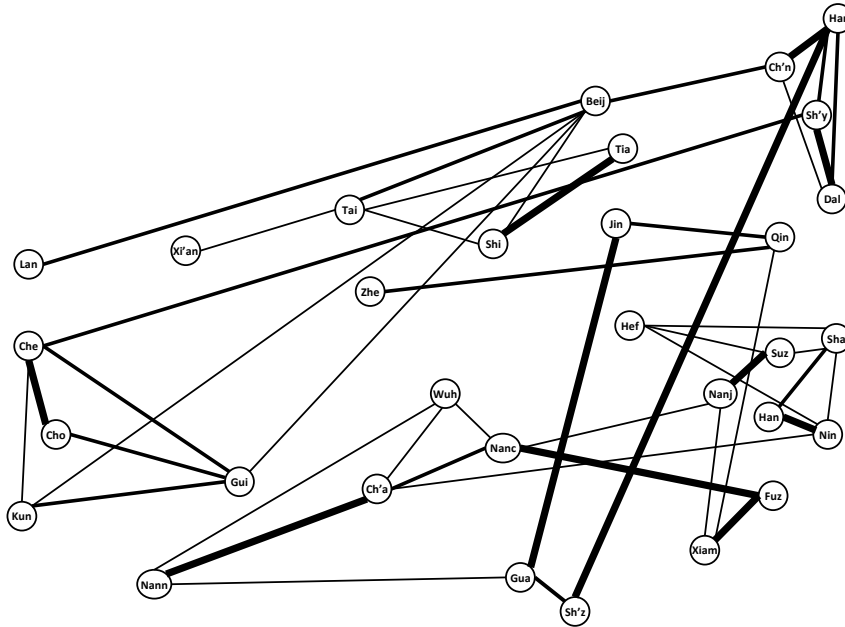


Figure 4. Strong intercity co-authorship links in China, 2008-2010

Table 7. Top ten over-represented links, 2008-2010

City <i>i</i>	City <i>j</i>	% over-representation
Xiamen	Fuzhou	791.3
Hangzhou	Ningbo	728.5
Chengdu	Chongqing	512.7
Harbin	Shenzhen	507.9
Guangzhou	Jinan	417.0
Changsha	Nanning	386.5
Tianjin	Shijiazhuang	385.9
Changchun	Harbin	385.7
Shenyang	Dalian	346.1
Nanjing	Suzhou	334.6

The second tendency is proximity clustering in regional bands. In addition, it seems that cities in the same province cooperate with each other more than is attributable to size and distance

alone. There are six intra-provincial pairings of cities, four of which are among the ten links with the greatest observed-to-expected ratios (see Table 7). The remaining two intra-provincial links are also stronger than expected.

Each of the eight city pairs in bold font in Table 7 represents a link between cities in the same part of China, which implies proximity clustering. Although short geographic distances may be a partial explanation, both Figure 4 and Table 7 hint at an independent provincial effect. In the Yangtze River Delta region, Suzhou in Jiangsu is more strongly linked to Nanjing (Jiangsu) than to Shanghai, though it is nearer. Hangzhou in Zhejiang links to Ningbo (Zhejiang), but not to Suzhou, which is at about the same distance. And Nanjing does not have a strong link to Hefei in Anhui. This could be an indication that second-ranked provincial cities seek linkages to the provincial capital, which tend to host national universities as well as provincial funding organizations. A conjecture is therefore that China's science network consists of at least three levels. There is also the possibility that each province makes up a band of closely connected cities, with hierarchical control functions vested in the provincial capital city. So in some ways the above fits with our gravity finding of a spatial provincial political bias and thus suggestive that Chinese science is not as nationally integrated we think. A consequence of this as has been argued, is that this could impede effective knowledge transfer across China and likely result in an inefficient resource allocation (Chen and Wang, 2003; Hui, 2007, Yoon, 2011).

The Guangzhou-Jinan and Shenzhen-Harbin links are unexpected outliers. Though at first it seems puzzling it can be explained as part of a politically-driven explanation of Chinese science, yet one of a deliberate strategy by these cities government in choosing an alternative means to achieve scientific growth. In fact looking at the situation in these cities in the earlier period reveals that Guangzhou was a middling science city, while Shenzhen was bottom ranked. Thus, they saw encouraging scientific cooperation with other science centers as one

way to achieve rapid scientific growth, which in turn could explain their rapid rise. The instrument to achieve this for Guangzhou was probably instituted by the various government funded programs such as the 211 program and the 973 program. While the 973 program funds large-scale research projects which could potentially span research groups working on a specific topic in different cities, instead the universities part of the 211 program not only get the bulk of most research funding in China but also house most of the national key laboratories which are known to be sometimes shared by multiple universities across provinces (Hu and Jefferson, 2008; Jonkers, 2010, p.25)¹¹. This could also explain our significant regression result for our UNIMASS variable, which is proxied as the product of number of national universities funded by project 211. The case of Shenzhen is special in that around 2002 the local government decided to build a university town and where several national universities were supported and encouraged to set their graduate schools, with Harbin Institute of Technology being one. This could explain how Shenzhen has not only progressed rapidly in scientific collaboration after the 2002-04 period but why the Shenzhen-Harbin link stands out. Though outliers they still epitomize the politically driven nature of Chinese science.

Overall, the network patterns suggest that there is a strong connection between the spatial structure of Chinese science and the political allocation of resources. Beijing dominates nationally, and provincial capitals dominate provinces. All top universities are public, and research funds are governmental. Rich cities with a strong market orientation but with lower political power—such as Ningbo, Shenzhen and Suzhou—tend to have modest publication volumes, albeit with high rates of output growth. Though scientific growth in smaller cities is on the upward trend, yet the deck is still stacked in Beijing's favor.

¹¹ We thank a referee for pointing this out to us. Our own search of the Ministry of Education and Ministry of Science and Technology sources revealed that Sun Yat-Sen University (Guangzhou-based) and Shandong University (Jinan-based) have well-established links and as an example together participate in a research project also involving Nankai University, Peking University and Hangzhou Normal University.

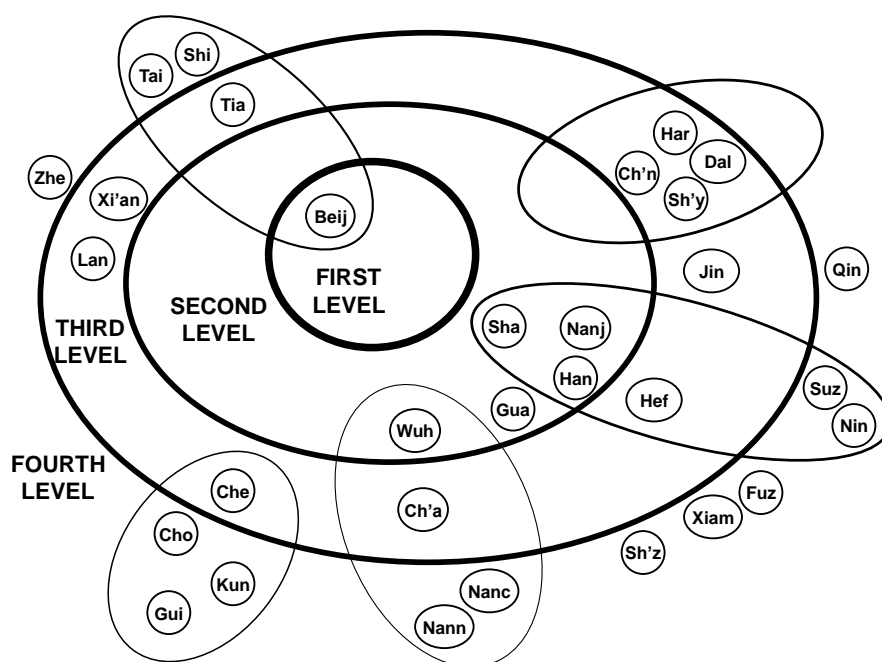


Figure 5. Levels and bands in the Chinese system of science cities

Figure 5 shows an exploratory Chinese system of science cities¹². It depicts China's publication and co-authorship structure along the lines of earlier studies of world science cities; cities thus belong to hierarchical levels and possibly also to bands of strong links. The uppermost level consists of Beijing alone, with the second-tier cities being Shanghai, Nanjing, Wuhan, Guangzhou and Hangzhou. A higher hierarchical level implies greater overall network connectivity. On the whole, the picture that emerges is a monocentric network, possibly closer to the French system than the polycentric system in America and elsewhere in Europe.

¹² While Beijing picks itself up in such system at the first level, to demarcate the other cities we use the following criteria after having defined four levels of hierarchies for the most recent period. The first criterion is the total number of papers, as a city's capacity to produce co-authored papers is determined by its absolute size (with cut-off points for levels 2 and 3 being ≥ 15000 and ≥ 8000 respectively). The second criterion is the total number of co-authored papers with other cities, as connections are an important facet of being placed in such 'network of science cities' (with cut-off points for levels 2 and 3 being ≥ 6500 and ≥ 4000 respectively). The third criterion is given a city's total scientific production, how well is it connected with the majority of cities and as such we also consider the city's overall connectivity within the Chinese science system to decide where they are placed in the hierarchy. This means the greater the hierarchical level the greater the connectivity. This latter criterion follows from the 'world network of science cities' literature where cities closer to the centre circle are 'globally' more connected. An example of the criteria at work can be seen with respect Xi'an and Jinan. Though Xi'an produces more than 15000 papers, still connection-wise it is less connected than Jinan which, however, capacity-wise is much smaller (see Table 2 and Figure 1). Thus, these two cities fall short of level 2.

There are several instances of regional bands involving cities at different levels. The indicated bands are the Beijing-led North, the Shanghai-led Yangtze River Delta, non-hierarchical Northeast, the Wuhan-led Center/Central-South; and the Chengdu-led West/Southwest.

7. Conclusion

Chinese science is on the rise. This paper explored this rise as part of a study on the role of geography on scientific collaboration between Chinese cities, with a focus not only on the distance effect but also a political bias involving a Beijing effect and a spatial provincial bias (same-province effect). Gravity-type models of Chinese interaction reveal that mass and distance variables conform to the global pattern, but with slightly less spatial friction and with a significant orientation towards co-authorship links involving Beijing-based scientists. The relatively low level of spatial friction alludes to large center-periphery distances and relatively well-functioning transport and communication infrastructures for intercity flows of people and ideas.

The presence of a same-province effect documents spatial political bias or regional protectionism at work in Chinese science and more suggestively that Chinese science being less integrated, even less so over time. This is in contrast to Europe where not only regional but national boundaries are a lesser impediment over time.

Our exploratory network analysis investigated scientific collaboration further and found a spatial organization of Chinese science where Beijing alone occupies the highest hierarchical level. Though there is scientific growth elsewhere in the system, Beijing continues to dominate. The network analysis is also revealing about regional bands of cities that cluster in a hierarchical way and confirms that strong ties at the provincial level depicts a spatial political bias at work, more so than a distance effect.

Overall, our results (especially Beijing effect and spatial provincial bias) bear out that political decisions rather than markets shape the spatial allocation of resources that support scientific research where the Chinese system of science cities seems to be following the monocentric French model rather than the more polycentric American one. But even more so is that the scientific resource allocation seems to have led to a less-than-integrated Chinese science with only pockets of integration at localized regional level. If the goal is to have a full-integrated research system that allows knowledge transfer across the whole system of science cities then further reform may be needed.

While China has arrived on the world stage of science, it is an emerging rather than established power. Even Beijing lacks the international orientation and citation impact of Western cities with similar publication volumes, such as London or Paris (Nature, 2013; Royal Society, 2011). The main challenge will be to break out of this isolation. The problem is all the more daunting since it may be more cultural than political. It is a problem that Beijing and Shanghai share with Seoul, Taipei and Tokyo (Andersson et al., 2013). When scientists around the world look for path-breaking ideas they still prefer Cambridge—whether in England or Massachusetts—over Beijing or Tokyo. To break out of this impasse, China may need a new cultural revolution more than it needs money.

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