China Economic Review 23 (2012) 1164–1175

Contents lists available at SciVerse ScienceDirect

China Economic Review

The role of regional knowledge spillovers on China's innovation

Qingyan SHANG [a,*], Jessie P.H. POON [b], Qingtang YUE [c]

[a] Department of Economics, State University of New York at Buffalo, Buffalo, NY 14260, United States
[b] Department of Geography, State University of New York at Buffalo, Buffalo, NY 14261, United States
[c] Business School, China University of Political Science and Law, Beijing102249, China

A R T I C L E I N F O

Article history:
Received 15 February 2012
Received in revised form 2 August 2012
Accepted 22 August 2012
Available online 30 August 2012

JEL classification:
O31
O53
R11
R12

Keywords:
Innovation
Regional knowledge spillovers
Research institutes and universities
Spatial autoregressive model
China

A B S T R A C T

The new economic geography has increased attention on the spatial dimension of knowledge spillovers and innovation. In this paper, we test the hypothesis that regional knowledge spillovers positively influence China's innovation growth from 2001 to 2008. As knowledge is subjected to spatial decay, innovation of a region is enhanced when location in neighboring regions encourages the formation of regional knowledge and information flows. Applying a spatial autoregressive model to China's provinces, the paper finds that regional knowledge spillovers have a favorable effect on design, invention and utility patents. This indicates that proximate location to innovative neighbors can help to raise the innovation capability of a province. In addition, evidence also shows that R&D expenditure and skilled personnel of research institutes and universities positively affect invention and utility patents. This suggests a favorable role for the government in enhancing indigenous innovation capability.

Published by Elsevier Inc.

1. Introduction

The extent to which knowledge spillovers from enterprise R&D and university research are geographically bounded has attracted much attention in economic studies of innovation (Anselin, Varga, & Acs, 1997). In this paper, we examine the role of regional knowledge spillovers in China's innovation growth from 2001 to 2008. The new economic geography (Krugman, 1991a, 1991b; Grossman & Helpman, 1991) highlights the role of externalities in the spatial agglomeration and regional concentration of economic production. In their article, Audretsch and Feldman (1996) suggest that knowledge spillovers reinforce the spatial agglomeration of innovation. Regional knowledge spillovers reflect the diffusion and transfer of information and ideas among knowledge producers in proximate locations. Transfer mechanisms include spatial linkages forged through university, research institutes and industry interactions (Anselin et al., 1997). Yet the role of regional spillovers on knowledge production remains poorly studied (Audretsch & Feldman, 2004), despite the fact that Marshallian externalities as a source of economic growth have long been noted in the works of Romer (1986) and Lucas (1988). Jaffe and Trajtenberg (2002) contend that there is a "geographic component to the spillover mechanism" (p. 155) and urge "renewed attention" on the issue (p. 156).

The framework of regional spillovers hypothesizes that because tacit knowledge is subjected to spatial decay, innovation is greater when innovating agents are located in spatial proximity because it encourages the formation of regional scientific and R&D networks (Jaffe, Trajtenberg, & Henderson, 1993; Audretsch & Feldman, 1996). This paper seeks to test the hypothesis that proximate location to innovative neighbors can help to raise the innovation capability of a province in China. As a developing

* Corresponding author.
E-mail addresses: qshang2@buffalo.edu (Q. Shang), jesspoon@buffalo.edu (J.P.H. Poon), qtyue@126.com (Q. Yue).

1043-951X/$ – see front matter. Published by Elsevier Inc.
http://dx.doi.org/10.1016/j.chieco.2012.08.004

country, China's innovation activities warrant our attention because its patent growth of more than 2000% between 1999 and 2009 is higher than more technologically advanced neighbors such as Taiwan (79%) and South Korea (160%).

While Cheung and Lin (2004) recently examined China's innovation, they did not model spillover effects across provinces. Consistent with the new economic geography, we investigate innovation spillovers in the context of geographical effects where knowledge reflects the regional cooperation of firms, universities and research teams among proximate regions (Moreno, Paci, & Usai, 2005). Moreover, Cheung and Lin's study covers the period from 1995 to 2000. Similarly, Hu and Jefferson's (2009) study is concerned with China's innovation, but they focused on the effect of patent law on China's innovation from 1995 to 2001.

We test the relationship between regional knowledge spillovers and innovation using a spatial autoregressive model (SAR) which directly explores the interconnection between neighboring geographical units, in this case, provinces. A knowledge production function is estimated in which innovation is influenced by R&D resources and accessible knowledge, including knowledge generated in nearby regions as measured by the innovation outcomes of these regions. Regional knowledge spillovers exist if the innovation outcome (measured by patent increase) of a region is affected by the innovation outcomes of other regions that are spatially proximate. Given China's explosion in patent activities since 2000, our analysis will be conducted for the period 2001 to 2008.

Section 2 outlines the role of regional knowledge spillovers in influencing a country's innovation levels. This is followed by an outline of the spatial autoregressive model and description of the distribution and growth trends of patents, R&D expenditure and skilled personnel by organizational types. The fifth section reports the results of the regressions and the paper concludes with some policy implications of the findings.

2. Regional knowledge spillovers and innovation

The new economic geography has highlighted the role of regional effects on economic activities. Krugman (1991a, 1991b) and others provide the microeconomic foundations of spatial economic agglomerations. Feldman (1994) demonstrates that spatial concentration is particularly strong for innovation. Agglomeration externalities may arise from knowledge spillovers that yield increasing return. The regional knowledge spillover framework hypothesizes that geographical proximity between innovating agents leads to greater knowledge spillovers (Henderson, 2007). This is because tacit knowledge tends to be more readily transmitted when exchanges consist of face-to-face interactions. Knowledge that is tacit-rich is subjected to spatial decay. Jaffe et al. (1993) showed that knowledge flows, measured by patent citations, display a strong spatial decay.

In early studies, knowledge is thought to spill-over from university and research institutes (RI&Us) to industry innovation within a geographical unit. Jaffe (1989) showed that state-level corporate patent activity is influenced by university research within the state. This was confirmed by Acs, Audretsch, and Feldman (1992, 1994) using different measures of innovation activity. Similarly, Anselin et al. (1997) distinguished between research conducted by industry, and research conducted by universities. They show that knowledge spillovers from universities on innovations are strong if the spatial dimension is explicitly modeled. Spillovers from universities are found to be regionally concentrated and geographically localized within the same metropolitan statistical areas. However, they also show that knowledge from university research spill-overs from surrounding neighboring counties.

More recently, the framework of regional knowledge spillovers has been extended to study the role of neighborhood effects in the spatial agglomeration of innovation. Here, knowledge is hypothesized to spill-over across neighboring regions. Studies conducted predominantly in Europe confirm that the innovation activity of a region is influenced by the technological specialization of its neighbors in other regions (Moreno et al., 2005). Using European patent data, Bottazzi and Peri (2003) found that innovation outcome of a region is affected by R&D spending in neighboring regions. This finding is further reinforced in Peri (2005) who shows that the geographical diffusion of ideas is much more effective between proximate regions. Cabrer-Borras and Serrano-Domingo (2007) found that proximity to other innovative regions helps to enhance a less developed region's innovation in Spain.

Knowledge produced in a region may result in positive spatial externalities when a neighboring region absorbs the knowledge. Grossman and Helpman (1990) show that innovation results in a stock of knowledge that accumulates with subsequent innovations. Romer (1994) demonstrates that spillovers from research efforts improve the public stock of knowledge. Knowledge exchange and cooperation between two neighboring areas increase the aggregate stock of knowledge regionally because knowledge of firms in an area and its surrounding neighbors is raised as more differentiated products are developed that contribute to endogenous growth. Cooperation and collaboration of agents in nearby regions occur through the joint research activities of firms, universities, research institutes and research teams (Henderson, 2007). Networks of knowledge flows, that is, trade and transactions between firms and universities also facilitate knowledge spillovers (Acs, Anselin, & Varga, 2002).

Like Bottazzi and Peri (2003), we test the hypothesis that proximate location to innovative neighbors can help to raise the innovation capability of a province in China. We specify a knowledge production function below that explicitly relates a region's innovation to neighboring patenting activities. Unlike Bottazzi and Peri (2003), knowledge generated in nearby regions is measured by the patent outcomes of these regions instead of indirectly through R&D spending of the other regions. If the patenting activities in neighboring regions have a significant effect, this implies that regional knowledge spillovers are present.

In light of China's aim to develop indigenous capability, we include two major inputs in the knowledge production function in addition to regional spillovers. These are R&D (Bottazzi & Peri, 2003) and skilled workers (Audretsch & Feldman, 1996). R&D is undertaken to create new ideas and products, and the two main R&D producers are firms and universities. Arrow (1962) shows that firms are likely to under-invest in R&D because it is risky, hence public spending at research institutes and universities

(RI&Us) contributes to knowledge production. In China, the government has been an important source of R&D projects among RI&Us. Huang and Wu (2012) show that government spending on nanotechnology from 2005 to 2007 was US$893 million compared to enterprise funding of US$348 million. One reason for the prominent role of government R&D funding is that as late as 1999, domestic enterprises expended more effort on the importation of foreign technology than the production of domestic technology (Cao, Simon, & Suttmeier, 2009). Given their growing scientific networks, RI&Us are important public institutions for building indigenous innovation linkages that can lead to knowledge spillovers.

Universities not only generate knowledge through scientific research but also train engineers and scientists and are thereby a source of human capital. China has expanded university education significantly to speed up its supply of skilled labor pool (Zhong, 2011). While Audretsch and Feldman (1996) suggest that skilled workers should be a major input to innovation, this variable has generally commanded far less attention compared to R&D. In this paper, we suggest that human capital is relevant in China's aim to develop indigenous innovation capability. Ding and Knight (2009) found that human capital explains China's economic growth and innovation in the post-reform years. Dinopoulos and Segerstrom (1999) show that skill is complementary in innovation because skilled workers such as scientists and engineers possess the knowledge to conduct research.

3. Model and data

We estimate the knowledge production function where innovation outcome in region *i* depends on technology inputs in region *i*, and knowledge available for region *i*, which include ideas generated in other regions. As detailed earlier, two major inputs are included, that is, R&D and skilled workers. Both enterprises and research institutes and universities are major agents of such inputs, hence we distinguish between R&D and labor that are found in enterprises, and R&D and labor that are associated with research institutes and universities. The accessible share of knowledge generated in another region *j* to region *i* is a function of the distance between the two regions. Spatially proximate or neighboring regions are linked by flows of ideas, goods and skilled workers resulting in a greater likelihood of regional knowledge exchange and networks. In the absence of regional knowledge spillovers, the knowledge production equation is:

$$\mathrm{P} = \beta_0 + \beta_1 \mathrm{RE} + \beta_2 \mathrm{RU} + \beta_3 \mathrm{LE} + \beta_4 \mathrm{LU} + \varepsilon \tag{1}$$

where P is an $n \times 1$ vector of observations on regional innovation outcomes (that is patents, including patents granted to all agents in the region). RE is an $n \times 1$ vector of observations on enterprise R&D expenditure, RU is government R&D expenditure at RI&Us, LE refers to enterprise skilled labor, LU denotes skilled labor at RI&Us and ε is the error term. We distinguish between enterprises and RI&Us in R&D and skilled labor to capture the role of public institutions in the production of knowledge and human capital as part of the Chinese government's aim to develop more indigenous innovation capability. However, if knowledge generated in neighboring regions affect region *i*'s knowledge production, ignoring the effect of spatial interaction will lead to biased estimates of model (1).

To test the hypothesis of regional knowledge spillovers, we include its effect in the above knowledge production function by adopting a spatial autoregressive specification (SAR) of the form:

$$\mathrm{P} = \beta_0 + \lambda \mathrm{WP} + \beta_1 \mathrm{RE} + \beta_2 \mathrm{RU} + \beta_3 \mathrm{LE} + \beta_4 \mathrm{LU} + \beta_5 \mathrm{X} + \varepsilon \tag{2}$$

where RE, RU, LE and LU are as defined in Eq. (1). *W* is an $n \times n$ row-normalized spatial weight matrix with zero diagonal elements, which defines the surrounding neighbors for region *i* and their weights on the accessible knowledge for region *i*. The choice of the spatial weight is elaborated in a later paragraph below. *WP* is an $n \times 1$ vector of spatial lagged dependent variable, the *i*th observation of which is a weighted average of the innovation outcomes of the neighboring areas of region *i*, measuring the accessible knowledge generated in nearby regions for region *i*. Regional knowledge spillovers exist if the innovation outcome in a region is affected by the innovation outcomes of surrounding regions, and this is captured by the spatial autoregressive coefficient λ. A positive λ implies that holding other variables constant, a region that is surrounded by innovative neighbors has a higher level of innovation through knowledge spillovers.

In Bottazzi and Peri (2003), knowledge generated by other regions for region *i* is captured by R&D resources employed in neighboring regions. Regional knowledge spillovers exist if the R&D production in a region is affected by the amount of R&D resources used in neighboring regions. Their results show that knowledge spillovers exist within a distance of 300 km. In contrast with Bottazzi and Peri (2003), the SAR approach we adopt explicitly specifies spatial dependence across provincial units using the spatial lagged variable. Innovation outcomes generated in nearby regions are a direct measure of knowledge generated in these regions.

In addition to R&D and skilled worker inputs, three control variables are included in *X*, that is, foreign direct investment (FDI), location, and economic size. Cheung and Lin (2004) as well as Hu and Jefferson (2009) have demonstrated that FDI is relevant in the context of China. FDI affects innovation through technology transfer or imitation of foreign firms' protection of proprietary knowledge among Chinese firms. In addition, the distribution of economic activities in China is highly uneven spatially: there is a distinct coastal-interior geographical divide in income, FDI, and industry (Lee, Peng, Li, & He, 2012; Zheng, 2011). We use three regions, that is, coastal, central and western regions, to control for locational structure. The economic size of a province is measured by its GDP per capita.

The most commonly used specifications for the spatial weight matrix *W* are contiguity, inverse-distance, and k-nearest neighbor. China's eastern and central provinces are characterized by smaller land areas, relatively better-developed infrastructure, and higher population densities. However, its western provinces tend to be larger with less developed infrastructure and sparser populations. Such a spatial structure has implications for the choice of the spatial weight matrix. When a cutoff distance which ensures that at least one neighbor for each province is applied, only one first order geographically contiguous neighbor to province *i* may be found for some western provinces. This may exclude some influential first order neighbors. On the other hand, for provinces that are located in central and eastern China, the same cutoff distance will result in the inclusion of second order and even third order neighbors.[1] Consequently, spatial dependence for these provinces will be weak. Anselin and Bera (1998) have suggested that using a cutoff distance leads to loose spatial connections and many isolated islands. Tian, Wang, and Chen (2010) further caution that the K-nearest neighbor specification will destroy the underlying spatial structure. For example, Heilongjiang has two geographically contiguous neighbors, while Shaanxi, eight neighbors. A four-nearest neighbor specification, for example, will result in the inclusion of second order neighbors for Heilongjiang, but exclude at least four contiguous neighbors for Shaanxi.

Given the limitations of distance and K-nearest neighbor measures, we will apply contiguity-based spatial weights. Contiguity-based spatial weights may be specified in two ways. The first is to assign equal weight for the contiguous provinces, so a region is assumed to be equally affected by the innovation outcomes of the provinces that it shares borders with. The second applies an inverse distance weight for contiguous neighbors. In this case, the accessible share of knowledge generated in contiguous province *j* to province *i* depends on the distance between the two provinces. Given that the land area of China's provinces varies greatly, the inverse distance measure is more appropriate for the analysis. A large neighbor, for example, will be assigned a smaller weight than a smaller neighbor. The greater weight of the smaller neighbor allows us to capture its relative geographical proximity because the distance will be smaller. Hence, we apply the inverse distance contiguity-based weights in the analysis below.

Under the SAR model, innovation outcomes of the provinces are determined simultaneously, which imply that the ordinary least squares (OLS) estimator is inconsistent (Anselin, 1988). Maximum-likelihood (ML) estimator is consistent when error terms are homoskedastic (Lee, 2004). However, it is generally not consistent when the error terms are heteroskedastic (Arraiz, Drukker, Kelejian, & Prucha, 2010). We estimate the SAR model using the generalized spatial two-stage least-squares (GS2SLS) estimator, allowing the error term to be heteroskedastic of an unknown form. The GS2SLS estimator is consistent in both homoskedastic and heteroskedastic cases (Kelejian & Prucha, 1998, 1999, 2010; Arraiz et al., 2010).

Thompson's (2006) analysis of innovation the United States shows that regional spillovers are best detected at the sub-national scale whether at the city or state/provincial levels. Given that relatively good data may be found at the provincial level in China, this paper will focus on regional spillovers at the provincial scale. All of the variables in Eq. (2) are measured in terms of change or increase levels from 2001 to 2008. Looking at patent growth also allows us to net out the effects of time-invariant regional characteristics that affect the distribution of economic activities. Table 1 provides a summary of the variables and their measurements.

The period under consideration is 2001 to 2008. This period is selected for two reasons. First, the 2000 amendment of the 1984 patent law and its implementation in 2001 led to a dramatic increase in patents. Hence 2001 is a reasonable base year to begin. Second, the third amendment which brought about reforms that are more foreign direct investment friendly took place in 2008. This last amendment is likely to further affect the pattern of patent production; for this reason, the analysis does not extend to 2009. Data is obtained from various issues of the China Statistical Yearbook and China Statistical Yearbook for Science and Technology.

4. Overview of patents, R&D expenditure and skilled personnel

China's patents are composed of three types of innovation outcomes, that is, design, invention and utility patents. Of the three types of patents, invention patents need to demonstrate the highest degree of novelty and inventiveness. They are protected for twenty years. Utility and design patents require lower levels of inventiveness and thus tend to be more incremental. Consequently, they are protected for only ten years. Utility patents, for example, are granted on the basis of the practical applicability of the innovation (Ministry of Science and Technology, 2007).

Table 2 reports the distribution and growth rate of invention, utility and design patents. It shows that Beijing's innovation advantage lies in invention patents. Its neighbor Tianjin is not far behind and ranks third after Beijing and Shanghai in 2008 invention patents productivity. Inland provinces such as Anhui, Chongqing, Shaanxi, and Hunan display significant growth suggesting a centripetal process of spatial decentralization at work. The table further shows that coastal provinces dominate in utility and design patents. Around 90% of the patents generated in Guangdong, Zhejiang, and Jiangsu are associated with such patents. One explanation for this is that many enterprises and their research facilities are concentrated along the coast where market transition is furthest along. According to the Ministry of Science and Technology (2007), domestic enterprises' production in these two patents has grown dramatically along the coast driving the level and pace of innovation activities in the country.

Table 3 reports the spatial distribution of skilled personnel and R&D expenditure by organizational sources in 2001 and 2008. Comparing skilled personnel for RI&Us, the table indicates that Beijing's level of human capital surpasses that of other provinces by manifolds and is at least twice that of Shanghai's, the second largest host of human capital. But growth rates are the highest in Zhejiang, Guangdong, Guizhou, and Jilin. Dramatic growth in Guizhou and Jilin reflects the government's redistributive attempts

[1] Second and third order neighbors refer to provinces that are geographically contiguous to first and second order neighbors respectively. For example, Hubei is considered to be the first order neighbor of Sichuan whereas Anhui and Jiangsu would be second and third order neighbors respectively.

Table 1
Definition and summary statistics.

Variable	Definition	Mean	Std. dev.
Invention	Change in invention patent, 2001–2008 (per 10,000 persons)	0.353	0.685
Utility	Change in utility patent, 2001–2008 (per 10,000 persons)	0.871	1.117
Design	Change in design patent 2001–2008 (per 10,000 persons)	0.530	1.075
Skill (research institutes and universities)	Change in full-time equivalent of R&D personnel in research institutes and university and colleges, 2001–2008 (person-year per 10,000 persons)	1.301	1.884
Skill (enterprises)	Change in full-time equivalent of R&D personnel in large and medium size enterprises, 2001–2008 (person-year per 10,000 persons)	4.106	3.998
R&D(research institutes and universities)	Log of change in R&D expenditure in research institutes and university and colleges, 2001–2008 (RMB per person)	3.231	1.129
R&D (enterprises)	Log of change in R&D expenditure in large and medium size enterprises, 2001–2008 (RMB per person)	4.240	1.191
FDI	Log of change in per capita FDI, 2001–2008 ($ per person)	3.453	1.308
GDP	Log of change in GDP per capita, 2001–2008 (RMB)	9.169	0.503
Western	Xinjiang, Gansu, Qinghai, Shaanxi, Ningxia, Guizhou, Yunnan, and Guangxi	0.267	0.450
Central	Chongqing, Sichuan, Heilongjiang, Jilin, Shanxi, Henan, Hubei, Hunan, Hebei, Anhui, Jiangxi, and Neimeng	0.4	0.498
Coastal	Beijing, Tianjin, Shandong, Shanghai, Zhejiang, Fujian, Hainan, Guangdong, Liaoning, and Jiangsu	0.333	0.479

to spread innovation away from traditional centers. In contrast, enterprise R&D personnel favor coastal provinces including Shanghai, Jiangsu and Zhejiang: these provinces also experience high growth rates. While Beijing's enterprise skilled personnel are not low, it is behind Guangdong and Tianjin, and is comparable to Zhejiang and Jiangsu.

For R&D expenditure for RI&Us, Beijing's per capita level is disproportionately high: at RMB1548 in 2008, it is three times higher than Shanghai's and more than thirty times higher than other provinces. The spatial concentration of RI&Us including elite universities Peking University, Tsinghua University and the Chinese Academy of Science explains this as the government has favored elite universities and reputable research institutes in it funding allocation. Enterprise R&D expenditure however is higher in Shanghai, Tianjin, and Jiangsu. It is less prominent in Beijing compared to RI&U expenditure of R&D. Taken together, the spatial

Table 2
Level and growth of invention, utility and design patents, 2001 to 2008.

Province	Invention patents			Utility patents			Design patents		
	2001	2008		2001	2008		2001	2008	
	(per 10,000 persons)	(per 10,000 persons)	Growth (%)	(per 10,000 persons)	(per 10,000 persons)	Growth (%)	(per 10,000 persons)	(per 10,000 persons)	Growth (%)
Total	0.04	0.31	694.59	0.37	1.25	240.96	0.29	0.98	233.11
Beijing	0.68	3.82	458.73	2.60	5.18	98.91	1.23	1.47	19.65
Tianjin	0.10	1.37	1331.80	1.21	3.41	182.42	0.52	0.99	91.47
Hebei	0.03	0.08	167.12	0.27	0.56	105.42	0.11	0.14	27.89
Shanxi	0.04	0.12	205.22	0.20	0.46	123.54	0.08	0.09	16.98
Inner Mongolia	0.03	0.06	88.84	0.19	0.36	93.80	0.10	0.13	37.85
Liaoning	0.08	0.35	325.86	0.83	1.91	131.25	0.15	0.21	37.34
Jilin	0.05	0.21	309.40	0.37	0.73	99.74	0.12	0.15	25.75
Heilongjiang	0.04	0.19	408.48	0.37	0.87	135.49	0.08	0.13	58.34
Shanghai	0.15	2.26	1404.15	1.38	6.34	361.05	1.80	4.36	142.06
Jiangsu	0.03	0.46	1277.40	0.51	2.09	310.83	0.30	3.24	996.35
Zhejiang	0.04	0.64	1592.70	0.77	3.91	407.74	0.99	5.80	482.80
Anhui	0.01	0.08	610.40	0.13	0.41	213.68	0.06	0.22	264.12
Fujian	0.02	0.15	516.93	0.32	1.09	238.08	0.61	0.97	57.92
Jiangxi	0.02	0.05	169.35	0.13	0.35	167.79	0.09	0.13	38.72
Shandong	0.04	0.20	431.93	0.51	1.99	294.12	0.20	0.64	220.27
Henan	0.02	0.07	295.86	0.20	0.56	184.18	0.05	0.33	519.43
Hubei	0.03	0.20	547.99	0.25	1.00	296.36	0.08	0.26	208.69
Hunan	0.03	0.19	644.87	0.26	0.54	105.93	0.08	0.23	205.24
Guangdong	0.04	0.80	1960.12	0.67	2.63	289.74	1.63	3.08	88.31
Guangxi	0.01	0.04	275.58	0.15	0.30	94.39	0.06	0.12	88.19
Hainan	0.02	0.06	173.80	0.09	0.23	163.65	0.27	0.11	−58.76
Chongqing	0.01	0.19	1315.48	0.22	0.97	346.19	0.15	0.54	246.13
Sichuan	0.03	0.13	346.90	0.17	0.65	275.78	0.19	0.86	362.82
Guizhou	0.01	0.07	543.87	0.09	0.31	231.90	0.06	0.07	13.35
Yunnan	0.03	0.08	219.84	0.15	0.23	47.96	0.13	0.13	−1.02
Shaanxi	0.04	0.26	608.83	0.26	0.74	181.34	0.07	0.17	142.60
Gansu	0.02	0.08	269.19	0.14	0.26	89.51	0.04	0.06	47.43
Qinghai	0.03	0.04	44.75	0.11	0.18	62.77	0.05	0.19	254.02
Ningxia	0.03	0.08	191.52	0.24	0.43	82.20	0.15	0.47	220.50
Xinjiang	0.05	0.04	−19.79	0.28	0.52	85.51	0.08	0.15	91.46

Table 3
Level and growth of R&D fulltime equivalent personnel and R&D expenditure, 2001 to 2008.

Province	R&D personnel (research institutes and universities)			R&D personnel (large and medium enterprises)			R&D expenditure (research institutes and universities)			R&D expenditure (large and medium enterprises)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2001 (person.year per 10,000 person)	2008 (person.year per 10,000 person)	Growth (%)	2001 (person.year per 10,000 person)	2008 (person.year per 10,000 person)	Growth (%)	2001 (RMB per person)	2008 (RMB per person)	Growth (%)	2001 (RMB per person)*	2008 (RMB per person)*	Growth (%)
Total	2.97	4.03	35.78	3.00	7.77	159.13	30.89	91.99	197.82	34.96	205.40	487.48
Beijing	44.94	54.62	21.54	8.88	15.87	78.73	804.23	1548.38	92.53	151.64	347.16	128.93
Tianjin	8.63	11.19	29.62	9.20	18.54	101.44	71.55	261.58	265.62	127.95	612.45	378.66
Hebei	1.40	1.75	24.97	1.78	3.63	104.00	9.40	29.69	215.85	17.20	81.33	372.81
Shanxi	2.53	3.25	28.48	2.03	8.77	332.02	11.22	26.81	138.98	17.27	100.93	484.42
Inner Mongolia	1.68	2.40	42.44	1.22	4.68	282.41	4.61	13.46	191.70	7.29	84.32	1056.98
Liaoning	4.33	6.09	40.48	7.14	9.27	29.85	44.36	88.86	100.33	63.51	230.35	262.68
Jilin	3.99	6.99	75.14	1.27	3.03	138.52	23.54	65.14	176.65	17.36	74.02	326.48
Heilongjiang	3.08	5.06	64.30	4.67	6.97	49.29	18.48	67.08	262.94	28.77	98.17	241.26
Shanghai	15.75	20.80	32.03	8.05	19.43	141.30	207.74	489.71	135.73	239.97	770.83	221.22
Jiangsu	3.34	4.05	21.20	5.33	15.57	192.32	46.32	86.43	86.60	55.12	386.80	601.78
Zhejiang	1.82	3.01	64.74	2.58	15.50	499.79	18.14	50.18	176.67	32.77	293.95	797.14
Anhui	1.62	2.12	31.12	1.67	4.51	170.24	16.62	34.31	106.40	13.19	76.12	476.95
Fujian	1.62	2.13	31.07	2.46	8.93	263.59	6.95	21.84	214.06	35.06	149.81	327.35
Jiangxi	1.32	2.02	53.40	1.95	3.28	67.69	3.27	21.04	543.20	12.87	75.70	488.15
Shandong	1.46	2.27	55.70	3.57	11.42	219.56	6.45	22.44	247.98	51.67	276.03	434.16
Henan	1.16	1.49	28.03	2.07	4.92	137.40	10.42	17.66	69.47	14.79	71.89	385.99
Hubei	3.89	4.24	8.89	2.76	6.24	125.70	27.46	72.13	162.66	27.63	104.39	277.77
Hunan	1.64	2.20	33.62	1.98	4.00	102.54	11.93	29.14	144.19	13.71	72.52	428.93
Guangdong	1.82	2.24	23.33	5.56	18.60	234.46	12.61	28.61	126.83	114.90	348.46	203.27
Guangxi	0.80	2.36	194.86	0.67	1.47	118.36	2.49	12.95	420.49	9.59	33.02	244.51
Hainan	0.77	1.16	50.12	0.20	0.49	140.05	4.94	21.19	329.07	4.23	5.61	32.59
Chongqing	2.18	3.13	43.46	2.21	7.35	233.08	8.54	33.25	289.58	16.25	116.62	617.47
Sichuan	3.11	4.05	30.23	1.80	4.71	162.14	44.48	76.79	72.66	14.48	53.75	271.09
Guizhou	0.62	1.17	88.78	1.79	1.49	−16.45	2.61	8.42	223.28	9.56	29.85	212.27
Yunnan	1.67	2.18	30.83	0.55	1.52	175.11	8.29	28.16	239.82	6.11	18.54	203.26
Shaanxi	9.04	9.03	−0.19	5.61	6.61	17.74	90.49	188.44	108.25	37.56	82.11	118.58
Gansu	1.92	2.85	48.21	4.08	3.60	−11.69	14.50	38.83	167.81	10.88	50.16	360.95
Qinghai	1.26	2.14	69.04	1.46	1.41	−2.89	3.84	14.75	283.85	12.59	34.71	175.75
Ningxia	1.85	2.06	11.32	2.11	4.58	117.49	3.37	9.67	187.01	15.24	76.10	399.40
Xinjiang	1.64	1.92	17.53	0.59	2.04	248.12	6.62	12.22	84.68	9.10	40.97	350.28

distribution of skilled personnel and R&D expenditures display some differences between RI&Us and enterprises with Beijing retaining a favorable position in government R&D spending and a major host to human capital. As we will see below, the two organizational types influence the growth of patenting activities differently.

5. Regression results

To examine the effect of regional knowledge spillovers and RI&Us on 2001–2008 patent change, we report the SAR results in Table 4. The table presents the regression outputs for invention, utility and design patents. Columns (1), (3) and (5), consist of the results for all provinces. Positive and significant regional knowledge spillovers, captured by the coefficient λ, are detected for all three patent types. The spillover effects are larger for design and utility patents than invention patents. One possible explanation may lie in the nature of design and utility-led innovations. They tend to be adaptive and incremental. They are also predominantly undertaken to cater to the domestic market. This involves a relatively high level of communication and coordination among workers of R&D, marketing and engineering firms. Such regional contact and cooperation may have facilitated the process of knowledge diffusion and spillovers. The positive findings for λ support the hypothesis that knowledge and ideas generated by neighboring provinces result in a province's increase of innovation.

RI&U skilled personnel and R&D expenditure are significant for invention and utility patents but not for design patents. Among them, RI&U skilled personnel have the strongest effect for invention patent, while R&D expenditure has the strongest effect for utility patent. Skilled personnel among enterprises are significant for all three patent types. The effect is the largest for design patents, but it is much smaller for invention patents. However, R&D spending among enterprises has no effect on any of the patents. The results suggest that human capital and R&D expenditure associated with RI&Us and enterprises have relatively different effects on patenting activities. The distribution of different types of patents among different sources may explain this. For 2008 design patents, about 60% were granted to individual inventors. Among the patents granted to non-individuals, some 93% were granted to enterprises. Individual inventors (62%) and enterprises (36%) account for most of the increase in design patents between 2001 and 2008 while RI&Us only account for 2%. This may explain why RI&U skilled personnel and R&D expenditure have no effect on design patent. However, for invention patents, RI&Us are an important source. In 2008, approximately 70% of invention patents were granted to non-individual inventors. Among them, 38% were granted to RI&Us. RI&Us contribute to nearly 31% of the increase in invention patents over the period examined here. More novel innovation is likely to emerge from public educational institutions where exploratory and basic scientific knowledge is produced. Case studies provided by Chen and Li-Hua (2011) are instructive of this. They show that basic scientific research at Peking University's Physics Department resulted in the development of a fourth generation Chinese language laser typesetting system. The research was undertaken with a funding from the government.

Like design patents, individual inventors formed the majority of utility patents (52%) that were granted in 2008, while enterprises were responsible for a sizeable share of patents (85%) that granted to non-individual inventors. RI&Us are not an important source of utility patents, contributing only to 5% of the increase between 2001 and 2008. But it is noteworthy that RI&U

Table 4
Results of spatial autoregressive regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Invention		Utility		Design	
λ	0.116**	0.119**	0.327*	0.247**	0.321**	0.343**
	(0.052)	(0.048)	(0.197)	(0.120)	(0.137)	(0.170)
Skilled labor (RI& U)[a]	0.260***	0.201***	0.149**	0.379***	−0.052	−0.030
	(0.026)	(0.060)	(0.074)	(0.121)	(0.050)	(0.111)
Skilled labor (enterprises)	0.064***	0.064***	0.165***	0.169***	0.256***	0.254***
	(0.016)	(0.016)	(0.040)	(0.033)	(0.098)	(0.094)
R&D expend (RIs&U)	0.106**	0.117***	0.178***	0.136	0.005	0.002
	(0.046)	(0.033)	(0.067)	(0.091)	(0.106)	(0.095)
R&D expend (enterprises)	−0.039	−0.023	0.054	0.011	−0.113	−0.127
	(0.036)	(0.038)	(0.088)	(0.074)	(0.130)	(0.136)
FDI	0.005	0.011	0.045	0.032	0.170	0.164
	(0.047)	(0.040)	(0.080)	(0.083)	(0.156)	(0.152)
GDP per capita	−0.067	−0.083	−0.377	−0.343	−0.316	−0.282
	(0.158)	(0.136)	(0.234)	(0.244)	(0.345)	(0.319)
Western	0.153	0.158	0.060	0.033	0.784	0.788
	(0.110)	(0.104)	(0.316)	(0.262)	(0.493)	(0.498)
Central	−0.062	−0.064	−0.409*	−0.417**	0.107	0.120
	(0.088)	(0.080)	(0.232)	(0.198)	(0.338)	(0.339)
Constant	0.124	0.203	2.390	2.285	1.887	1.636
	(1.266)	(1.075)	(1.781)	(1.965)	(2.731)	(2.479)
Observations	30	29	30	29	30	29

Notes: Robust standard errors in parentheses.
[a] RIs&U stand for research institutes and universities.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 5
Marginal effects of SAR regressions: ATDI and ATI.

	Invention		Utility		Design	
	ATDI	ATI	ATDI	ATI	ATDI	ATI
Skilled labor (RI&U)	0.261***	0.293***	0.154**	0.219**	−0.054	−0.076
Skilled labor (enterprises)	0.064***	0.072***	0.170***	0.243***	0.264***	0.373***
R&D expend (RIs&U)	0.107**	0.120**	0.183***	0.262***	0.005	0.007
R&D expend (enterprises)	−0.039	−0.044	0.056	0.080	−0.116	−0.165

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

skilled personnel and R&D expenditure are significant for utility patents. Together with the findings for invention patents, it appears that R&D expenditure and personnel in research institutes and universities are associated with more basic and applied research. This in turn may have led to knowledge spillovers from university to enterprises for both utility and invention patents. However, industrial design knowledge requires the development of a set of creative tasks and concepts that are targeted at visual and aesthetic appeal. Design characteristics include price, shape, color or pattern, and flexibility of use (Lewis & Bonollo, 2002). R&D in research institutes and universities may be less relevant for design-oriented innovation.

The government has encouraged S&T investment among enterprises in recent years, and enterprises are becoming more active in R&D. However, Table 4 shows that R&D spending among enterprises has no effect on any of the patents. Part of the reason may be explained by enterprises' tendency to improve upon imported technology rather than develop indigenous innovation capability. The study of China's nanotechnology industry sheds some light. This is an industry that targets invention patents: 93% of patents filed are invention patents. Huang and Wu (2012) found that the majority of patents, that is, 56% of patents, are filed by research institutes. Enterprises account for only 18% of the applications. Cao et al. (2009) maintain that most domestic firms' in-house R&D capability remains weak, and R&D expenditure ratio to sales is well below that of firms in industrialized countries. They conclude that China has yet to develop an enterprise system of innovation. Many firms are still more interested in pursuing short-term payoffs than investing in R&D.

Unlike Cheung and Lin (2004), FDI has no significant effect on any of patents. This implies that technological catch-up may be occurring as innovation capability grows among RI&Us and domestic enterprises. Indeed the majority of utility and design patents are filed by domestic enterprises rather than foreign companies. Similarly, no significant effect may be found for economic size. Lastly, holding other variables constant, provinces in the central region experienced smaller increase in utility patents than coastal regions in the period examined.

Under the SAR model, spatial dependence implies that a change in one observation of an exogenous variable may affect the values of the dependent variable for all observations. It could be difficult to interpret the impact associated with the coefficients. To assess impacts of R&D personnel and expenditure, Table 5 reports the average total direct impact (ATDI) and average total impact (ATI) (LeSage & Pace, 2009). The ATDI measures the average of the changes in the predicted value of y_i attributable to the change in x_i. The ATI measures the average of the changes in the predicted value of y_i that is attributable to the simultaneous change in x_1 to x_n. For invention patent, if growth in RI&U R&D personnel increases by one person-year per 10,000 persons for a province, the province's growth in invention patents should increase by 0.261 per 10,000 persons. If growth in RI&U R&D personnel for all provinces increases simultaneously by one person-year per 10,000 persons, then a province's growth in invention patents will increase by 0.293 per 10,000 persons. Because of the reinforcing effects of simultaneous increase in RI&U R&D personnel, the total effect is larger than the direct effect. For utility patent, the corresponding effects are 0.154 and 0.219 respectively. In the case of RI&U R&D expenditure, if the growth in R&D expenditure increases by 10%, the estimated direct effect and total effect are 0.0107 and 0.0120 for invention patent, and 0.0183 and 0.0262 for utility patent. As for enterprise skilled personnel, the ATDI and ATI are: invention patents (0.064 and 0.072), utility patents (0.170 and 0.243), and design patents (0.264 and 0.373).

Beijing is a principal center of innovation with approximately 71 universities and 371 research institutes (Chen & Kenney, 2007). In 2008, some 26.3% of R&D spending and nearly one-fifth of the R&D personnel in RI&Us are associated with Beijing. It ranks first for per capita invention patent, and is second to Shanghai with respect to per capita utility patent (Table 2). As such, it is possible that Beijing's primacy in innovation may influence the regressions. To investigate if the SAR results are robust in columns (1), (3) and (5), we re-ran the regressions without Beijing to account for potential outlier effect and report the results in (2), (4) and (6). The regression outputs are generally consistent. There is evidence of positive regional spillovers in all types of patents. The magnitude of spillover effects for invention and design patents is also similar with or without Beijing. RI&Us' skilled personnel and R&D expenditure are significant for invention patents and are not significant for design patents. But some minor differences exist: RI&U R&D skilled personnel now have a larger effect while RI&U R&D expenditure turns insignificant for utility patents. Regional spillover effect for utility patent is smaller without Beijing, although the difference is not statistically significant.

Finally, diffusion of knowledge across provinces may carry a temporal dimension. We explore regional knowledge spillovers over time in Figs. 1 to 3 through bivariate Moran scatterplots of OLS regression residuals associated with the knowledge production equation in (2).[2] A Moran scatterplot relates the 2008 residuals of patents (after controlling for other input variables) at each location along the x-axis to the average patents of the neighboring regions at a previous year on the y-axis. The latter thus

[2] The number of patents (per 10,000 persons) granted each year is regressed on RI&U and enterprise R&D expenditure and skilled personnel in that year as well as the three control variables.

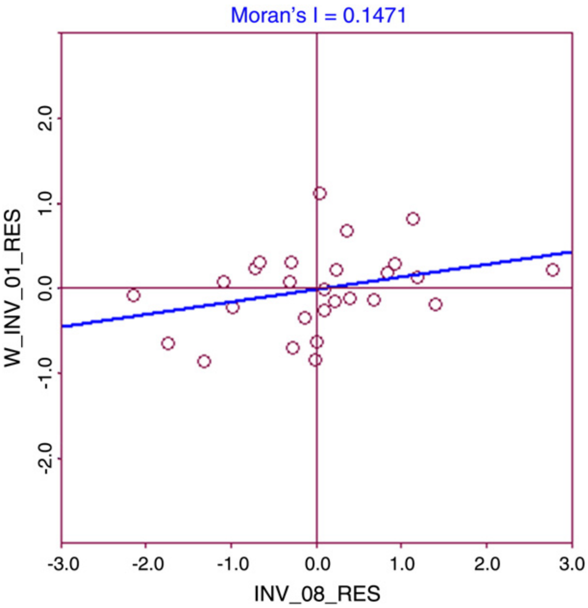

Fig. 1. Moran scatterplot: invention patent. Pseudo p-value: 0.062.

composes of spatial-time lag residuals. The variables in the scatterplots are standardized such that the mean is zero and standard deviation equals one. The four quadrants of each scatterplot correspond to four types of spatial association. The two most relevant spatial associations are those found in the upper right and lower left quadrants. The upper right quadrant (high–high) is described by high spatial-time lag and high 2008 patent level after controlling for R&D inputs and other control variables. The opposite is true for the lower left quadrant (low–low): here, the relationship is underscored by low spatial-time lag and low 2008 patent level. A linear association between spatial-time-lag and patent levels may be calculated using the Moran's I statistic (Anselin, Syabri, & Smirnov, 2002):

$$I = \frac{z_{t_1}^{'} W z_{t_0}}{z_{t_1}^{'} z_{t_1}}.$$

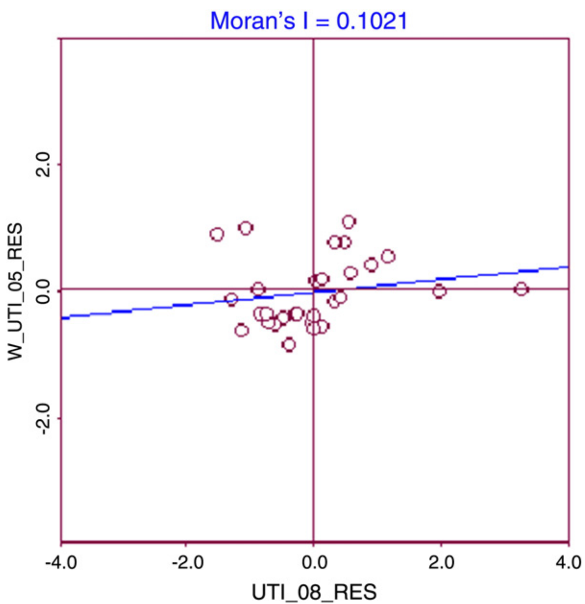

Fig. 2. Moran scatterplot: utility patent. Pseudo p-value: 0.119.

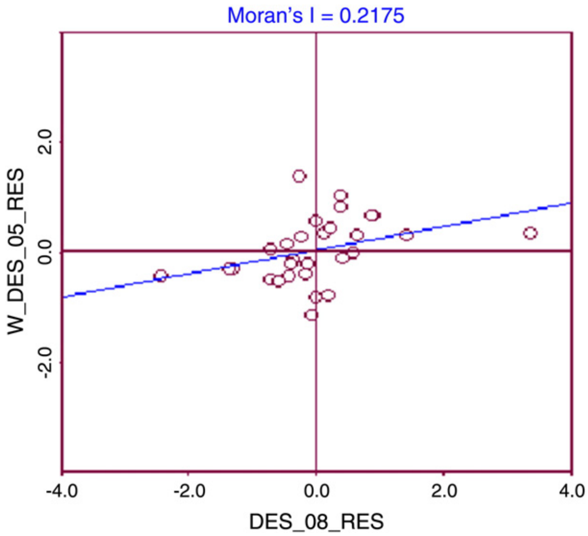

Fig. 3. Moran scatterplot: design patent. Pseudo p-value: 0.015.

The pseudo p-value of the statistic is based on a random permutation procedure and indicates the extent to which the observed spatial association is compatible with spatial randomness.

In examining the scatterplots, we are interested in capturing the effect of neighboring knowledge flows over time on a province's 2008 innovation level. In introducing a spatial time lag, we hypothesize that a province's 2008 innovation level is influenced by past knowledge flows from its neighbors. Given the more uncertain and experimental nature of knowledge associated with invention patent, we use a 7-year time lag. This is consistent with Sternitzke's (2010) review of the literature which shows that more novel exploration-oriented innovation entails a longer period of learning and knowledge dissemination, that is, between 7 and 10 years. On the other hand, a shorter time lag is expected for design and utility patents because innovations here are likely to emerge from an existing body of knowledge that characterize less novel and more exploitative innovation. In this case, a 3-year time lag is applied.

The results in Figs. 1–3 show that the Moran's I is positive for all three patent types, that is, 0.1471 (invention patent), 0.1021 (utility patent) and 0.2175 (design patent). The pseudo p-values indicate significance levels at 10% of less for invention and design patents suggesting the presence of spatial dependence. Together with I, the Moran's scatterplots indicate some evidence that past innovation activities of neighbors positively influence a province's 2008 level of patenting activities for invention and design-oriented innovations. This and Table 4's results support the paper's hypothesis that knowledge diffusion and information flows across proximate neighbors positively impact a province's innovation growth.[3]

6. Conclusion

In a recent article, Gilboy (2004) maintains that China's economic transformation is a “myth” because progress in technology and innovation is dependent on FDI. This may have characterized the technological development of China in the period before 2000. In the past ten years however, the Chinese government has shifted to more domestic drivers of innovation through the introduction and implementation of science and technology policies. This in turn has encouraged the geographical spread of knowledge and patenting activities away from traditional innovation centers. The government's goal is to dramatically increase its R&D expenditure to a level that is comparable to OECD, from 0.6% in 1996 to 2.5% of GDP by 2020 (OECD 2007). Concomitantly, it has also increased efforts to build the human capital necessary to generate more endogenous forms of innovation growth. While both R&D expenditure and skilled R&D personnel may be important, this paper finds a positive relationship between regional knowledge spillovers and patent growth. Positive spatial externalities enable the exploitation of increasing returns that have contributed to regional productivity found in many industrialized countries. Such spatial externalities are also driving the growth of innovation in China.

Applying the spatial autoregressive model to assess geographical effects on patent activities from 2001 to 2008, evidence is found for regional knowledge spillovers in all types of patenting activities. The effect is larger for design and utility patent. It points to research collaborative behavior and trade networks from location in an innovative regional neighborhood. The paper also finds that RI&U personnel and R&D expenditure positively impact the growth of invention and utility patents. Skilled personnel among enterprises favorably affect all three types of patent increase but R&D expenditure has no effect at all. Taken together, the results suggest that the Chinese government's effort to develop more indigenous capability has yielded some fruits

[3] It should be noted that the regressions in Table 4 also contain a temporal dimension because the patents are measured in terms of levels of increase from 2001 to 2008.

through their funding of R&D projects at public educational institutions and expansion of university education. Among enterprises, skilled personnel appear to play a greater role compared to R&D investment perhaps because the latter is still relatively low and is not yet a priority among firms.

Three policy implications may be drawn from the paper's findings. First, innovation spillovers are found among geographically proximate neighbors indicating that knowledge flows are subjected to spatial decay. Less innovative provinces that are located next to more innovative provinces can exploit such spatial linkages by establishing networks that are conducive for regional exchanges and cooperation. This is consistent with Cabrer-Borras and Serrano-Domingo (2007) who found that proximity to surrounding innovative regions helps to enhance a less developed region's innovation in Spain. Second, the government's aim to develop more indigenous capability appears to work best when R&D funding is directed at building basic scientific knowledge because it contributes positively to invention patenting activity. Hence supporting R&D and raising the human capital level at research institutes and universities is a relevant endeavor. This point is particularly relevant in light of criticisms levied against China's lack of basic and exploration innovation that is typically associated with inventions (Dobson & Safarian, 2008). Third and finally, if China is to move to a more enterprise-centered system of innovation, it will need to establish mechanisms for greater university–industry linkages. This would mean encouraging universities, research institutes, and firms to locate in proximate neighborhoods in order to facilitate research collaborations.

References

Acs, Zoltan J., Anselin, Luc, & Varga, Attila (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, *31*(7), 1069–1085.

Acs, Zoltan J., Audretsch, David B., & Feldman, Maryann P. (1992). Real effects of academic research. *The American Economic Review*, *82*(1), 363–367.

Acs, Zoltan J., Audretsch, David B., & Feldman, Maryann P. (1994). R&D spillovers and recipient firm size. *The Review of Economics and Statistics*, *100*(2), 336–367.

Anselin, Luc (1988). *Spatial econometrics: Methods and models.* Dordrecht: Kluwer.

Anselin, Luc, & Bera, Anil (1998). Spatial dependence in linear regression model with an introduction to spatial econometrics. In A. Ullah, & D. Giles (Eds.), *Economic statistics and social welfare comparisons* (pp. 237–285). Basel: Marcel Drekker.

Anselin, Luc, Syabri, Ibnu, & Smirnov, Oleg (2002). Visualizing multivariate spatial correlation with dynamically linked windows. *Proceedings of the SCISS Specialist Meeting "New Tools for Spatial Data Analysis". Santa Barbara, California, USA. May 10–11, 2002*.

Anselin, Luc, Varga, Attila, & Acs, Zoltan (1997). Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics*, *42*(3), 422–448.

Arraiz, Irani, Drukker, David M., Kelejian, Harry H., & Prucha, Ingmar R. (2010). A spatial Cliff–Ordtype model with heteroskedastic innovations: Small and large sample results. *Journal of Regional Science*, *50*(2), 592–614.

Arrow, Kenneth J. (1962). Economic welfare and the allocation of resources for invention. In R. Nelson (Ed.), *The rate and direction of inventive activity*. Princeton: Princeton University Press.

Audretsch, David B., & Feldman, Maryann P. (1996). R&D spillovers and the geography of innovation and production. *American Economic Review*, *86*(4), 253–273.

Audretsch, David B., & Feldman, Maryann P. (2004). Knowledge spillovers and the geography of innovation. In V. Henderson, & J. F. Thisse (Eds.), *Handbook of regional and urban economics: Cities and geography*, *Volume 4*. (pp. 2713–2779)Amsterdam: Elsevier Science.

Bottazzi, Laura, & Peri, Giovanni (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review*, *47*(4), 687–710.

Cabrer-Borras, Bernardi, & Serrano-Domingo, Guadalupe (2007). Innovation and R&D spillover effects in Spanish regions: A spatial approach. *Research Policy*, *36*(9), 1357–1371.

Cao, Cong, Simon, Denis F., & Suttmeier, Richard P. (2009). Commentary: China's innovation challenge. *Innovation: Management, Policy & Practice*, *11*(2), 253–259.

Chen, Kun, & Kenney, Martin (2007). Universities/research institutes and regional innovation systems: The cases of Beijing and Shenzhen. *World Development*, *35*(6), 1056–1074.

Chen, Dezhi, & Li-Hua, Richard (2011). Modes of technological leapfrogging: Five case studies from China. *Journal of Engineering and Technology Management*, *28*(1–2), 93–108.

Cheung, Kui-yin, & Lin, Ping (2004). Spillover effects of FDI on innovation in China: Evidence from provincial data. *China Economic Review*, *15*(1), 25–44.

Ding, Sai, & Knight, John (2009). Can the augmented Solow model explain China's remarkable economic growth? A cross-country panel data analysis. *Journal of Comparative Economics*, *37*(3), 432–452.

Dinopoulos, Elias, & Segerstrom, Paul (1999). A Schumpertarian model of protection and relative wages. *The American Economic Review*, *89*(3), 450–472.

Dobson, Wendy, & Safarian, A. E. (2008). The transition from imitation to innovation: An enquiry into China's evolving institutions and firm capabilities. *Journal of Asian Economics*, *19*(4), 301–311.

Feldman, Maryann P. (1994). *The geography of innovation.* Boston: Kluwer.

Gilboy, George J. (July/August). The myth behind China's miracle. *Foreign Affairs*, 33–45.

Grossman, Gene M., & Helpman, Elhanan (1990). Trade, innovation and growth. *The American Economic Review*, *80*(2), 86–91.

Grossman, Gene M., & Helpman, Elhanan (1991). Trade, knowledge spillovers and growth. *European Economic Review*, *35*(2–3), 517–526.

Henderson, Vernon (2007). Understanding knowledge spillovers. *Regional Science and Urban Economics*, *37*(4), 497–508.

Hu, Albert G., & Jefferson, Gary H. (2009). A great wall of patents: What is behind China's recent patent explosion? *Journal of Development Economics*, *90*(1), 57–68.

Huang, Can, & Wu, Yilin (2012). State-led technological development: A case of China's nanotechnology development. *World Development*, *40*(5), 970–982.

Jaffe, Adam B. (1989). Real effects of academic research. *American Economic Review*, *79*(5), 957–970.

Jaffe, Adam B., & Trajtenberg, Manuel (2002). *Patents, citations, innovations: A window on the knowledge economy.* Cambridge: MIT press.

Jaffe, Adam B., Trajtenberg, Manuel, & Henderson, Rebecca (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, *108*(3), 577–598.

Kelejian, Harry H., & Prucha, Ingmar R. (1998). A generalized spatial two-stage least squares procedure for estimating a spatial autoregressive model with autoregressive disturbances. *Journal of Real Estate Finance and Economics*, *17*(1), 99–121.

Kelejian, Harry H., & Prucha, Ingmar R. (1999). A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review*, *40*(2), 509–533.

Kelejian, Harry H., & Prucha, Ingmar R. (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics*, *140*(1), 53–130.

Krugman, Paul (1991a). *Geography and trade.* Cambridge: MIT Press.

Krugman, Paul (1991b). Increasing returns and economic geography. *Journal of Political Economy*, *99*(3), 483–499.

Lee, Lung-Fei (2004). Asymptotic distributions of quasi-maximum likelihood estimators for spatial autoregressive models. *Econometrica*, *72*(6), 1899–1925.

Lee, Bong-Soo, Peng, Jiangang, Li, Guanzheng, & He, Jing (2012). Regional economic disparity, financial disparity, and national economic growth: Evidence from China. *Review of Development Economics*, *16*(2), 342–358.

LeSage, James P., & Pace, R. Kelley (2009). *Introduction to spatial econometrics.* Boca Raton, FL: CRC Press Taylor & Francis Group.

Lewis, W. P., & Bonollo, E. (2002). An analysis of professional skills in design. *Design Studies*, *23*(4), 385–406.

Lucas, Robert E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*, 3–42.
Ministry of Science and Technology (2007). www.most.gov.cn accessed 12th February 2011.
Moreno, Rosina, Paci, Raffaele, & Usai, Stefano (2005). Geographical and sectoral clusters of innovation in Europe. *The Annals of Regional Science*, *39*(4), 715–739.
OECD (2007). *OECD reviews of innovation policy: China.* Paris, France: OECD Publishing.
Peri, Giovanni (2005). Determinants of knowledge flows and their effect on innovation. *The Review of Economics and Statistics*, *87*(2), 308–322.
Romer, Paul M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, *94*, 1002–1037.
Romer, Paul M. (1994). The origins of endogenous growth. *The Journal of Economic Perspectives*, *8*(1), 3–22.
Sternitzke, Christian (2010). Knowledge sources, patent protection, and commercialization of pharmaceutical innovations. *Research Policy*, *39*(6), 810–821.
Thompson, Peter (2006). Patent citations and the geography of knowledge spillovers: Evidence from inventor- and examiner-added citations. *The Review of Economics and Statistics*, *88*(2), 383–388.
Tian, Lei, Wang, Holly H., & Chen, Yongjun (2010). Spatial externalities in China regional economic growth. *China Economic Review*, *21*(S1), S20–S31.
Zheng, Ping (2011). The determinants of disparities in inward FDI flows to the three macro-regions of China. *Post-Communist Economies*, *23*(2), 257–270.
Zhong, Hai (2011). Returns to higher education in China: What is the role of college quality? *China Economic Review*, *22*(2), 260–275.