Innovation and Spillovers in China: Spatial Econometric Approach

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This paper examines spatial dependence in China's regional innovation using the spatial econometric approach. Dataset covers 30 Chinese provinces for the period from 2000 to 2009. The main findings are as follows: First, an interdependent and simultaneous influential relation in regional innovation is observed in most of the spatial panel models. Second, R&D activity significantly affects regional innovation. The effect of entrepreneurial activity on innovation is generally lower than that of R&D. In addition, the indirect spillover effect of R&D activity and entrepreneurial activity among adjacent provinces is limited. Third, the spillover effect of R&D and entrepreneurial activity among provinces diminishes with distance based on the regression analysis that formulated spatial weight matrixes for three different range segments. That is, the spillover effect of entrepreneurial activity is limited by spatial proximity, and the spillover effect of R&D activity is attenuated by the increase in distance.

Keywords: Innovation, R&D activity, Entrepreneurial activity, Spatial panel data model, China

JEL Classification: O3, P2

I. Introduction

Recently, regional variations in innovation performance have been observed. In the current knowledge-based economy, innovation capability has become the most important factor in the success of a region. Accordingly, the central and local governments need to measure innovation

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capability, compare it with those of other governments, and manage it. Many studies have examined the innovative competences of the region and their determinants (Fritsch 2002; Furman *et al.* 2002; Li 2009). However, previous studies are limited by their failure to consider spatial dependence as determinant of the knowledge spillover in innovation. Innovation is embedded in regions (Lundvall 1988; Lam 2000; Maskel and Malmberg 1999) and the diffusion of these innovations within regions is restricted by spatial proximity (Bottazzi and Peri 2003). The spatial dependence in knowledge spillover has to be highlighted preferentially prior to any other factors.

Against this background, this study examines spatial dependence in China's regional innovation as a determinant of regional disparity at the provincial level. As noted by Li (2009), there are definite advantages to analyzing Chinese innovation at the regional level rather than at the national level. We employ the spatial econometric approach to consider spatial proximity among analysis units and examine the spillover effect of R&D and entrepreneurial activity (Fischer 2011; Fujita *et al.* 1999). The rest of this paper is organized as follows: Section II reviews the theoretical discussions of regional innovation and knowledge spillover in China. Based on this background, Section III shows the construction of the empirical model and describes the dataset. Section IV presents the empirical results and their analyses. Section V states our conclusion.

II. Literature review

A. Previous Studies and Research Strategy

Studies that scrutinize the innovative competences of the region begins with the endogenous theory (Romer 1986; Grossman and Helpman 1991). The theory regards knowledge as an endogenous variable of the production function and explains the knowledge spillover effect as the key factor in increasing return and endogenous growth. Based on this theory, many studies have highlighted the regional knowledge accumulation and spillover processes. The regional innovation system approach is a representative research tradition that concentrates on knowledge accumulation and knowledge spillover in regional innovation (Cooke *et al.* 1997; Maskel and Malmberg 1999; Asheim and Gertler 2005). The theory maintains that network connections and interactions of regional innovators are keys of regional innovation. It proposes that the regional innovation can be fostered by increasing the knowledge acquisition capability of the region.

The innovation index approach asserts that region-specific characteristics related to knowledge capital could explain innovation and maintains that regression analysis could identify those variables (Furman *et al.* 2002; Li 2009). It suggests that innovation could be improved by managing these determining factors. The knowledge function model approach, which is based on the knowledge production function of traditional economics, presents questions on arbitrary variable selection of other research (Fritsch 2002).

Previous studies, however, have limitations. First, the endogenous growth theory makes the estimation of actual spillover effects difficult, which is ironic as it considers that such effect lies at the core of endogenous growth. Second, as the regional innovation system approach relies on case studies, comparing regions is a challenge. Additionally, the regional innovation index approach has theoretical and statistical problems as it employs inductive and arbitrary methods for selecting independent variables, which influence innovative competences. Finally, the knowledge function model approach does not consider the spatial aspects that determine the knowledge spillover effects.

To overcome these limitations, this study attempts to deal with issues that have not yet been studied through two research strategies. First, entrepreneurial knowledge spillover is added to the empirical model. Following Acs *et al.* (2004), we suppose that entrepreneurial activities contribute to the diffusion of knowledge and regional innovation. If scientists, engineers and other researchers in existing institutes face the decision-making bureaucracy or expect large profits from spin-offs, they can choose to start new enterprises for knowledge appropriation. In these cases, knowledge of incumbent institutes is embodied by the entrepreneurs of new enterprises and their entrepreneurial activities can be directly linked to knowledge spillover (Audretsch and Keilbach 2004). Subsequently, knowledge, such as new business know-how and new manufacturing methods, accumulate in a regional economy. Accumulated knowledge capital from new firm creation is copied and absorbed by other enterprises. Therefore, it is valid to assume that entrepreneurial activity influences knowledge spillover and regional innovation.

Second, this study defines knowledge spillover based on spatial units and employs the spatial econometrics model to measure the spatial dependence in innovation. Following Bottazzi and Peri (2003), we define R&D knowledge spillover as the effect of R&D of adjacent spatial units in the knowledge accumulation in the province of interest. R&D activities in the adjacent spatial units are diffused through personal contact and contribute to knowledge accumulation of the adjacent regions. Entrepreneurial knowledge spillover can also be assumed to be limited by distance because the abovementioned copying and transferring activities largely depend on spatial proximity. Subsequently, this spillover effect is measured with the spatial econometric model. Ever since many technical problems in spatial econometrics analysis were resolved by Yu (2007) and Elhorst (2010), the development in the field has been accelerating.

B. Innovation and Spillover in the Chinese Context

Two variables, R&D and patents, have often been used as proxies for the direct measurement of innovation (Griliches 1990). R&D input can be used as a proxy for the early part of innovation, and patents as a proxy variable for the outcomes of innovation. R&D and patents function as the major axes of the innovation process. For innovation that is measured with patents, entrepreneurial activities have an important meaning (Acs *et al.* 2004). Newly founded small and medium-sized enterprises (SMEs) do not have enough resources such as marketing organizations; thus, patents become an important mechanism for appropriating their innovations.

The recent rapid growth in Chinese patenting has attracted the attention of many innovation researchers. After China's entrance to the World Trade Organization and the enactment of the revised Patent Act, the number of patent applications and grants reached record highs. After the reduction in government funding starting 1999, universities and research institutes have accumulated patents to win commercial projects and accelerate innovation (Liu and White 2001). Thus, the annual rate of growth of Chinese invention patent applications has risen to 23% (Hu and Jefferson 2009). In 2011, the State Intellectual Property Office (SIPO) of China surpassed all other countries including the USA in terms of the number of patent applications (Thoma 2013).

Figure 1 shows the cumulative number of patents in China per unit population by region. Megacities of coastal regions such as Beijing, Shanghai, and Tianjin as well as adjacent coastal provinces have filed large numbers of patents. As these areas are experiencing rapid GDP growth, and investments in R&D and personnel are increasing much more quickly than anywhere else in the world (Li 2009). In particular, foreign multinational enterprises (MNEs) are actively pouring capital investments in coastal regions where they can access the export market

Source: Reorganized by the authors based on SIPO data (Available at: http://www.sipo.gov.cn/)

FIGURE 1
REGIONAL DISTRIBUTION OF PATENTS GRANTED

more easily. These MNEs have made significant R&D efforts in order to secure Chinese markets and appropriate technology, and thus, their contribution to regional innovation is enormous (Goldberg *et al.* 2008). As their technology spill over to new Chinese start-ups through facility purchases and labor mobility, these foreign firms play a crucial role in promoting regional innovation and knowledge spillover.

Regions with a high number of private sector start-up rates have also filed large numbers of patents (Moon and Rho 2012). The noteworthy cases are those of Zhejiang, Guangdong, and Jiangsu, which show high cumulative number of patents per unit population. Zhejiang has a number of SME clusters including Wenzhou, Yiwu, and Shaoxing. Guangdong is the base of operation for "Shanzhai" mobile phones and many private SMEs are actively operating in the province.

Figure 1 shows that the innovative competences of innovators in the regions have been enforced quickly, but unevenly, a phenomenon that has been discussed extensively. Some scholars have predicted that China will become one of the world leaders in innovation soon. Jefferson *et al.* (2006) have shown that R&D activities in China show high marginal productivity by measuring the effect of R&D activities at the individual firm level. Hu and Jefferson (2004) have reported that knowledge capital constructed from R&D expenditures has a strong impact on the productivity and profitability of China's industrial enterprises. Kang and Lee (2008) have found that R&D activity has significant positive effect on the performance and growth of firms. On the contrary, other scholars argue that the increase in R&D activity and consequent patent increase are not guarantees of innovation (Thoma 2013; Goldberg *et al.* 2008) as most of the technologically important patent applications in the Chinese market are made by foreign MNEs operating in China. Indeed, in a China-generated United States Patent Trademark Office patent analysis, only 20% of China's firm assignee US patents are assigned by Chinese firms.

III. Research design

A. Model description

Following the endogenous growth model with "knowledge filter" of Acs *et al.* (2004), we assume that innovation in a specific region depends on R&D activity (R&D), entrepreneurial activity (*Ent*), and existing knowledge stock (*A*). In addition, by using the study of Bottazzi and Peri (2003) as basis, we hypothesize that the knowledge stock of other regions can create a spillover effect on the innovation of regional unit i. We propose the following knowledge production function:

$$\Delta A_i = B(R\&D)_i^{eR}*(Ent)_i^{eE}*A_i^{e0}*(\Pi_{j\neq i}A_j^{\rho w_{ij}}), \qquad (1)$$

where ΔA_i represents the change in the stock of knowledge in region *I* over the period. We define ΔA_i as the innovation of the region (*Inno*). It is measured by the number of new patents granted in that region. The elasticity of innovation to R&D activity and entrepreneurial activity is defined by e_R and e_E, whereas the knowledge stock of other region *j* enters with an elasticity ρw_{ij} that depends on spatial proximity between region *i* and region *j*. We can achieve a simple functional form of knowledge spillover as follows:

$$Inno(\Delta A) = f(R\&D,\ Ent,\ wR\&D,\ wEnt). \qquad (8)$$

Details are shown in Appendix A.

Equation (8) means that innovation of region *i* can be regressed by two innovative activities of the region *i* and its neighboring regions. The spatial econometrics empirical model allows us to explicitly account for the "direct effects" of these two innovative activities on regional innovation and the "indirect spillover effect" of two activities of neighboring regions (Fischer 2011; Fujita *et al.* 1999).

We employ three empirical models in this paper. The first is the spatial lag model, which specifies spatial dependence among observations. The second is the spatial error model, which assumes that the dependent variable depends on a set of local variables and that the error terms are spatially correlated. The third is the spatial Durbin model. The spatial lag model is shown below:

$$\ln(\Delta \boldsymbol{A})_{it} = \sigma \Sigma_{j=1}^{N} \boldsymbol{w}_{ij} \ln(\Delta \boldsymbol{A})_{it} + \boldsymbol{x}_{it}\boldsymbol{\beta} + \mu_i + \eta_t + \varepsilon_{it}, \tag{9}$$

where the subscripts i and t refer to provinces and years, respectively; $\delta \Sigma_{j=1}^{N} w_{ij} \ln(\Delta \boldsymbol{A})_{it}$ denotes the interaction effect of the dependent variable $\ln(\Delta \boldsymbol{A})_{it}$ with the dependent variables $\ln(\Delta \boldsymbol{A})_{jt}$ in a spatially related regional unit; $\boldsymbol{w}_{ij}$ is an element of a pre-specified non-negative $N \times N$ spatial weight matrix; and w describes the arrangement of the cross-sectional units in the sample. ε_{it} is an independently and identically distributed error term for i and t with zero mean and variance σ^2 and μ_i denotes the spatial effect and η_t denotes the time-period effect. According to Elhorst (2010), the spatial lag model can posit the spatial process in which the value of the dependent variable for analysis unit is jointly determined with that of the adjacent unit. In this study, the spatial lag model is consistent with the situation in which the innovation rate of a specific region interacts with that of the nearby region and knowledge accumulation in each region occurs simultaneously. Thus, we detect the existence of the "the endogenous interaction effect" (Manski 1993).

$$\begin{aligned} \ln(\Delta \boldsymbol{A})_{it} &= + \boldsymbol{x}_{it}\boldsymbol{\beta} + \mu_i + \eta_t + \phi_{it} \\ \phi_{it} &= \rho \sum_{j=1}^{N} \boldsymbol{w}_{ij}\phi_{it} + \varepsilon_{it}. \end{aligned} \tag{10}$$

The spatial error model attributes spatial correlation to an unobservable error term. The error term of unit i, ϕ_{it} depends on the error terms of the spatially related regional units of j according to the spatial weights matrix $\boldsymbol{w}_{ij}$ and idiosyncratic component ε_{it}. ρ denotes the spatial auto-correlation coefficient. According to Elhorst (2010), the spatial error model can be regarded as a special case of a non-spherical error covariance matrix. The model used in this study is formulated based on the assumption that the mutual influence among spatial units is included in the error term except for the independent variables of the knowledge production function. That is, this model hypothesizes that unobserved determinants are spatially interconnected.

However, the two models cited above cannot explain the "exogenous interaction effect" of Manski (1993) with the endogenous interaction effect and correlated effect. The simplest solution seems to be the inclusion of the lagged dependent variable from the spatial lag model, the spatially correlated error term, and the lagged independent variable simultaneously. However, Manski (1993) have warned that three factors cannot be included at the same time because of identification error. Two alternative methods are therefore suggested. Florax and Folmer (1992) have argued that researchers must test whether spatially lagged independent variables are significant, and then test successively whether the model should include spatially dependent variables or a spatially correlated error term. This is called the specific to general approach. Another direction is to use the spatial Durbin model, and then test whether this model can be simplified (Elhorst 2010). This is the general to specific approach.

$$\ln(\Delta \boldsymbol{A})_{it} = \delta \sum_{j=1}^{N} \boldsymbol{w}_{ij} \ln(\Delta \boldsymbol{A})_{it} + \boldsymbol{x_{it}}\beta + \sum_{j=1}^{N} \boldsymbol{w}_{ij}\boldsymbol{x_{it}}\gamma + \mu_i + \eta_t + \varepsilon_{it}. \qquad (11)$$

This spatial Durbin model contains spatially lagged dependent variables and spatially lagged independent variables together. γ is a $k\times1$ vector of fixed but unknown parameters. This model should be used to test the hypothesis $H_0 : \gamma=0$, to determine whether the model can be simplified into the lag model, and $H_0 : \gamma+\delta\beta=0$, to ascertain whether the spatial model can be simplified to the spatial error model. Elhorst (2010) has suggested the concrete estimation processes of the three spatial panel models. The spatial Durbin model can distinguish the indirect spillover effect of R&D activity from that of entrepreneurial activity and estimate the significance of each effect separately.

Another important issue in employing the spatial panel model is the assumption on the error term μ_i. The spatial-specific effects can be dealt with as fixed or random effects. The fixed-effect model assumes that unit-specific characteristics can be captured by introducing dummy variables. By contrast, the random effect model assumes that error term μ_i is independently and identically distributed with zero mean and fixed variance. This model regards μ_i and ε_{it} as independent of each other. In this study, we use the Hausman test results as basis for specification. When the Hausman test rejects the systemic difference between the fixed effects model and random effects model, we can conclude that the fixed effects model is better fitted. The fixed effect can be regarded as one case among three different effects. That is, it can be interpreted as the spatial fixed effect or the time period effect. These two cases are called one-way effect. Moreover, it can be interpreted as the spatial effect and the time period effect simultaneously in two ways. Since we are interested in the spatial interaction effect, our analysis concentrates on the spatial fixed effect and the two-way time period and spatial fixed effect regression result.

B. Data description

The set of data employed in the empirical model is summarized below. As an indicator of innovation (*Inno*), the number of patents granted within specific regions is used. R&D activity (*R&D*) is measured by full-time equivalent R&D personnel per 10,000 persons in specific regions and periods. In terms of consistency with entrepreneurial activity (*Ent*) measurement, R&D personnel performs better than R&D expenditure. This proxy establishes the variable *R&D*. As a proxy for regional entrepreneurial activities, we use the CPEA index, which is the three-year net increase in the establishment of private enterprises (SiyingQiye) divided by available labor persons for specific provinces and years. This proxy index establishes the variable *Ent*. This method of index construction is called the "labor market approach" (Audretsch and Fritsch 1994). All variables are regressed after log transformation. See Appendix B for details.

In addition, we perform regression analysis by employing two kinds of spatial weight matrices. First, we use a binary type spatial weight matrix defined by first order contiguity, where an "adjacent" province is identified based on a common border. Thus, we assign 0 to the relation with a non-adjacent province and 1 to that with an adjacent province. Second, we perform regression by modifying the spatial weight matrix based on the distance between provincial capitals. A spatial weight matrix is created for 30 provinces, excluding Tibet, based on the railroad distance between the capitals of each pair of provinces. We divide the distribution of the sample into three distance segments of 1000, 2000, and 3000 kilometers and formulate three binary-type spatial weight matrixes based on the division. The first matrix is built by assigning 1 to the relations among the provinces within 1000-kilometer distance from the capital,

TABLE 1
BASIC STATISTICS

Variable	Unit	Mean	Std. Dev.	Min	Max	Obs
ln Inno	ln (patent)	7.778036	1.552759	1.94591	11.37695	300
ln R&D	ln (person)	10.1074	1.337345	5.393628	12.5555	300
ln Ent	ln (enterprises)	10.2358	1.248179	6.907755	12.65396	296

Note: See the Appendix B for the definition of variables.

and 0 to the rest. For the second matrix, 1 is assigned to the relations among provinces within the 2000-kilometer distance from the capital, and 0 to the rest. For the third matrix, 1 is assigned to the relations among provinces within the 3000 kilometer distance from the capital, and 0 to the rest. The regression analysis places the three spatial weight matrices into the model alternately and compares the results.

IV. Empirical Results

A. Estimation of empirical models with the first order contiguity weight matrix

Table 2 presents the first results of the regression analysis. The three left hand columns show the results from models with spatial-specific effects (μ_i). The three middle columns show the empirical results from models with time-period specific effects (η_t). The latter three columns present two-way models with the province-specific effects (μ_i) and time-specific effects (η_t). As R&D is closely related to the increase in the number of patents, the empirical model shows high R-square and correlation-square results. Through likelihood ratio tests, we can reject the model without the spatially lagged dependent variable and spatially autocorrelated error term. The results of almost all the Hausman tests, except for those of the fixed effect spatial lag model, reject the random effect model.

The coefficients of *R&D* and *Ent* show the expected sign. *R&D* shows a consistently significant positive effect on regional innovation. *R&D* is statistically significant and positive in the time period effect, spatial fixed effect one-way models, and two-way model. By contrast, entrepreneurial activities reveal limited effect. The positive effect of entrepreneurial activities is observed only in the time period fixed model. The most remarkable result is the spatial interdependence in regional innovation (*Inno*). Table

TABLE 2

ESTIMATION RESULT OF SPATIAL PANEL MODELS WITH THE FIRST ORDER CONTIGUITY WEIGHT MATRIX

	Innovation (Patent increase)								
	One way (Spatial fixed effect)			One way (Time period fixed effect)			Two way- (Spatial and time period fixed effect)		
Variables	Spatial lag/ RE	Spatial error/ FE	Spatial Durbin	Spatial lag/ FE	Spatial error/FE	Spatial Durbin	Spatial lag/ FE	Spatial error/ FE	Spatial Durbin
Ent	0.038469 (2.748307)***	0.014531 (1.337561)	0.013860 (1.110140)	0.123342 (5.037208)***	0.096501 (4.303868)***	0.115830 (4.88375)***	-0.001730 (-0.141413)	0.003102 (0.269714)	0.001161 (0.090675)
R&D	1.001201 (20.050627)***	0.583342 (8.28553)***	0.519622 (6.70433)***	0.936435 (31.26340)***	0.963966 (33.77276)***	0.953809 (32.9137)***	0.366645 (4.715216)***	0.373815 (4.89937)***	0.371279 (4.56467)***
W*Ent			0.016190 (0.922129)			0.055676 (1.497947)			-0.014038 (-0.696554)
W*R&D			0.111995 (1.064677)			-0.398873 (-5.5727)***			-0.213583 (-1.591981)
W*Inno	0.204990 (4.885715)***	0.750989 (20.28263)***	0.526984 (9.56260)***	0.101974 (3.418023)***	0.421955 (6.739545)***	0.374994 (6.61102)***	0.061969 (0.815107)	0.290992 (4.1862)***	0.352420 (5.3049)***
LR test	490.3781 (0.00000)	648.9051 (0.0000)		205.4881 (0.0000)	218.5708 (0.00000)		728.6026 (0.0000)	738.0935 (0.0000)	
Hausman test	-0.5519 (0.9073)	-16.0790 (0.0011)		50.8107 (0.0000)	-28.2226 (0.0000)		-113.0914 (0.0000)	-111.9067 (0.0000)	
R-square	0.9714	0.9450	0.9806	0.8992	0.8886	0.9091	0.9813	0.9809	0.9824
Corr-square	0.8847	0.6994	-	0.8847	0.8780	-	0.0672	0.0666	-

Notes: (1) Numbers in ( ) are T statistics.
(2) * $p<0.1$, ** $p<0.05$, *** $p<0.01$

TABLE 3
INDIRECT SPILLOVER EFFECT OF REGIONAL INNOVATIVE ACTIVITY

		One-way (Spatial fixed effect)	One-way (Time period fixed effect)	Two-way (Spatial and time period fixed Effect)
Variable		Spatial Durbin	Spatial Durbin	Spatial Durbin
Direct effect	Ent	0.0179 (1.2619)	0.1258*** (5.1990)	-0.0001 (-0.0060)
	R&D	0.5850*** (8.0072)	0.9495*** (34.1061)	0.3660*** (4.3058)
Indirect effect	Ent	0.0450 (1.2484)	0.1461*** (2.6586)	-0.0185 (-0.5973)
	R&D	0.7543*** (5.9929)	-0.0596 (-0.8790)	-0.1234 (-0.6499)

Notes: (1) Numbers in ( ) are T statistics.
(2) * p<0.1, ** p<0.05, *** p<0.01

2 shows the positive and significant coefficients of spatially-lagged dependent variable (*W* Inno*). This result is observed consistently in most of the models used, indicating that innovation represented by patents has a significantly higher mutually influential relation between adjacent provinces than that between non-adjacent provinces. Therefore, a spillover mechanism between adjacent provinces that promotes the innovation of the provinces exists.

According to LeSage and Fischer (2008) and Elhorst (2010), we can interpret the coefficients of *R&D* and *Ent* in the spatial Durbin model as the direct effect on innovation within a specific region. However, we must be careful in interpreting the results of the indirect spillover effect. Elhorst (2010) and Fischer (2010) show that the coefficients of spatially lagged determinants (*W* Ent*, *W* R&D*) cannot be regarded as indirect spillover effects. Thus, we summarize the results in Table 3 separately using a routine through which we can calculate the indirect spillover effect of determinants. Elhorst (2010) has established this routine for MATLAB. Moon and Rho (2012) has provided a more in-depth discussion.

Based on the results, the R&D activity of adjacent provinces appears to have a significant indirect effect on the innovation of an individual province. We can observe this result from the spatial Durbin model with the spatial fixed effect. Previous studies have interpreted spatial fixed effect as short term; thus, we can infer that the indirect effect of R&D

TABLE 4

DIRECT AND INDIRECT INNOVATION EFFECT OF R&D AND ENTREPRENEURSHIP

		Innovation effect								
		1000km			2000km			3000km		
		Spatial fixed	Time Fixed	Two way	Spatial fixed	Time fixed	Two way	Spatial fixed	Time fixed	Two way
Direct effect	R&D	0.5849 (7.4116)***	0.9713 (30.291)***	0.3903 (4.711)***	0.3819 (4.7154)***	0.9756 (29.3950)***	0.4320 (4.7934)***	0.4510 (5.1776)***	0.9938 (32.1686)***	0.4025 (4.4287)***
	Ent	0.0013 (0.0912)	0.1041 (4.1612)***	-0.0037 (-0.2764)	-0.0008 (-0.0636)	0.1191 (4.6223)***	0.0014 (0.1090)	0.0005 (0.0338)	0.1113 (4.3810)***	0.0034 (0.2408)
Indirect effect	R&D (1000km)	0.6815 (6.7001)***	-0.0704 (-0.969)	0.3169 (2.4643)***						
	Ent (1000km)	0.0815 (2.6536)***	0.1272 (1.777)	0.0951 (2.9944)***						
	R&D (2000km)				1.0610 (6.7458)***	-0.0754 (-0.0738)	1.4336 (2.772)***			
	Ent (2000km)				0.0312 (0.5340)	0.1059 (1.1326)	0.0455 (0.6278)			
	R&D (3000km)							1.0052 (5.4104)***	-0.1865 (-0.1228)	-0.1108 (-0.2131)
	Ent (3000km)							0.3404 (0.0249)	0.1722 (0.9625)	0.1350 (1.0893)
	R-square	0.9784	0.9065	0.9821	0.9809	0.9026	0.9820	0.9796	0.9105	0.9820
	Corr-square	0.7869	0.8365	0.1257	0.8011	0.8927	0.1164	0.7960	0.8933	0.0737

Notes: (1) Numbers in ( ) are T statistics.
(2) * $p<0.1$, ** $p<0.05$, *** $p<0.01$

activity in specific regions adjacent to a province is valid for short run. In case of entrepreneurial activity, however, the influence of space dependency on the adjacent region is hardly significant, as only a weak indirect effect is observed in the time period fixed effect model.

B. Estimation result of the stepwise distance-based spatial weight matrix

The regression using the first distance segment (1000 km) spatial weight matrix shows that R&D activity is significant in both direct and indirect effects; that is, the spillover effect is observed. The direct effect of entrepreneurial activities shows a positive effect only in the time period observation. However, the indirect spillover effect on other provinces is significant, although weaker than that of R&D. In the matrix that extends the spatial weight matrix to 2000 kilometers, the direct effect is only slightly different, but the indirect effect is considerably different. The indirect effect of entrepreneurial activities vanishes. In other words, when the distance is extended to 2000 kilometers, the spillover effect of entrepreneurial activities is neutralized. The indirect effect of R&D activity is attenuated relative to the spatial weight matrix of 1000 kilometers. In the spatial weight matrix that extends the range to 3000 kilometers, this trend is stronger and the indirect spillover effect of R&D activity shows significant decrease. In summary, the indirect spillover effects of R&D and entrepreneurial activities are clearly different according to distance. The indirect effect, namely, the spillover effect is diminished and becomes less significant with increasing distance.

C. Discussion

We discuss the effects of R&D activity and entrepreneurial activity on China's regional innovation. The regression analysis clearly shows the direct effects of R&D activity on innovation, as measured by the increase in the number of patents. By contrast, the direct effect of entrepreneurial activity is significant only in the time-period effect model, which seems intuitive. Interesting implications can be put forward when the empirical results of other studies are compared. For example, Moon and Rho (2012) have found that the effects of R&D activity and entrepreneurial activity on GDP growth are moving at different directions. Rho and Gao (2012) have shown that increases in R&D input are negatively correlated with the regional private sector employment increase. Thus, we can argue that the increase in R&D investment of China can encourage innovation, but such innovation is not commercial enough to be directly connected with economic growth. This finding is consistent with the "strategic patenting hypothesis" in China (Hu 2010).

We also discuss the significant spatial interdependence of the three spatial econometric models with the increase in patents. This result implies the existence of certain spillover mechanisms among adjacent provinces that promote each region's innovation. In other words, innovation from knowledge spillover is limited by spatial proximity. The high number of Chinese patents can be explained by the evolution of innovation systems (Hu 2010; Hu and Jefferson 2009; Thoma 2013). Improvements in the Intellectual Property Rights (IPR) regimes such as the Patent Act, and the increase in the number of consulting services for the IPR application, firms supplying research facility or equipment, and educational and research institutes that nurture and supply qualified human resources to the market, are evolving in China's regional innovation system. Innovations have been made first in the regions where people can access such institutions easily and obtain information during the early stage. When a firm acquires benefits through patent application, such as government support or efficient market protection, competitors or neighboring firms learn from these experiences. This process becomes a cycle of innovation promotion. This is the natural process of regional knowledge spillover.

As innovation competition between local governments becomes more heightened, spatial dependence in regional innovation becomes stronger. As noted by Elhorst (2010), local government expenditures between adjacent regions show significant spatial correlation because of "yardstick competition." R&D expenditure among adjacent local governments also becomes more competitive. Many studies indicate that China's innovation system is government driven. The distribution of R&D resources in China is entirely controlled by government entities such as the Ministry of Science and Technology, the National Development and Reform Commission, and the National Natural Science Fund Committee. Politics governs the decision making. As political competition among regions induces R&D expenditure competition, spatial correlation in innovation increases.

Finally, we review the results using three stepwise distance-based spatial weight matrixes. We conduct spatial Durbin model regression with the routine from the study of Elhorst (2010) routine. The results show that indirect spillover effects are attenuated by the increase in distance. As the threshold distance of the spatial weight matrix increase, regression samples with the spatial relation increase, which dilutes the significance of coefficients used to show significant spatial correlation at a short distance. This confirms the result of Bottazzi and Peri (2003). It is also consistent with existing literature on spillover in China (Ying 2000; Brun *et al.* 2002) that show the occurrence of knowledge spillover in a relatively limited geographical scope.

The physical distance limitation of knowledge spillover can be explained by the importance of face-to-face information exchange, which has remained despite the rapid development of the Internet and IT technology. In China, innovative actors have complicated relationships and generally, unreliable information is exchanged and distributed. The Chinese have strong regional identities and strive to maintain good reputations locally. Regional spreading of implicitly valuable information, such as business opportunity and production know-how through kinship is a common phenomenon. The innovation of firms or research institutions depends on this direct information exchange. Knowledge diffusion resulting from direct contact is quite important, and such knowledge exchange depends on physical distance. Thus, spatial proximity has a positive influence on innovation and this is reflected in the empirical results.

V. Conclusion

This paper examines spatial dependence in China's regional innovation using the spatial econometric approach. The main findings are as follows: First, an interdependent and simultaneous influential relation in regional innovation is observed in most of the spatial panel models. Second, R&D activity significantly affects regional innovation. The effect of entrepreneurial activities on innovation is generally lower than that of R&D. In addition, the indirect spillover effect of R&D activity and entrepreneurial activity among adjacent provinces is limited. Third, in the regression analysis that formulated spatial weight matrixes for three different range segments, the long distance reduces the spillover effect among provinces. The spillover effect of entrepreneurial activities is limited by distance and the spillover effect of R&D is attenuated.

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Appendix A

We assume that innovation in specific regions depends on R&D activity, entrepreneurial activity, and existing knowledge stock of region i and other regions. Thus, we can construct the following knowledge production function:

$$\Delta A_i = B(R\&D)_i^{e_R} * (Ent)_i^{e_E} * A_i^{e_0} * (\Pi_{j \neq i} A_j^{\rho w_{ij}}). \quad (1)$$

Dividing both sides by A_i, we can obtain the growth rate of the stock of knowledge. If we suppose that the system is in a balanced growth path, all regions grow at the same rate and the common growth rate g can be fixed. Subsequently, we can achieve following equation:

$$\text{for } \forall i, \frac{\Delta A_i}{A_i} = g \Rightarrow \ln \Delta A_i - \ln A_i = \ln g \Rightarrow \ln(A_i) = \ln \Delta A_i - \ln g. \quad (2)$$

The log-linearized expression of the initial equation is as follows:

$$\ln \Delta A_i = \ln B + e_R \ln(R \,\&\, D)_i + e_E \ln(Ent)_i + e_0 \ln A_i + \sum_{j \neq i} \rho w_{ij} \ln A_j. \quad (3)$$

Using the balanced growth path property, we can derive:

$$\left(1 - e_0 - \sum_{j \neq i} \rho w_{ij}\right) \ln \Delta A_i = \ln B - \left(e_0 + \sum_{j \neq i} \rho w_{ij}\right) \ln g + e_R \ln(R \,\&\, D)_i + e_E \ln(Ent)_i. \quad (4)$$

We can express this equation as a matrix form as follows:

$$\begin{aligned} &[I - e_0 I - \rho W] \ln \Delta A = C + e_R \ln(R\&D) + e_E \ln(Ent) \\ &\Rightarrow \ln \Delta A = [I - e_0 I - \rho W]^{-1} [C + e_R \ln(R\&D) + e_E \ln(Ent)]. \end{aligned} \quad (5)$$

In the balanced growth path, the innovation of specific regions depends on R&D activity, entrepreneurial activity, and the spillover of innovation activity from other regions. While inverting the matrix $[I - e_0 I - \rho W]$ would be extremely complicated, we can consider linear approximation of the inverse. If we assume ρ^* is not far from 0, then we can use the linear approximation ($\rho^* \approx 0$):

$$f(\rho) \approx f(\rho^*) + (\rho - \rho^*)\ f'(\rho^*)$$
$$\text{Let } f(\rho) = [I - e_0 I - \rho W]^{-1}$$
$$f'(\rho^*) = \frac{\boldsymbol{W}}{[\boldsymbol{I} - e_0\boldsymbol{I}]^2} \tag{6}$$
$$f(\rho) = \frac{\boldsymbol{I}}{[\boldsymbol{I} - e_0\boldsymbol{I}]} + \rho\,\frac{\boldsymbol{W}}{[\boldsymbol{I} - e_0\boldsymbol{I}]^2}$$

Then, we obtain the following expression:

$$\ln \Delta\boldsymbol{A} = \left[\frac{\boldsymbol{I}}{[\boldsymbol{I} - e_0\boldsymbol{I}]} + \frac{\rho\boldsymbol{W}}{[\boldsymbol{I} - e_0\boldsymbol{I}]^2}\right][\boldsymbol{C} + e_R \ln(\boldsymbol{R}\,\&\,\boldsymbol{D}) + e_E \ln(\boldsymbol{Ent})]$$

$$\begin{aligned}\Rightarrow \ln \Delta\boldsymbol{A} = \boldsymbol{C}\left[\frac{\boldsymbol{I}}{[\boldsymbol{I} - e_0\boldsymbol{I}]} + \frac{\rho\boldsymbol{W}}{[\boldsymbol{I} - e_0\boldsymbol{I}]^2}\right] + \frac{e_R}{[\boldsymbol{I} - e_0\boldsymbol{I}]}\boldsymbol{I}\ln(\boldsymbol{R}\,\&\,\boldsymbol{D}) \\ + \frac{e_e}{[\boldsymbol{I} - e_0\boldsymbol{I}]}\boldsymbol{I}\ln(\boldsymbol{Ent}) + \frac{e_R\rho\boldsymbol{W}}{[\boldsymbol{I} - e_0\boldsymbol{I}]^2}\boldsymbol{I}\ln(\boldsymbol{R}\,\&\,\boldsymbol{D}) \\ + \frac{e_e\rho\boldsymbol{W}}{[\boldsymbol{I} - e_0\boldsymbol{I}]^2}\boldsymbol{I}\ln(\boldsymbol{Ent}).\end{aligned} \tag{7}$$

Based on this, we can derive the simple functional form of knowledge spillover as follows:

$$Inno(\Delta A) = f(R\,\&\,D,\ Ent,\ \boldsymbol{w}R\,\&\,D,\ \boldsymbol{w}Ent). \tag{8}$$

Appendix B

The data base of this study comes from 30 provinces and megacities excluding *Tibet* and covers the period from 2000 to 2009. Thus, the numbers of observations are 300. Data sources are from various years of “China’ Statistics Yearbook,” “China Population & Employment Statistics Yearbook,” and “China Statistics Yearbook on High-tech Industry.”

(1) Inno=Accumulated invention patents granted per 10,000 population in specific region and time
(2) R & D=R & D personnel index substantiated from full time equivalent R & D personnel for 10,000 labor available population

(3) Ent=CPEA index. Three year net increase of private enterprises with higher than eight employees per 10,000 labor available population

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