Methods and Initial Results – What's the Effect of FDI on Domestic Innovation Capability

Ying Sun

May 22, 2019

As an important part of globalization, Foreign Direct Investment (FDI) plays an irreplaceable role in many aspects. FDI not only includes transnational flow of tangible capital, but also the international transfer of intangible capital such as technology and management methods. According to some countries' practical experience, it has many effects on host countries such as promoting technological progress, stimulating economic growth and updating the industrial structure. While it may be a different story in another country. But there is commonly accepted viewpoint that with deeper and further utilization of FDI, the technology spillover effects of FDI has increasingly become an important factor affecting regional technological innovation capabilities. However, whether FDI can enhance the level of regional technological innovation has not yet been formed consensus in the academic community. This paper mainly investigates the relationship of FDI and innovation capabilities in China considering the geographical correlation of regions and contribute to this issue from the spatial analysis perspective. First of all, I use the map data to generate the Spatial Weights Matrix based on the binary adjacency rule. Then I conduct the Spatial Autocorrelation Test to confirm that there is a positive spatial correlation in terms of the regional innovation capability. Next, I set and test the spatial panel model and finally obtain the estimated results.

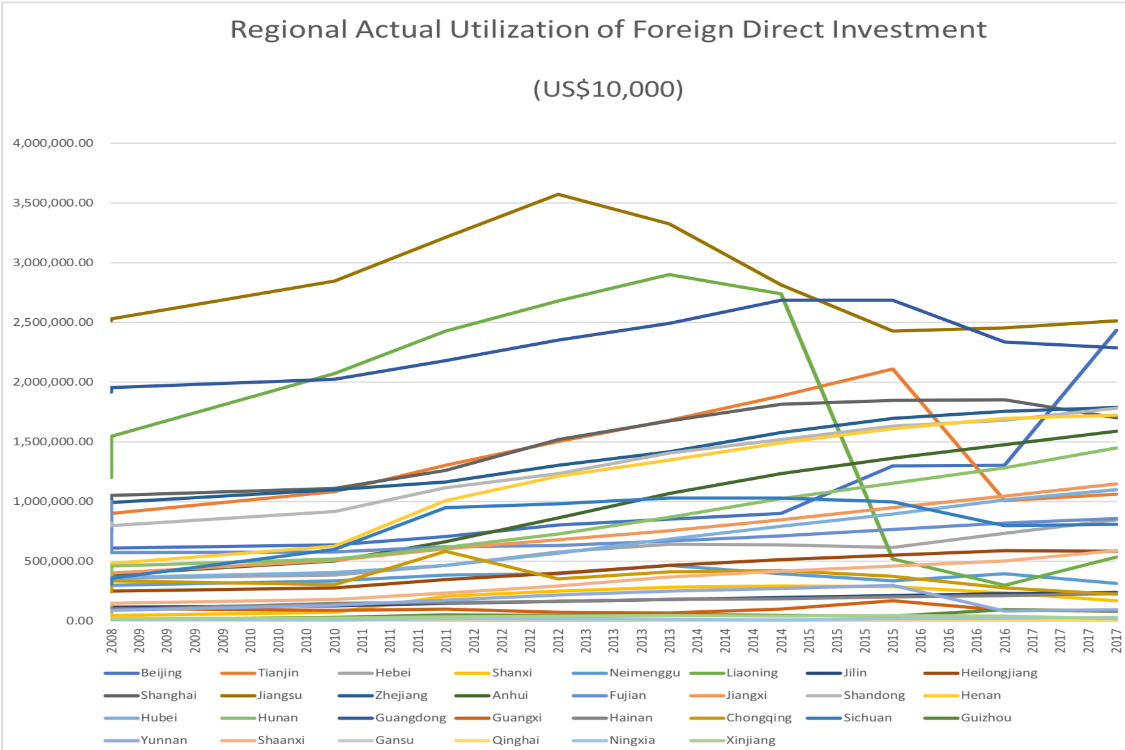
1. Data

The data used in this research are mainly from the macroeconomics part of Wind database, China Statistical Yearbook and China National Bureau of Statistics . This paper selects the patent authorization quantity as the dependent variable to reflect the regional innovation capability. In the existing empirical research, the acceptance of patent applications or the amount of patent authorization are usually selected as the indicators to measure the technological innovation capability. However, the quality of patents covered in the data of patent application acceptance in China is uneven. There are some patents of inferior quality. Therefore, the data may be inaccurate. In the contrast, the amount of patent authorization can reflect the number of high-quality patents because the authorization process is subjected to strict approval procedures. Thus this paper finally chooses the number of patent authorizations to reflect the regional innovation capability.

This paper chooses the regional actual utilization of foreign direct investment as the independent variable. In terms of the selection of control variables, based on the literature review, this paper considers it from two perspectives – Regional Innovation Environment and Regional Absorption Capacity. For the regional innovation environment, this paper uses the degree of regional openness (international imports and exports), market competition level (total score of marketization process) and economic power (GDP). As for the regional absorption, this research selects the regional R&D investment (Industrial Enterprises above Scale: R&D Funds) and human capital (Average number of students per 100,000 population: higher education).

Due to the serious lack of data in the Tibet Autonomous Region, this paper does not consider the relevant issues of Tibet. As a result, this research conducts the empirical analysis based on the panel data of 30 provinces, autonomous regions and municipalities from 2008 to 2017. First of all, we can have a rough idea of the FDI data to see the trend and regional difference. From the the Figure1.1, we can find that the scale of China's use of foreign direct investment continues to expand, showing an overall upward trend. Besides, there are significant regional

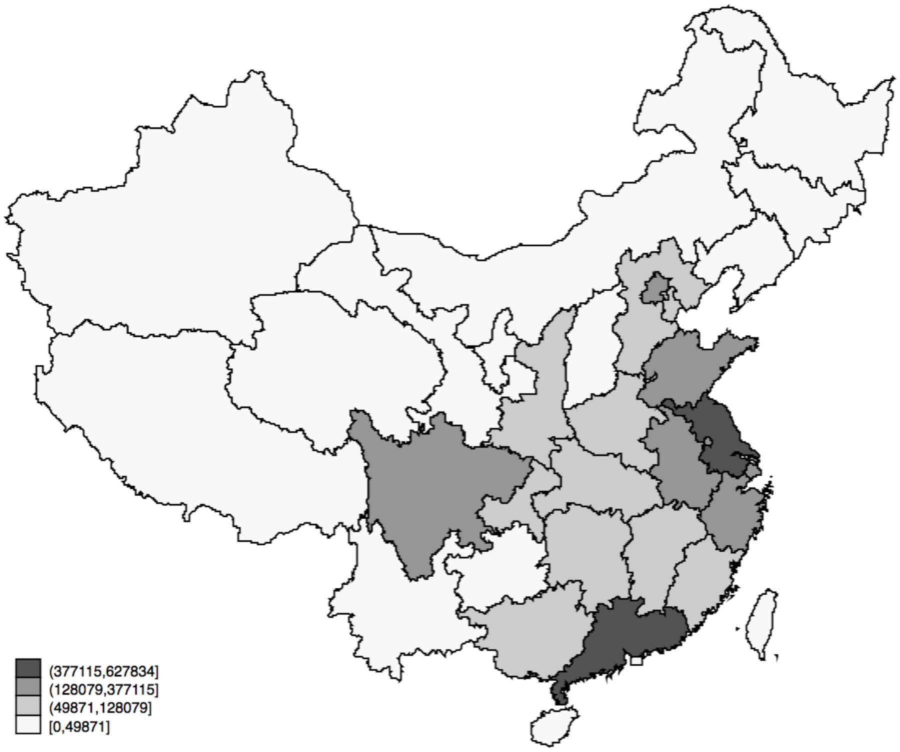
Figure 1: Regional Utilization of Foreign Direct Investment



differences in the actual utilizatio of foreign investment in China.

Then we can use the map data combined with the number of patent authorizations to see the distribution of patent authorizations. Figure 1.2 shows that there is a serious regional imbalance in the amount of patent authorization. More than 2/3 of the authorized patents are concentrated in the eastern region while the number of authorized patents in the central and western regions is extremely limited. The unbalanced spatial distribution of patent authorization can reflect the regional differences of innovation capability.

Figure 2: Patent Authorizations Distribution in 2017



2. Model & Methods

LeSage (2008) demonstrates the principles of spatial panel model. In terms of Spatial Autoregressive model (SAR) (SDM model has the similar theoretical explanation):

$$y = \rho W y + X\beta + \iota_n \alpha + W X \theta + \varepsilon \tag{1}$$

$$(I_n - \rho W) y = X\beta + W X \theta + \iota_n \alpha + \varepsilon \tag{2}$$

Denotes $S_r(W) \equiv V(W)(I_n \beta_r + W\theta_r)$ and $V(W) = (I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots$, then we can rewrite the (2):

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \sum_{r=1}^{k} \begin{pmatrix} S_r(W)_{11} & S_r(W)_{12} & \cdots & S_r(W)_{1n} \\ S_r(W)_{21} & S_r(W)_{22} & \cdots & S_r(W)_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ S_r(W)_{n1} & S_r(W)_{n2} & \cdots & S_r(W)_{nn} \end{pmatrix} \begin{pmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{pmatrix} + V(W)\iota_n \alpha + V(W)\varepsilon \tag{3}$$

$S_r(W)_{ij}$ is the (i, j) element of $S_r(W)$, So we can get the following equation:

$$\frac{\partial y_i}{\partial x_{jr}} = S_r(W)_{ij} \tag{4}$$

(4) means the variable x_{jr} in region j may have effects on the dependent variable in region j. This is the key characteristic in the spatial econometrics. Then we can get the average direct effect and average total effect:

$$Average\,Direct\,Effect = \frac{1}{n}trace[S_r(W)] \tag{5}$$

$$Average\,Total\,Effect = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}S_r(W)_{ij} \tag{6}$$

3. Results

3.1 Generate the Spatial Weights Matrix (SWM)

The spatial autocorrelation analysis is based on the spatial weights matrix. In order to evaluate spatial autocorrection, it is necessary to determine the distance measurements which are expressed in the form of weight matrix. Choosing the appropriate spatial weight matrix can reflect the spatial correlation of variables in the model. For specific spatial entities, incorporating their own spatial attribute information into the spatial weight judgement method can effectively enhance the ability to adapt and express the adjacent relationships between different spatial units. More specifically, the spatial weights matrix can be set up mainly based on the geographical correlation and socio-economic characteristics. This paper adopts the binary adjacency matrix, in which the element W_{ij} represents the adjacency relationship of unit i and unit j. If the two units are adjacent, the value is 1, otherwise 0. By implementing the map data of China, this paper generates the 30×30 binary adjacency matrix in GeoDa.

3.2 Spatial Autocorrelation Test

Global spatial autocorrelation test is mainly used to determine whether there is a spatial correlation between variables, that is, to judge whether the observed value of the spatial unit and its adjacent spatial units are related because of its adjacency in geographical space.

Before implementing spatial econometric models, it is usually necessary to test the spatial autocorrelation of data. Global Moran's I is the ideal index to test the spatial autocorrelation.

$$Moran\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X - \bar{X})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(X - \bar{X})^2}$$

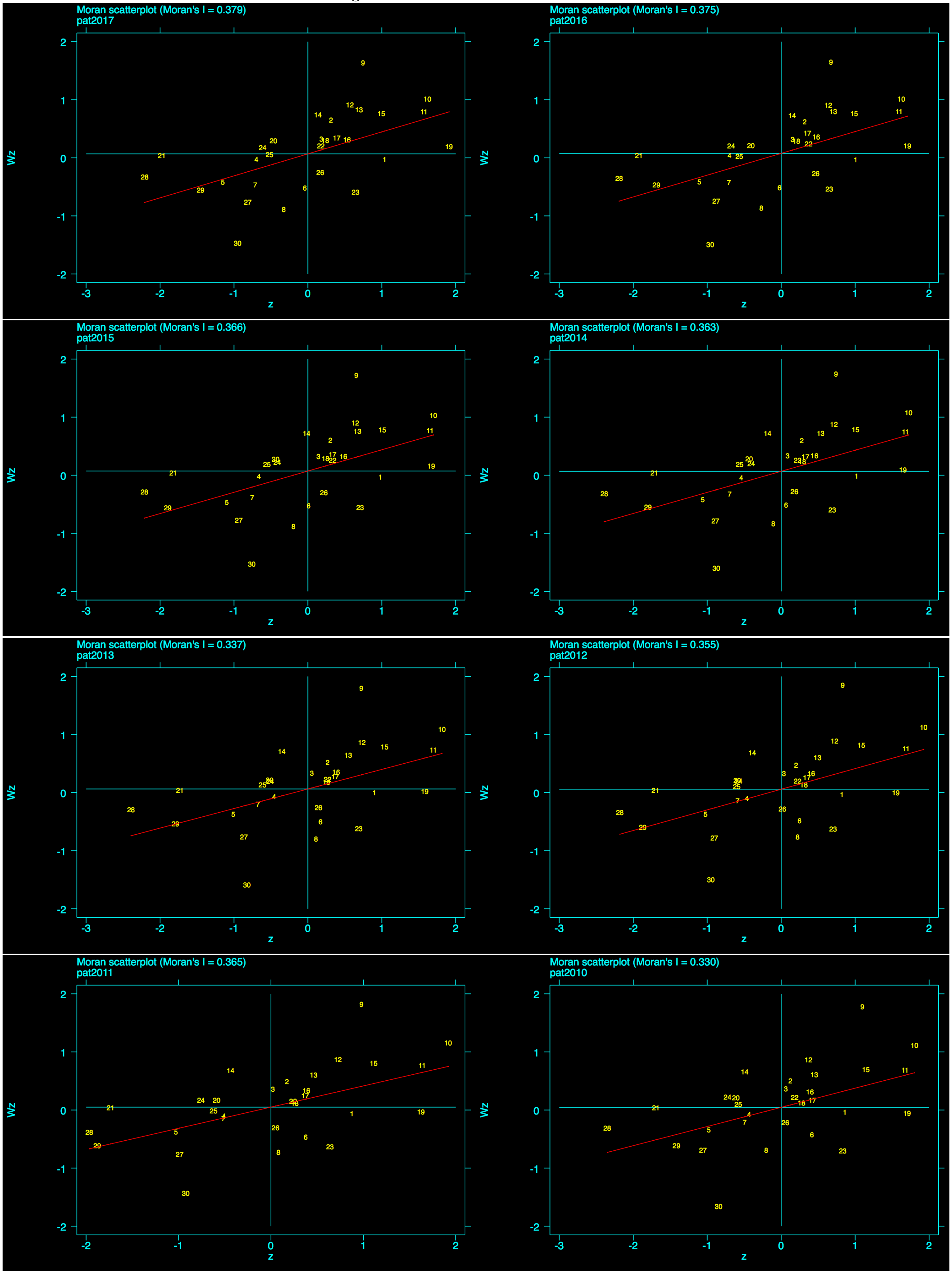
The values calculated by Moran I are between 1 and -1, less than 0 means negative spatial correlation, more than 0 means positive spatial correlation and equal to 0 means that there is no spatial correlation. The caluculated Global Moran I shows in Table 1. The result shows that there is a positive spatial correlation in terms of the regional innovation capability. Therefore, the paper chooses the spatial panel model to study the regional innovation capability.

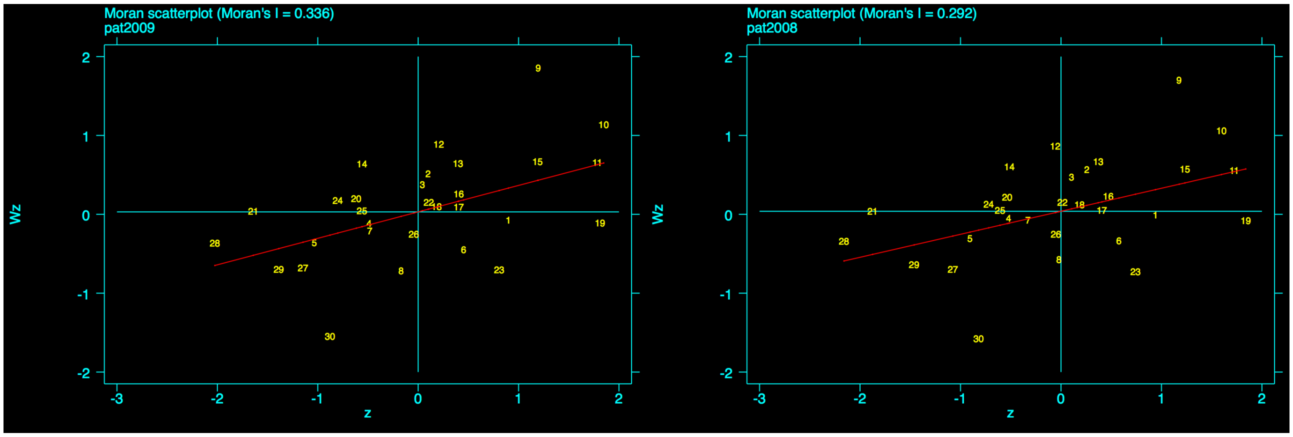
Table 1: Global Moran' I

Variables	I	E(I)	Sd(I)	z	p-value*
Pat2017	0.337	-0.034	0.109	3.398	0.001
Pat2016	0.335	-0.034	0.109	3.373	0.001
Pat2015	0.334	-0.034	0.109	3.374	0.001
Pat2014	0.321	-0.034	0.109	3.264	0.001
Pat2013	0.296	-0.034	0.109	3.039	0.002
Pat2012	0.311	-0.034	0.109	3.159	0.002
Pat2011	0.316	-0.034	0.109	3.193	0.001
Pat2010	0.268	-0.034	0.109	2.766	0.006
Pat2009	0.269	-0.034	0.109	2.764	0.006
Pat2018	0.226	-0.034	0.109	2.382	0.017

Then standardize the spatial weights matrix and see the Moran scatter plot:

Figure 3: Moran'I Scatter Plot





3.3 Setting and Testing of Spatial Panel Model

For the selection of spatial panel model, two Lagrangian Multipliers and their robust forms are generally tested. The results are as follows:

Table 2: Model Test Statistics

Spatial Panel AutoCorrelation Tests		
Ho: Error has No Spatial AutoCorrelation Ha: Error has Spatial AutoCorrelation		
GLOBAL Moran MI = 0.4953	P-Value > Z(15.168)	0.0000
GLOBAL Geary GC = 0.5035	P-Value > Z(-10.878)	0.0000
GLOBAL Getis-Ords = -2.1579	P-Value > Z(-15.168)	0.0000
Moran MI Error Test = 3.7264	P-Value > Z(113.654)	0.0002
LM Error (Burridge) = 188.5863	P-Value > Chi2(1)	0.0000
LM Error (Robust) = 143.6681	P-Value > Chi2(1)	0.0000
Ho: Spatial Lagged Dependent Variable has No Spatial AutoCorrelation Ha: Spatial Lagged Dependent Variable has Spatial AutoCorrelation		
LM Lag (Anselin) = 82.0032	P-Value > Chi2(1)	0.0000
LM Lag (Robust) = 37.0851	P-Value > Chi2(1)	0.0000
Ho: No General Spatial AutoCorrelation Ha: General Spatial AutoCorrelation		
LM SAC (LMErr+LMLag_R) = 225.6714	P-Value > Chi2(2)	0.0000
LM SAC (LMLag+LMErr_R) = 225.6714	P-Value > Chi2(2)	0.0000

As shown in Table 2, they all reject the original hypothesis at a significant level of 1%. According to the criteria of LM test, the robust forms of LMLAG, LMLAG, LMERR and LMERR are significant. That is to say, the spatial lag model (SAR) and the spatial error model (SEM) should be satisfied at the same time. Therefore, we need to develop a more generalized spatial panel Durbin model (SDM).

In addition, the Wald statistics of the spatial lag model (SAR) and the spatial error model

(SEM) can be calculated to determine whether the spatial Durbin model will degenerate into the spatial lag model or the spatial error model.

Furthermore, the Wald statistic of the spatial lag model is 552.1884 (0.0000) and 622.3739 (0.0000) for the spatial error model, which indicates that it is appropriate to select a more generalized spatial Durbin model (SDM) on this basis. Besides, LeSage (2008) also compares different spatial models in this paper. He assumes that the original data satisfy the data generation process of SAR, SEM, SDM and SAC respectively and analyzes the estimation results caused by model misspecification. The result shows that SDM model is the only model that can obtain unbiased estimation.

Finally, Hausman test shows that the statitics value is 0.78 (0.9925) so the the original hypothesis of random effects can not be rejected. Therefore, through the above calculations and tests, this paper finally chooses the spatial Durbin model of random effects.

3.3 Estimated Results

Table 3: Estimated Results

SDM with random-effects			
Main			
	FDI		-0.031
	Regional Innovation Environment	Regional Openness	0.144**
		Market Competition	0.426**
		Economic Power	1.156***
	Regional Absorption Capacity	R&D	0.390***
		Human Capital	0.631***
Spatial			
	rho		0.424***

Note: p-value in parentheses. * p<0.1, **p<0.05, ***p<0.01

The estimated results in Table 3 show that FDI has no significant positive spillover effect on regional innovation capability and it is contrary to our expectation. In terms of regional innovation environment, regional openness, market competition and economic power all have positive effects on the regional innovation capability. From the perspective of regional absorption capacity, R&D investment intensity and human capital all have significant positive effect on the regional innovation capability.

References

[1] Haskel, Jonathan E., Sonia C. Pereira, and Matthew J. Slaughter. "Does inward foreign direct investment boost the productivity of domestic firms?." The review of economics and statistics 89.3 (2007): 482-496.

[2] Smarzynska Javorcik, Beata. "Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages." American economic review 94.3 (2004): 605-627.

[3] Blomström, Magnus. "Foreign investment and productive efficiency: the case of Mexico." The Journal of Industrial Economics (1986): 97-110.

[4] Bishop, Paul, and Nick Wiseman. "External ownership and innovation in the United Kingdom." Applied Economics 31.4 (1999): 443-450.

[5] Aitken, Brian J., and Ann E. Harrison. "Do domestic firms benefit from direct foreign investment? Evidence from Venezuela." American economic review 89.3 (1999): 605-618.

[6] Yudaeva, Ksenia, et al. "Does foreign ownership matter? The Russian experience." Economics of transition 11.3 (2003): 383-409.

[7] Konings, Jozef. "The effects of foreign direct investment on domestic firms: Evidence from firm-level panel data in emerging economies." Economics of transition 9.3 (2001): 619-633.

[8] Borensztein, Eduardo, Jose De Gregorio, and Jong-Wha Lee. "How does foreign direct investment affect economic growth?." Journal of international Economics 45.1 (1998): 115-135.

[9] Harris, Richard, and Catherine Robinson. "Productivity impacts and spillovers from foreign ownership in the United Kingdom." National Institute economic review 187.1 (2004): 58-75.

[10] Zheng Li, Siying Yang and Bin He. "Does FDI Inhibit or Promote China's Regional Innovation Efficiencey?". Economics Management 39(2017): 6-19.

[11] LeSage, James P. "An introduction to spatial econometrics." Revue d'économie industrielle 123 (2008): 19-44.

[12] Anselin, Luc. Spatial econometrics: methods and models. Vol. 4. Springer Science & Business Media, 2013.

[13] Anselin, Luc. "Thirty years of spatial econometrics." Papers in regional science 89.1 (2010): 3-25.