What's the Effect of FDI on Domestic Innovation Capability in China? *

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Abstract

The effect of Foreign Direct Investment (FDI) has received a great deal of research attention since last decades. However, whether FDI can enhance the domestic innovation capability has not yet been formed consensus in the academic community. This research is expected to investigate the relationship of FDI and innovation capability in China considering the geographical correlation of regions and contribute to this issue from the spatial analysis perspective. First, this paper generates the Spatial Weights Matrix based on the binary adjacency rule. Then it conducts the Spatial Autocorrelation Test using Global Moran's I to confirm that there is a positive spatial correlation in terms of the regional innovation capability. Next this paper does multiple model setting tests to select the optimal spatial panel model. Finally the estimated result shows that FDI has no significant positive spillover effect on the regional innovation capability while regional innovation environment (regional openness, market competition and economic power) and absorption capability (R&D investment intensity and human capital)both have positive effects on the regional innovation capability.

***keywords**:* Foreign Direct Investment, regional innovation capability, spatial correlation, spatial panel model.

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1 Introduction

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 great significance in promoting technological progress, stimulating economic growth and updating the industrial structure. While it may be a different story in other countries. But there is commonly accepted viewpoint that with deeper and further utilization of FDI, the technology spillover effects of FDI has become an increasingly 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. My research is expected to investigate 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.

The effect of FDI on Domestic Innovation capability has received a great deal of research attention since last decades. Scholars hold different views on whether FDI can enhance the technological innovation capability of domestic countries. The mainstream viewpoints basically can be divided into three categories: promotion theory, inhibition theory and uncertain influence theory.

Promotion Theory

Haskel et al. (2007) uses the plant-level panel for U.K. manufacturing covering 1973-1992 to estimate production function for domestic plants augmented with terms measuring foreign presence in the industry and region, they conclude that there is a significant positive correlation between a domestic plant's TFP and the foreign share of employment in that plant's industry, while no significant effects for foreign share of employment by region. From industrial level, Smarzynska Javorcik (2004) obtains the similar conclusion that there are positive productivity spillovers from FDI taking place through contacts between foreign affiliates and their local suppliers in upstream sectors. But the spillover effects are limited in the shared ownership. Based on the Mexican manufacturing industries data, Blomström (1986) proposes that foreign presence in an industry has positive effects on structural efficiency and the most important source of spillover efficiency is the competitive pressure induced by the foreign firms. Different form the previous literature, this paper focuses more on the mechanisms of the spillover efficiency of foreign investment took place based on the analysis of the effects of FDI on the productive efficiency of the industrial structure in Mexico.

Inhibition Theory

Bishop and Wiseman (1999) examine the impact of ownership on the likelihood of innovation using a sample of UK defense related firms and the results show that foreign owner- ship has a negative indirect impact upon innovation. Similarly, Aitken and Harrison (1999) analyze this problem on plants-level and find that the foreign equity participation is positively correlated with plant productivity, but this relationship is only robust for small enterprises using panel data on Venezuelan plants. Furthermore, they test the spillovers from joint ventures to pure domestic plants and conclude that FDI has negative effects on the productivity of domestically owned plants. Taking these two offsetting effects into consideration, the net impact of foreign investment is quite small. By comparing the productivity of Russian firms that received foreign direct investments and pure domestically owned firms, Yudaeva et al. (2003) find that the spillover effects of FDI on small firms are negative. Further, this paper think that the main reason of negative effects is the severe competition drives out those small firms at the beginning of transition and it is predominant on the local level. The most interesting finding in Yudaeva's study is that the spillover effect depends positively on the level of education in that region. A possible explanation for this finding is that better educated workers have a great potential for absorb- ing technologies and innovations from foreign firms. Similarly, Konings (2001) also finds the negative spillovers to domestic firms in Bulgaria and Romania. In this study, the author uses firm level panel data to investigate the effects of FDI on the productivity performance of domestic firms in three emerging economies of Central and Eastern Europe: Bulgaria, Romania and Poland and concludes that "a negative competition effect that dominates a positive technology effect" (Jozef Konings, 2000, p.5). In a word, there are many factors leading to the uncertainty of spillover effects, including limited hiring of domestic employees in higher-level positions, little labor mobility between domestic firms and foreign subsidiaries, limited ability to study and few incentives for multinationals to diffuse their knowledge to local competitors.

Uncertain Theory

Scholars who hold this view believe that the impact of FDI on the technological in- novation capability of host countries is uncertain and it has a complex and diverse nature. Borensztein et al. (1998) analyze the effect of FDI on economic growth in a cross-country regression framework with the data on "FDI flows from industrial countries to 69 developing countries over the last two decades" (Borensztein et al., 1998, p.116). Their results suggest that the positive effects of FDI holds only when the host country's human capital stock level is above the minimum threshold. Harris and Robinson (2004) measure the indirect impact of FDI on the total factor productivity of domestic plants in a number of UK manufacturing industries. Based on their results, the competition and "absorption capacity" effect sometimes outweighs potential benefits, causing the negative spillovers. The most innovative part is that the authors take account of both intra-industry spillovers and inter-industry spillovers, and also includes an agglomeration measure to see if there are any locational spillovers from FDI. The estimated results indicate much heterogeneity in the impact of foreign ownership and the spillovers could be positive as well as negative.

Based on the literature above, we can find that most of these differences are closely related to the problems of data selection, variable selection and empirical models.

China's innovation system is composed of regional innovation systems (provinces), which have the characteristics of unbalanced regional development level and obvious regional differentiation. Although some domestic researchers have a deep understanding of China's practical situation, most of them implement traditional econometric models without considering the geographical correlation of regions. Motivated by the facts above, my research is expected to investigate 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.

Zheng Li et al. (2017) use the spatial panel model and a perspective from administrative region to analyze the FDI's impact on China's regional innovation efficiency. Based on the data of 30 provinces during 2000-2014, the estimation result shows that FDI can improve the regional innovation efficiency significantly in general while there exists the regional differences. This paper follows a general standard procedure of spatial model analysis: they select the spatial weights matrix based on binary weight criterion, then implement Global Moran's I to test the global spatial autocorrelation and confirm that regional innovation efficiency has significant spatial dependence. Based on this test, the authors set up the spatial panel model to estimate the effect of FDI on regional innovation efficiency.

Inspired by this article, I adopt the same scope and data to analysis this problem. Because of the large number of missing data in Tibet, I finally select 30 provinces as my research objects. In order to estimate the effect of FDI on regional innovation capability, this paper follows the standard procedure of spatial model analysis: first, this paper generates the Spatial Weights Matrix based on the binary adjacency rule. Then it conducts the Spatial Autocorrelation Test using Global Moran's I to confirm that there is a positive spatial correlation in terms of the regional innovation capability. Next this paper does multiple model setting tests to select the optimal spatial panel model. Notice that, different from Zheng Li et al. (2017), my test results of model setting (Lagrange Multiplier (Lag), Robust LM (Lag), Lagrange

Multiplier (Error), Robust LM (Error) are all statistically significant which suggests SDM model is a more proper model to estimate. This is mainly because we select the different variables to represent regional innovation capability and I use the “Domestic Patent Application Authorization Quantity ” of provinces to represent the regional innovation capability. Finally the estimated result shows that FDI has no significant positive spillover effect on the regional innovation capability while regional innovation environment (regional openness, market competition and economic power) and absorption capability (R&D investment intensity and human capital)both have positive effects on the regional innovation capability.

2 Theory

LeSage and Pace (2009) demonstrates the principles of spatial panel model. In terms of Spatial Durbin Model (SDM):

$$y = \rho W y + X\beta + \iota_n \alpha + W X \theta + \varepsilon \qquad (1)$$

$$(I_n - \rho W)\, y = X\beta + W X \theta + \iota_n \alpha + \varepsilon \qquad (2)$$

Here we denotes $S_r(W) \equiv V(W)\,(I_n \beta_r + W\theta_r)$ and $V(W) = (I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + ...$, they we can rewrite (2):

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

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

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

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

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

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

3 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 and some patents are 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. Table 1 summaries the innovation capabilities of 30 provinces and we can see the unbalanced development levels of innovation capability among different regions.

Table 1: 2008-2017 Innovation Capability Summary Statistics

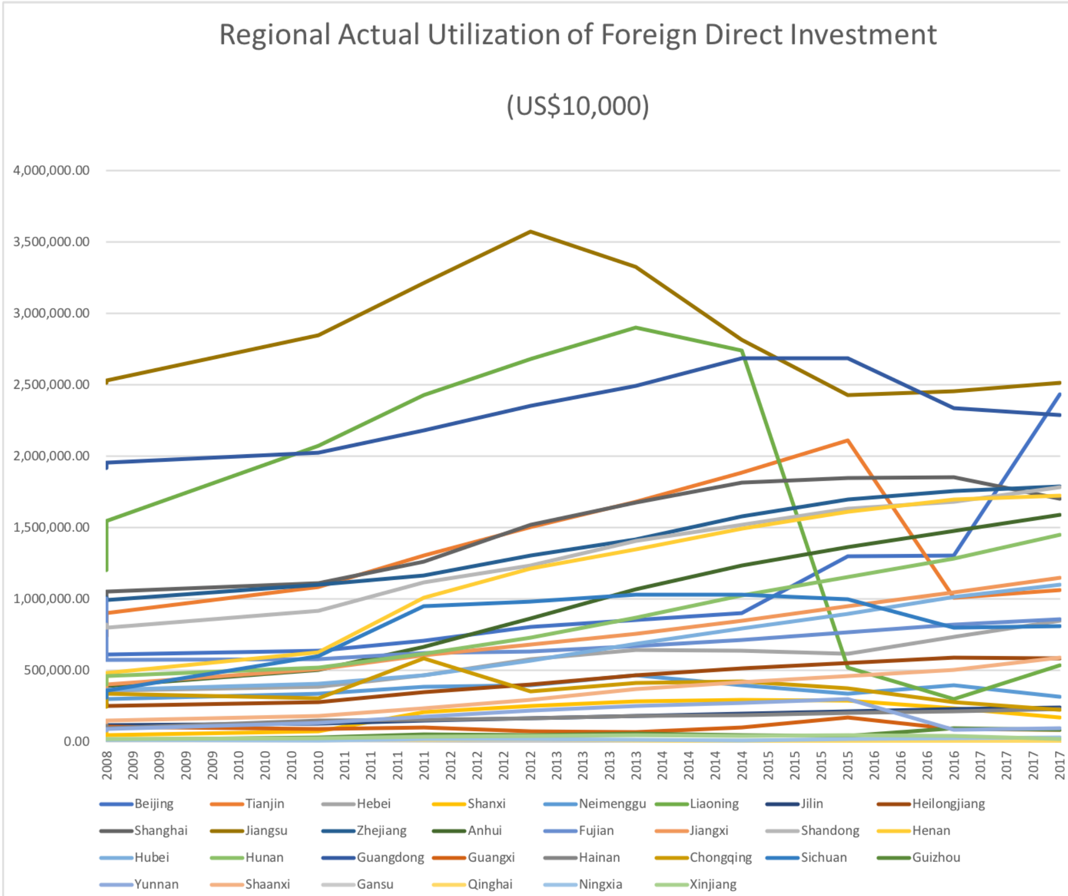
Provinces	Count	Mean	Std	Min	25%	50%	75%	max
Beijing	10	60446.70	32567.92	17747.00	35355.25	56591.00	89188.50	106948.00
Tianjin	10	22892.20	13293.98	6790.00	11750.00	22319.00	34594.25	41675.00
Hebei	10	18445.20	10751.48	5496.00	10325.50	16750.50	27630.50	35348.00
Shanxi	10	7075.70	3110.42	2279.00	4807.50	7783.50	9656.25	11311.00
Neimenggu	10	3577.00	1826.49	1328.00	2137.50	3460.00	5149.25	6271.00
Liaoning	10	19831.70	5337.62	10665.00	17613.75	20374.00	24242.00	26495.00
Jilin	10	6433.00	2773.83	2984.00	4487.25	6074.50	8332.50	11090.00
Heilongjiang	10	13937.80	6301.65	4574.00	8144.00	16729.00	18762.50	20268.00
Shanghai	10	50389.10	13844.55	24468.00	48023.75	49584.00	49584.00	72806.00
Jiangsu	10	188805.10	74641.88	44438.00	153740.00	213609.50	237492.00	269944.00
Zhejiang	10	162733.20	63641.13	52953.00	118529.75	188503.50	210941.25	234983.00
Anhui	10	38041.80	21453.39	4346.00	20179.25	45850.50	55872.00	60983.00
Fujian	10	36207.10	22670.75	7937.00	19011.50	34004.00	55680.00	68304.00
Jiangxi	10	13555.70	11763.99	2295.00	4649.25	8977.50	21578.50	33029.00
Shandong	10	69354.10	26237.06	26688.00	53328.50	74157.00	92813.75	100522.00
Henan	10	29831.30	16419.23	9133.00	17219.00	28136.50	44166.00	55407.00
Hubei	10	26462.50	12866.21	8374.00	17780.25	26382.50	36275.75	46369.00
Hunan	10	22466.10	11112.24	6133.00	14420.75	23802.00	32196.75	37916.00
Guangdong	10	173024.90	83758.52	62031.00	121610.50	162014.00	225870.25	332652.00
Guangxi	10	8012.80	5070.76	2228.00	3835.75	6892.00	12595.75	15270.00
Hainan	10	1260.40	649.43	341.00	726.75	1212.00	1853.50	2133.00
Chongqing	10	22586.20	13071.45	4820.00	12941.25	22338.00	32292.00	42738.00
Sichuan	10	42107.20	18409.25	13369.00	29387.50	44194.50	58613.75	64953.00
Guizhou	10	7146.40	4530.88	1728.00	3161.00	6987.00	10345.50	14115.00
Yunnan	10	7166.70	4229.29	2021.00	3917.00	6328.50	10774.50	14230.00
Shaanxi	10	20709.80	14280.11	4392.00	10441.00	17872.00	30717.50	48455.00
Gansu	10	4462.70	2971.78	1047.00	1996.75	4199.50	6458.25	9672.00
Qinghai	10	720.00	482.40	228.00	401.50	532.50	1067.50	1580.00
Ningxia	10	1547.50	1137.97	606.00	860.50	1146.00	1754.75	4244.00
Xinjiang	10	4620.90	2643.16	1493.00	2582.00	4218.50	6646.50	8761.00

Source: Wind Database

Furthermore, this paper chooses the regional actual utilization of foreign direct investment as the independent variable. In terms of the selection of control variables, this paper considers them 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 ab- sorption, 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) to represent regions' abilities to absorb new technologies .

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 distribution to see the trend and regional difference. From the the Figure 1 and Figure 2 , 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 differences in the actual utilization 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 3 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.



Regional Actual Utilization of Foreign Direct Investment
(US$10,000)
4,000,000.00
3,500,000.00
3,000,000.00
2,500,000.00
2,000,000.00
1,500,000.00
1,000,000.00
500,000.00
0.00
Beijing
Tianjin
Hebei
Shanxi
Neimenggu
Liaoning
Jilin
Heilongjiang
Shanghai
Jiangsu
Zhejiang
Anhui
Fujian
Jiangxi
Shandong
Henan
Hubei
Hunan
Guangdong
Guangxi
Hainan
Chongqing
Sichuan
Guizhou
Yunnan
Shaanxi
Gansu
Qinghai
Ningxia
Xinjiang

Figure 1: FDI

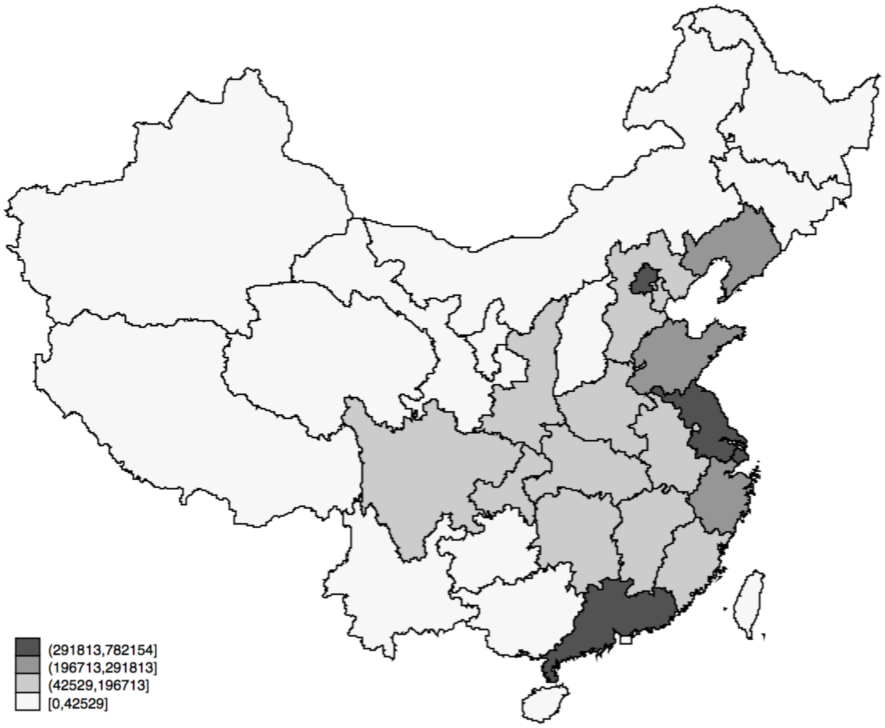


Figure 2: FDI Distribution

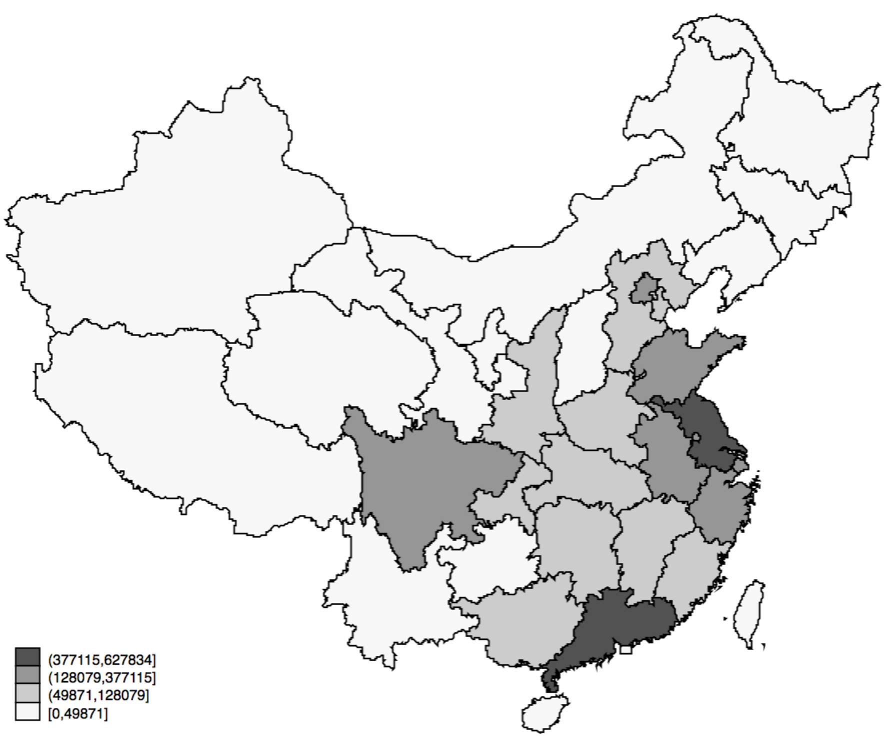


Figure 3: Patent Distribution

4 Analysis and Results

4.1 Generate the Spatial Weights Matrix (SWM)

The spatial autocorrelation analysis is based on the spatial weights matrix. In order to evaluate the 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 is 0. By implementing the map data of China, this paper generates the 30×30 binary adjacency matrix in GeoDa.

4.2 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 correlated 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.

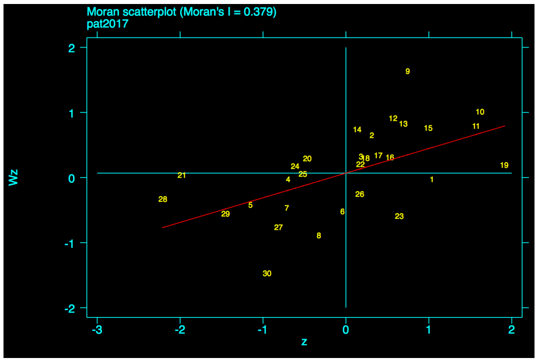
$$\text{Moran } I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(X - \overline{X})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \sum_{i=1}^{n} (X - \overline{X})^2}$$

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 calculated Global Moran I shows in Table 2. 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.

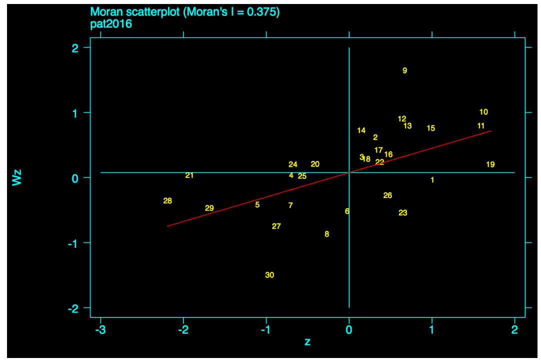
Table 2: Global Moran's I

Variables	I	E(I)	Std(I)	z	p-value*
Patent2017	0.337	-0.034	0.109	3.398	0.001
Patent2016	0.335	-0.034	0.109	3.373	0.001
Patent2015	0.334	-0.034	0.109	3.374	0.001
Patent2014	0.321	-0.034	0.109	3.264	0.001
Patent2013	0.296	-0.034	0.109	3.039	0.002
Patent2012	0.311	-0.034	0.109	3.159	0.002
Patent2011	0.316	-0.034	0.109	3.193	0.001
Patent2010	0.268	-0.034	0.109	2.766	0.006
Patent2009	0.269	-0.034	0.109	2.764	0.006
Patent2008	0.226	-0.034	0.109	2.382	0.017

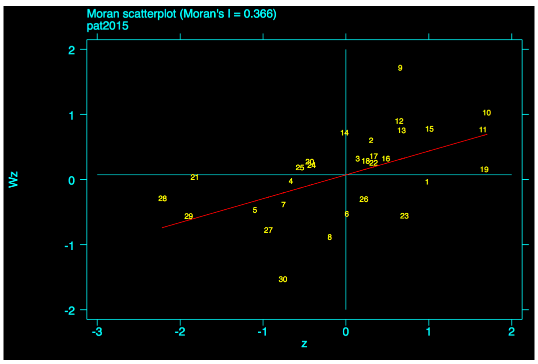
Then we can standardize the spatial weights matrix to form Moran scatter plot to see the spatial autocorrelation more clearly in Figure 4.



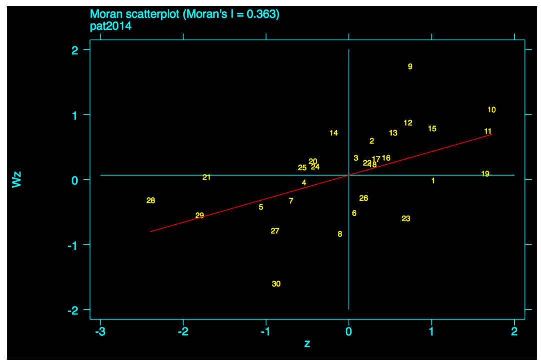
(a) patent2017



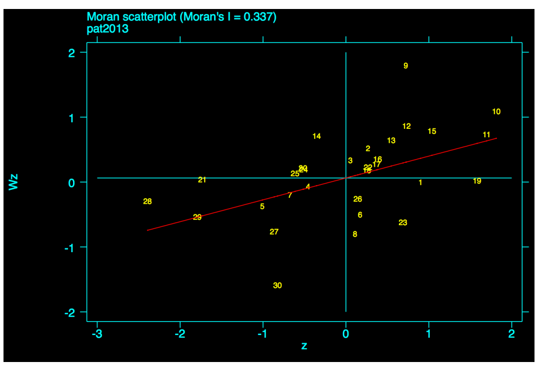
(b) patent2016



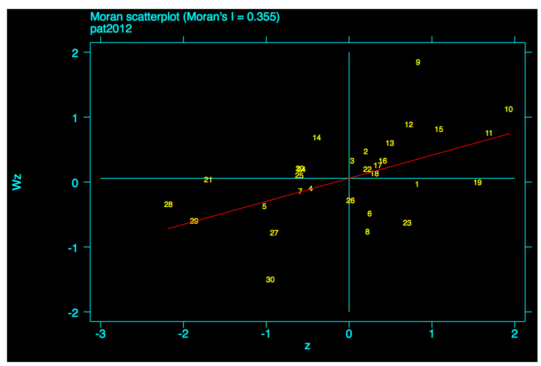
(c) patent2015



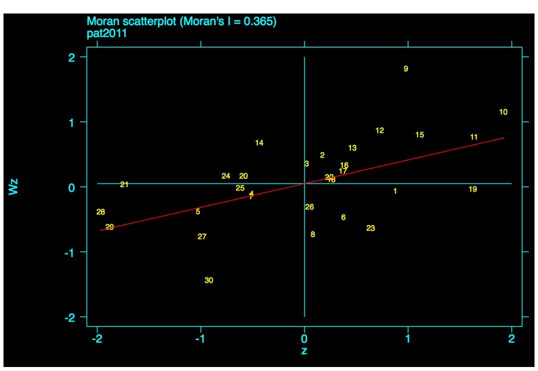
(d) patent2014



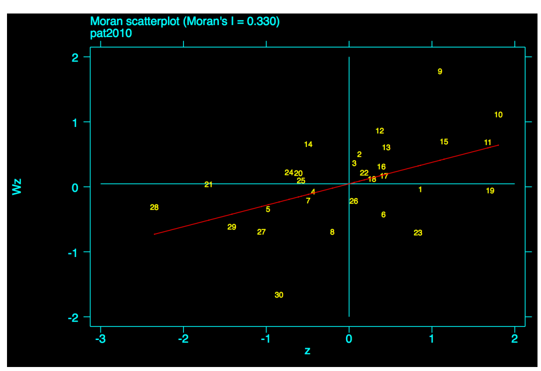
(e) patent2013



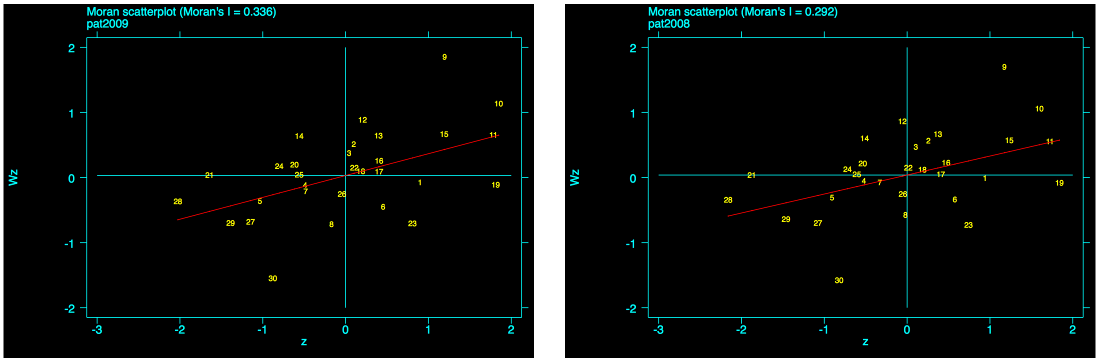
(f) patent2012



(g) patent2011



(h) patent2010



(i) patent2009 (j) patent2008

Figure 4: Moran Scatter Plot

4.3 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 3: 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 3, 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 general spatial panel–Spatial 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. The Wald statistics of the spatial lag model is 552.1884 (0.0000) and the spatial error model is 622.3739 (0.0000), which indicates that it is appropriate to select a more general spatial panel model on this basis. Besides, LeSage and Pace (2009) and Anselin (2010) also compare different spatial models in their papers. They assume that the original data satisfy the data generation process of SAR, SEM, SDM and SAC respectively and analyze 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 statistics 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.

4.4 Estimation Results

Table 4: Estimated Results

SDM with Random-effects			
	FDI		-0.031
Main	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<0.1, **p<0.05, ***p<0.001

The estimated result in Table 4 shows 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 both have significant positive effect on the regional innovation capability.

5 Conclusion

From the above estimates, it can be seen that FDI has no significant positive spillover effect on China's regional technological innovation and it is contrary to our expectations. This phenomenon may be explained by the following reasons: first, because foreign-funded enterprises have absolute technological advantages and they can take a larger share of the local market by virtue of this advantage. In this case, the living space of local enterprises is compressed and the domestic investment is squeezed out. So FDI can not produce a significant positive technology spillover effect. Secondly, in order to further obtain the monopoly profits, the acquisition and merger of local enterprises by foreign-funded enterprises may also result in the insufficient motivation for local enterprises to carry out technological innovation. Thirdly, in the special stage of market-oriented reform and economic transformation in China, inappropriate underestimation of the value of knowledge and technology may weaken the incentives for enterprises and individuals to carry out technological innovation. At the same time, due to the imperfection of relevant domestic regulation systems, it may become more difficult for domestic enterprises to learn advanced technology and innovate independently. Therefore, under such special socio-economic conditions, the technology spillover mechanism of FDI may be limited and thus can not produce significant positive technology spillover effect in China. Fourthly, the vast differences in natural conditions, human environment and economic development level among provinces in China may also be one of the main reasons for this phenomenon.

From the perspective of regional innovation environment, the regional openness, market competition and economic development level all have positive effects on the regional technological innovation, which is in line with our expectations. Because the expansion and deepening of opening-up can activate the trade between China and the leading innovative countries. Through trade channels, domestic enterprises can learn and absorb the advanced technology and management methods of these innovative countries and thus enhance their technological innovation ability. In addition, perfect market mechanism and competitive market environment also have a positive impact on technological innovation. At the same time, the level of regional economic development has a significant positive effect on technological innovation. The areas with higher level of economic development have relatively good infrastructure and numerous scientific research institutions in general, which provide good basic conditions for technological innovation.

From the perspective of regional absorptive capacity, regional R&D investment intensity and human capital both have significant positive effects on technological innovation, which conforms to our expectations. R&D investment, as a source of power for technological innovation, is generally considered to be an important guarantee to enhance the independent innovation capability of a country or region. At the same time, the empirical results show that the increase of human capital stock promotes the level of technological innovation. Human capital acts on technological innovation through the acquisition, digestion, transformation and utilization of knowledge.

6 Limitations and Future Work

Despite the practical contributions to current literature, we should acknowledge that there are some research limitations. First, as this paper shed light on drawing a large picture, it does not explore the specific channels for how the effects are yielded. In this vein, it will be interesting if future work could attempt to identify the mechanism or the path of how FDI acts on the regional innovation capability. Second, this paper uses the amount of patent authorization to represent the regional innovation capability and it may not be comprehensive enough. Future work could adopt more comprehensive methods such as using Data Envelopment Analysis (DEA) to calculate the regional innovation efficiency. Third, this paper mainly focuses on technological innovation at provincial level. Notice the serious regional imbalance, future work can try to study this problem from a larger regional scope such as the six geographic divisions.

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