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Effect of environmental regulation on the manufacturing FDI in China: spatial econometric studies

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Previous studies on the relationship between foreign direct investment (FDI) and environmental regulation have generally not considered the spatial characteristics. This paper applies spatial econometrics to explore whether or not environmental regulation inhibits the inflow of manufacturing FDI to China. Using a dataset across China's 29 provinces over the period from 2010 to 2015, we examined the spatial autocorrelation pattern about manufacturing FDI. We then used an improved spatial econometric model to explore the effect of environmental regulation on manufacturing FDI, incorporating other determinants of FDI, including the level of economic development, the degree of industrialization and the manufacturing labor cost. Our study reveals that manufacturing FDI exhibits clear spatial autocorrelation and regional agglomeration characteristics. Furthermore, the inhibitory effect of environmental regulation on manufacturing FDI inflow is gradually increasing with the passage of two stages, which confirms the "pollution shelter" hypothesis in China. We also find positive effects of the level of economic development and the industrialization degree on the manufacturing FDI inflow while, as expected, the manufacturing labor cost is found to be negatively correlated with FDI inflow.

Keywords: Environmental regulation, FDI, Spatial econometric models

INTRODUCTION

Foreign direct investment (FDI) is no doubt one of the important contributing factors to China's rapid economic growth. Attracted by the traditional comparative advantages of the Chinese economy, a staggering amount of foreign capital has continuously flowed to China's manufacturing sector each year. However, while China's manufacturing sector has been benefitted from tremendous infusion of FDI, the inflows of foreign capital also transferred pollution manufacturing into China, which has profound negative impact on China's ecological environment [1].

In the 1980s, China didn't impose essential environmental regulation measures to FDI. Consequently, the so-called "bottom competition" phenomenon in capital attraction resulted in increasingly serious environmental pollution. To prevent the environment from further worsening, Chinese central government and local governments have issued a series of environmental regulations since the 1990s, including raising the access threshold of FDI to manufacturing, closing down heavy polluting enterprises and reducing pollution sources. Meanwhile, heated debates and serious questions have been raised among researchers and policy makers regarding the issues surrounding environmental regulation and FDI, such as, whether or not the regional environmental regulation inhibits manufacturing FDI? Does the effect of environmental regulation on FDI exhibit regional differences?

In general, there are three views concerning the above questions. The first view states that environmental regulation has a negative effect on the inflow of manufacturing FDI [2-4]. The second view is that strict environmental regulation may not preclude the inflow of FDI or lead to regional industrial reset phenomenon, but could actually promote more inflow of FDI [5, 6]. The third middle-of-the-road view holds that the impact of environmental regulation on FDI inflows to various regions is uncertain [7, 8].

Despite the divergent views in the existing literatures concerning the effect of environmental regulation on FDI, we can still draw two common implications. First, environmental regulation can serve as a useful "filter" to screen out the "dirty" foreign capital, thereby improving the quality of FDI. So it is necessary to explore more deeply the broader statistical relationships among environmental regulation and FDI, as well as other determinants of FDI across regions and over years. Second, some spatial features that differ across regions may cause environmental regulations to exert different impacts on FDI. So it is necessary and more realistic to consider relevant spatial heterogeneity when exploring these variables' interrelationships [9]. Therefore, we apply a spatial

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econometric model to examine whether or not environmental regulation inhibits the manufacturing FDI inflow to China, hoping to provide more insights to the issues related to environmental regulation and foreign investments, and contribute to the literature in this field.

EXPERIMENTAL

Methods for spatial autocorrelation

We began our research by conducting spatial autocorrelation tests of manufacturing FDI. Spatial autocorrelation can be analyzed by two different methods: global spatial autocorrelation and local spatial association-LISA [10].

Global spatial autocorrelation is most extensively measured by Moran's I, which is defined as [11]:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \qquad (i \neq j) \tag{1}$$

where, $S^2 = \frac{1}{n}\sum_i (Y_i - \overline{Y})^2$, $\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$, W_{ij} is a matrix of spatial weights with zeroes on the diagonal terms, Y_i are the observed values of unit *i*, and *n* is the number of spatial units. Possible values of Moran's I range between 1 and -1. A Moran's I with value approaching 1 represents a situation in which similar values are clustered together, and a value near -1 represents a situation in which similar values repel one another [12].

The method outlined above provides summaries of global spatial pattern. However, there have been various adaptations to the standard approaches to allow assessment of local variation in spatial autocorrelation. Anselin defined a body of local indicators of spatial association (LISA) [9]. This study used Moran scatter plots (often mapped by Geoda based on each local Moran's I) and LISA cluster maps as indicators of the local spatial association. Local Moran's I is given as:

$$I_i = \frac{(Y_i - \overline{Y})}{S^2} \sum_{j=1}^{n} [W_{ij}(Y_j - \overline{Y})] \tag{2}$$

where I_i >0 indicates that unit i and its neighbors have strong positive spatial autocorrelation and agglomeration, while I_i <0 indicates that they have a negative correlation and discretization.

Protocols of estimating a spatial econometric model

In the standard linear regression model, spatial dependence can be incorporated in two alternative ways: the spatial lag model (SLM) and the spatial error model (SEM) [13].

Spatial lag model (SLM) is employed when there is a reason to postulate a direct effect on the dependent variable from neighboring locations [14]. SLM is expressed as:

$$Y = \rho WY + X\beta + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I) \tag{3}$$

where Y represents an $n\times1$ vector of dependent variables, X is an $n\times k$ matrix of explanatory variables, ρ is a spatial autoregressive coefficient, β is a $k\times1$ vector of the coefficients to be estimated, W is an $n\times n$ spatial weights matrix, and ε is an $n\times1$ vector of error terms.

Spatial Error Model (SEM) is adopted from a practical application where spatial autocorrelation is detected in the residuals of the typical linear regression model. In such case, SEM is used to obtain unbiased and efficient estimates of the regression parameters, and is expressed as:

$$Y = X\beta + \varepsilon, \varepsilon = \lambda W\varepsilon + \mu, \mu \sim N(0, \sigma^2 I) \tag{4}$$

where, λ is a spatial parameter similar to ρ in Equation (3) and all other notations are as previously defined.

Conditional on the specification of the intercept term (and the error term), the panel data regression equation can be estimated by either a fixed effect or a random effect model [15].

Generally, the model choice of either SLM or SEM is determined by Moran's I test statistics, two Lagrange multipliers (LM (error) and LM (lag)), and robust R-LM (error) and R-LM (lag). Anselin (2004) [16] proposed the following criterion: if the LM (lag) is statistically more significant than LM (error), and R-LM (lag) is significant but R-LM (error) is not significant, then SLM is considered to be a more suitable estimation model. Conversely, if the LM (error) is more notable than LM (lag), and R-LM (error) is significant but R-LM (lag) is not significant, then SEM is more suitable than SLM.

In addition to the above criterion for specification selection, other model selection criteria commonly used by the researchers are: Log Likelihood (logL), Akaike Information Criterion (AIC) and Schwartz Criterion (SC). In those cases, the larger LogL, the smaller SC and AIC test statistics, the better fitting the model would be.

Implementation of a spatial panel data model

Following the lead of Jaffe and Palmer (1997) [17], we measured environmental regulation (*Eregulation*) by the ratio of "three industrial wastes" (waste water, waste gas and solid waste) abatement expenditures to the total value of industrial output. We also added three more determinants of manufacturing FDI in our model: the level of economic development (*Elevel*, measured by *per capita* GDP in each province), the degree of industrialization (*Idegree*, measured by the province's total industrial output value) and the manufacturing labor cost (*Lcost*, measured by the average wage of manufacturing workers in this province). We then estimated the following improved spatial panel data model:

$$\ln FDI_{it} = \alpha_{it} + \beta_{1t} Eregulation_{it} + \beta_{2t} \ln Elevel_{it} + \beta_{3t} Idegree_{it} + \beta_{4t} \ln Lcost_{it} + \mu_{it} \quad (5)$$

In this equation, i denotes province i, t stands for the period or stage (1,2), $\ln FDI_{it}$, $Eregulation_{it}$, $\ln Elevel_{it}$, $Idegree_{it}$ and $\ln Lcost_{it}$ represent the manufacturing FDI, the extent of environmental regulation, the level of economic development, the degree of industrialization and the manufacturing labor cost of province i at t stage, respectively. β_{1t} to β_{4t} are the coefficients associated with the respective FDI determinants, α_{it} and μ_{it} are the constant term and random error term.

Raw data

This paper collected and used annual data from 29 provinces except Hainan, Tibet, Hong Kong, Taiwan, and Macao (due to the large amount of missing data) over the years from 2010 to 2015. The FDI in each province was measured by the actual amount of manufacturing FDI (unit: RMB'0000), and the data were collected from the 2011-2016 China Statistical Yearbook and the CEINET. In order to reflect the temporal and spatial characteristics of manufacturing FDI, we divided the studying years into two stages: the first stage (2010-2012) and the second stage (2013-2015). We took the average value of every observation in the sample in each stage in the empirical analysis.

RESULTS AND DISCUSSION

Global spatial autocorrelation of manufacturing FDI

We analyzed the global spatial correlation of FDI in China's provincial manufacturing by the matrix W based on binary Rook contiguity weight. The results are shown in Table 1.

Table 1. Global Moran's I indices of China's provincial manufacturing industry from 2010 to 2015

Stage	Moran's I	Average	SE	z	P
2010-2012	0.508	-0.035	0.119	4.578	0.001
2013-2015	0.526	-0.036	0.126	4.483	0.001

As can be seen from Table 1, the global Moran's I indices in the two stages are positive and the P-values are all significant at 1% level. So they indicate that the manufacturing FDI in these provinces have positive spatial correlation and exhibit agglomeration characteristics.

We further used the Monte Carlo simulation method to test the significance of Moran's I. The results of 999 times simulation arrangements calculations are shown in Figures 1 and 2.

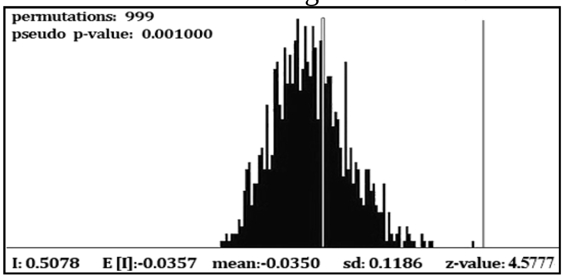

Fig. 1. Monte Carlo simulation results of China's provincial manufacturing FDI from 2010 to 2012

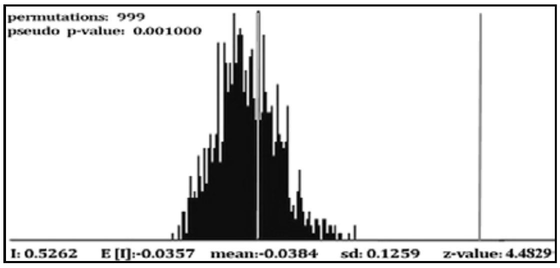

Fig. 2. Monte Carlo simulation results of China's provincial manufacturing FDI from 2013 to 2015

Local spatial association of manufacturing FDI by Moran scatter plots

Given that the local spatial correlation of provincial manufacturing FDI and the trend of local spatial agglomeration cannot be characterized by the global Moran's I indices, we applied the local index cluster analysis method, by the Moran scatter plots and LISA cluster maps, to further reveal the local spatial characteristics of manufacturing FDI. The Moran scatter plots analyses of the two stages are shown in Figures 3 and 4.

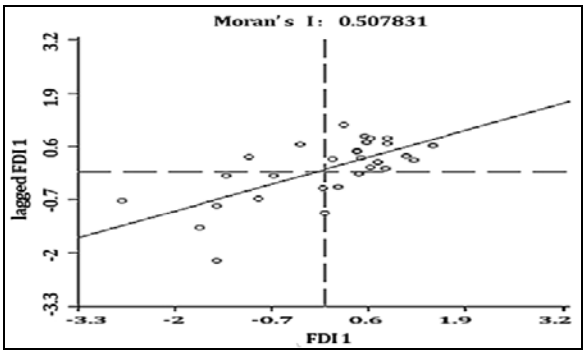

Fig. 3. Moran scatter plots of China's provincial manufacturing FDI from 2010 to 2012

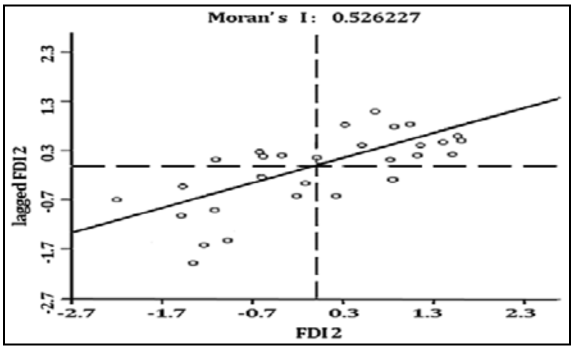

Fig. 4. Moran scatter plots of China's provincial manufacturing FDI from 2013 to 2015

As can be seen from Figures 3 and 4, most provinces fall in the first and third quadrants, rejecting the assumption that manufacturing FDI is spatially distributed in a random fashion, and indicating that there is a positive correlation of FDI among different geographical or spatial units. That is, the amount of manufacturing FDI inflows tends to be close to other provinces with the similar FDI amounts. It is interesting to note that this local spatial pattern of FDI is the same as the results presented from the global spatial autocorrelation.

Local spatial association of manufacturing FDI by LISA cluster maps

LISA cluster maps were drawn to further illustrate the above local spatial characteristics, as shown in Figures 5 and 6.

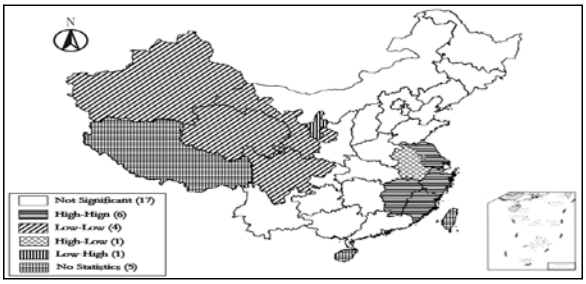

Fig. 5. LISA cluster map China's provincial manufacturing FDI from 2010 to 2012

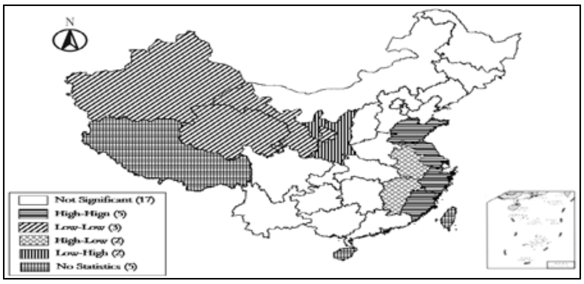

Fig. 6. LISA cluster map China's provincial manufacturing FDI from 2013 to 2015

We can see from the above figures that China's provincial FDI manufacturing is decreasing from the eastern to western regions. Specifically, Shanghai, Fujian and Zhejiang are all located in the H-H cluster regions in two stages. Whereas the western provinces of Xinjiang, Qinghai and Gansu are in the L-L cluster regions, which indicates that the amount of manufacturing FDI flowed into these provinces and their neighbors is less than that of eastern provinces. These distinctively different spatial characteristics of FDI further confirmed that we need to use the spatial econometric model to investigate the relationship between manufacturing FDI and its influence factors.

Baseline estimation results from Ordinary Least Squares (OLS)

For comparison purpose, we first estimated Equation (5) based on OLS by software OpenGeoDa. The OLS baseline estimation results are displayed in Table 2. It shows that the OLS estimation model is significant at 1% level in both stages, with adjusted R square of 78.16% and 77.30%, and F value of 26.0462 and 30.0060, respectively. However, the spatial correlation test results in the preceding section already showed that manufacturing FDI clearly exhibits a spatial correlation pattern, which will cause the simple OLS estimators to be bias and inconsistent. Therefore, we need to further estimate the relationship between these variables by spatial econometric models.

Spatial econometric estimation based on SLM

As can be seen from Table 2, the Moran's I indices and the two Lagrangian multipliers are all significant at the 5% level in the two stages, indicating the presence of spatial autocorrelation and the need to estimate spatial econometric models. Then, the question arises: which spatial econometric model is more suitable for our purpose here? Applying the criteria mentioned above, we can answer that the statistical properties of the SLM model are relatively more appropriate in analyzing the relationship between these variables from Table 2. For the purpose of comparison, we estimated Equation (5) with both SLM and SEM specifications. The results are shown in Table 3. Comparing Tables 2 and 3, we can see that the goodness-of-fit statistics by SLM and SEM are higher than those by OLS. In addition, the logL values of SLM in the two stages are larger than the corresponding values of OLS and SEM. Thus, the classical linear regression model based on OLS is not suitable to analyze manufacturing FDI as it does not consider the spatial autocorrelation.

Table 2. OLS estimation results

Variable	2010-2012				Variable	2013-2015			
	Coefficient	SE	t	P		Coefficient	SE	t	P
constant	41.4198	12.8241	3.2298	0.0036	constant	32.0112	11.7263	4.0611	0.0021
E*regulation*$_1$	-6.3448	1.2507	-5.0728	0.0000	E*regulation*$_2$	-7.0609	2.3140	-6.8126	0.0000
ln*Elevel*$_1$	1.4186	0.6969	2.0357	0.0530	ln*Elevel*$_2$	3.5061	0.7211	2.0857	0.0482
Idegree$_1$	0.1613	0.0682	2.3647	0.0265	*Idegree*$_2$	1.1232	0.0968	3.2323	0.0031
ln*Lcost*$_1$	-3.1134	1.6496	-1.8874	0.0713	ln*Lcost*$_2$	-2.9266	1.2434	-2.1008	0.0496
R^2adj	0.7816				R^2adj	0.7730			
F-statistic	26.0462			1.9954e-0	F-statistic	30.0060			2.0432e-0
*Log*L	-34.3096				*Log*L	-36.4724			
AIC	78.6192				AIC	89.2938			
SC	85.4557				SC	97.5309			
Spatial test	MI/DF	Value	P		Spatial test	MI/DF	Value	P	
Moran's I (error)	0.1041	1.6159	0.0361		Moran's I	0.1982	2.6202	0.0059	
LM(lag)	1	4.8934	0.0270		LM(lag)	1	7.2964	0.0043	
R- LM (lag)	1	4.4409	0.0351		R- LM (lag)	1	6.5732	0.0169	
LM (error)	1	0.6257	0.4290		LM (error)	1	0.7181	0.3962	
R-LM (error)	1	0.1731	0.6773		R-LM (error)	1	0.2023	0.5781	

Table 3. SLM and SEM estimation results

Stage	Variable	SLM				SEM			
		Coefficient	SE	Z	P	Coefficient	SE	Z	P
2010-2012	Constant	35.5243	10.7869	3.2933	0.0010	36.1401	11.6301	3.1075	0.0019
	E*regulation*$_1$	-5.5910	1.0765	-5.1935	0.0000	-5.6231	1.1252	-4.9972	0.0000
	ln*Elevel*$_1$	1.1978	0.5879	2.0376	0.0416	1.3243	0.6539	2.0254	0.0428
	Idegree$_1$	0.1416	0.0582	2.4352	0.0149	0.1663	0.0609	2.7303	0.0063
	ln*Lcost*$_1$	-2.9103	1.3748	-2.1168	0.0343	-2.5353	1.4878	-1.7041	0.0884
	ρ/λ	0.2608	0.1215	2.1461	0.0319	0.3086	0.1345	1.3746	0.1693
	Statistical	DF	Value	P		DF	Value	P	
	R-squared		0.8429				0.8235		
	LogL		-32.0044				-33.8028		
	LR	1	4.6105	0.0008		1	1.0136	0.3140	
	AIC		76.0087				77.6056		
	SC		84.2125				84.4421		
2013-2015	Constant	42.3928	12.6731	4.0911	0.0007	37.3831	11.9029	3.9820	0.0009
	E*regulation*$_2$	-5.6256	1.9033	-3.5009	0.0012	-3.5476	1.5324	-4.7620	0.0001
	ln*Elevel*$_2$	1.0197	0.4709	2.5866	0.0173	1.9831	0.5839	2.9304	0.0078
	Idegree$_2$	0.1307	0.1223	3.1034	0.0038	0.1243	0.1128	2.6677	0.0120
	ln*Lcost*$_2$	-3.8671	1.6685	-1.1056	0.0264	-3.3229	1.4661	-1.6252	0.1082
	ρ/λ	0.3719	0.1469	3.1231	0.0025	0.4165	0.1672	3.5328	0.0014
	Statistical	DF	Value	P		DF	Value	P	
	R-squared		0.7834				0.7529		
	LogL		-37.0623				-39.2788		
	LR	1	4.9238	0.0018		1	2.6707	0.0105	
	AIC		79.4313				87.0269		
	SC		80.8226				89.5217		

Furthermore, comparing the values of logL, LR, AIC and SC statistics, SLM clearly performs better than SEM, hence most of the discussion and interpretation of the estimation results in the following section are based on SLM results.

We also obtained four empirical results based on SLM model as follows: First, environmental regulation has a significant negative impact on FDI in both two stages. From Table 3, we can see that the impacts in the two stages are statistically significant at a 1% level. Also, the values of the coefficient estimates for this variable imply that a 1% rise in environmental regulation intensity can inhibit FDI inflow by around 5.5910% and 5.6256%, respectively. The inhibitory effect of environmental regulation on the inflow of manufacturing FDI is increasing over the two stages. This could be because more stringent environmental regulations were implemented from 2012 to 2015 in China, especially those against foreign capital investments in some pollution intensive manufacturing industries. As a result, environmental regulation gradually became an important negative determinant (inhibitor) of FDI inflows. Meanwhile, compared with the results of OLS in Table 2, the inhibiting effects estimated by the SLM model are weakened. This suggests that when considering the spatial lag effect, the environmental regulation of neighboring provinces can dilute the inhibitory effects of environmental regulation on manufacturing FDI in the provinces under study.

Second, the economic development level and industrialization degree variables have positive significant impacts on the manufacturing FDI inflow. From Table 3 we can see that the positive effect of economic development level on manufacturing FDI is statistically significant at 5% in two stages, and that a 1% increase in economic development level significantly promotes the FDI inflow by around 1.1978% and 1.0197%. The provincial degree of industrialization also has a positive effect at the 5% and 1% significance level respectively, and the FDI inflow increases by 0.1416% and 0.1307% following a 1% increase in industrialization level. Comparing the magnitude of the coefficient estimates for the two stages, we can also find that the impacts of these two factors on manufacturing FDI showed a downward trend, indicating that foreign investment in China's manufacturing is less and less impacted over time by the level of economic development and the degree of industrialization. This finding corroborates with the recent phenomenon that many foreign capitals are transferred (relocated) from the more developed and industrialized eastern provinces of China to the central and western provinces.

Finally, turning to the manufacturing labor cost variable, it appears that labor cost has a statistically significant negative impact on manufacturing FDI inflow at the 5% significance level in both stages. The value of the coefficient estimates indicates that a 1% increase in the labor cost significantly inhibits the FDI inflow by around 2.9103% and 3.8671% respectively. Evidently, China's main comparative advantage in attracting FDI still lies in the low labor cost in these two stages. As a result, most FDI is still concentrated in China's labor-intensive industries, which are at the lower end of the global industrial chain.

CONCLUSIONS

This study investigates the relationship between manufacturing FDI and environmental regulation, along with other relevant FDI determinants, using the spatial econometric models over the period from 2010 to 2015. Overall, we found that manufacturing FDI exhibits clear spatial autocorrelation and regional agglomeration characteristics. We also found a statistically significant negative relationship between environmental regulation and manufacturing FDI in China's 29 provinces. This finding implies that imposing more stringent environmental regulations would inhibit the manufacturing FDI. It was also found that the inhibitory effect is gradually increasing during the 2010-2015 study period. Furthermore, the level of economic development and degree of industrialization in a province are positively related to the inflow of manufacturing FDI when we consider the spatial correlations. But the positive effect is decreasing in the two stages. Finally, there is a statistically significant negative correlation between labor costs and manufacturing FDI inflows.

In summary, the foreign direct investment is inhibited by the environmental regulation in China in this six-year period. Other factors, such as factor prices, regional climate, and available market, have also be proved to be key determinants in the foreign capital inflowing decisions[4]. So we anticipate inducing these factors into our further research about this issue.

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