Journal of Research in Business, Economics and Management (JRBEM)
ISSN: 2395-2210

SCITECH RESEARCH ORGANISATION

Volume 10, Issue 3
March 7, 2018

Journal of Research in Business, Economics and Management
www.scitecresearch.com

Research on the Non-linear Relationship between Inter-Regional Industrial Transfer and Technological Innovation Ability of the Western Region

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Abstract

Based on the panel data of 11 provinces and autonomous regions in 2000-2015 in western region, this paper studies the non-linear relationship between inter-regional industrial transfer and technological innovation capability by using panel smoothing transformation (PSTR) model. Different from the existing research, this paper chooses variables such as the urbanization, human capital, economic openness and the technological gap between enterprises in the eastern, middle and western regions as the conversion variables. It is found that there is a single threshold for the above conversion variables. With the continuous increase of the level of the conversion variables, there is a smooth transition mechanism between inter-regional industries and technological innovation. The results show that all of the transitional variables have single thresholds respectively, and inter-regional industrial transfer has a positive impact on regional technology innovation capability when the transitional variables exceed their thresholds and PSTR models tend to high regime.

Keywords： Inter-Region Industry Transfer; Innovation Capability; PSTR Model; Chinese Western Region.

1. Introduction

Due to the long period of high-speed development, the eastern part of our country is facing the problem of rising factor costs and shortage of resources. In addition, in order to realize the rational flow of production factors and optimal allocation of resources in China, he government also actively encourages the industry in the eastern region to transfer to the western region at the macro level. According to the statistics of this paper, in 2000, the western provinces utilized 48.2 billion yuan of funds from all the provinces in the country, and in 2015 that figure rose to 6080.7 billion yuan. With the expansion of the scale of industrial transfer, the spillover of technological knowledge associated with the industrial transfer between the eastern and western regions has also boosted the innovation capability in the western region. In 2000, there were 16,353 patent applications in the western region, and the number in 2015 was up to 390,729. However, during this process we found that there is a big difference in the effect of innovation in the western region benefiting from the industrial transfer in the east. For example, Inner Mongolia received 351.4 billion yuan of industrial transfer capital, but the number of patent applications in the district was only 4,732, and the R&D investment of the region is as high as 8.6 billion yuan. Corresponding to this, Xinjiang received 220.2 billion yuan of industrial capital in 2012, which is lower than Inner Mongolia, but the number of patent applications in the area is 7044, which is more than that in Inner Mongolia, and its R&D investment in the area is also less than that in Inner Mongolia, which is 2.7 billion yuan. Inter-regional industrial transfer can promote the improvement of innovation capability in the western region. However, the technological spillover caused by this industrial transfer is not unconditional for the promotion of innovation in the western region. It is also affected by the absorptive capacity and the socio-economic environment influences in the western region. This paper first reviews the literature on industrial transfer and regional technological innovation and puts forward the research hypothesis. Secondly, the panel smoothing transformation model (PSTR) proposed by

González (2005) was used to test the impact of the industrial transfer on the innovation capability in the western region and its restriction condition. This empirical analysis uses four absorptive factors as threshold variables including the level of urbanization, human capital, economic openness and technology gap. Finally, a number of policy recommendations are proposed according to the results of empirical research.

2. Literature Review and Research Hypotheses

The foreign scholars have earlier studied the relationship between industrial transfer and the technological innovation of the undertaking region. Krugman (1991) thought that industrial transfer can form industry agglomeration, which was conducive to promoting the communication among industry manufacturers, accelerating the dissemination of knowledge, and improving the speed of innovation. Thangavelu and Pattnayak (2011) used Indian firm data to found that FDI had a negative back-spillover effect due to the large technology gap between domestic and foreign firms. Du (2012) used 1998-2007 years of industrial data in China to found that foreign industrial transfer had produced obvious technical spillover effects through the forward and backward correlation. Damijan et al. (2012) conducted a study of 10 economies in transition and found that absorptive capacity was an important factor affecting the technology spillover effect. Suyanto and Salim (2013) found that foreign industrial transfer had a positive spillover effect on Indonesia. Zhang G Z et al. (2015) used the data of Hunan Province from 2004 to 2011 to analyze the independent innovation effect of inter-regional industrial transfer. The conclusion is that inter regional industrial transfer has significant spillover effects on Hunan regions.

According to the literature, we find that the current research methods about the relationship between industrial transfer and the innovation ability are based on linear hypothesis. As a result of neglecting the nonlinear relationship caused by the threshold effect, these scholars have got different conclusions. In view of this, this paper analyzes the conditional mechanism of regional industrial transfer on the innovation effect of the region, especially the regulating effect of absorption capacity on the relationship between the two regions. According to the relevant literature, this paper uses the level of urbanization, human capital, economic openness and technology gap as substitution variables for absorptive capacity. At the same time, the panel smooth transition model (PSTR) proposed by González (2005) is used to empirically test the non-linear relationship between inter-regional industrial transfer and technological innovation undertaken, and to supplement existing research.

Based on this, the research hypothesis proposed in this paper is that the relationship between inter-regional industrial transfer and technological innovation is non-linear. And the relationship shows heterogeneity due to the differences in urbanization level, human capital, degree of opening to the outside world and technological gap.

3. Models, Variables and Data

3.1 Panel Smooth Transition Regression Model

In order to verify the nonlinear relationship between explained variables and explanatory variables, this paper adopts the panel smoothing model proposed by Gonzalez et al. Compared with the panel threshold regression model, the advantage of the PSTR model is that the regression coefficient can make continuous smooth nonlinear changes near the threshold without sudden changes, which is more in line with the reality. Therefore, this model is also increasingly popular among scholars. The basic two-system panel smooth transition regression model is as follows:

$$y_{it} = \mu_i + \beta_0 \chi_{it} + \beta_1 \chi_{it} g(q_{it};\gamma,c) + \varepsilon_{it} \quad i = 1,2,\cdots,N \quad t = 1,2,\cdots,T \tag{1}$$

The conversion function $g(q_{it};\gamma,c)$ is a continuous function about q_{it} ,which is between 0 and 1. q_{it} is the transformation variable or threshold variable. γ is the slope coefficient also known as smoothing parameters, which represents the conversion rate from one region to another. c is the position parameter or threshold parameter, and $\varepsilon_{\mathrm{it}}$ is the random disturbance term.

In general, the transformation function $g(q_{it};\gamma,c)$ is set to the following form of Logistic function:

$$g(q_{it};\gamma,c) = [1 + \exp(-\gamma \prod_{j=1}^{m} (q_{it} - c_j))]^{-1}$$

Among them, the number of position parameters is represented by m. If m=1, the model (1) corresponding to the transformation function $g(q_{it};\gamma,c) = 0$ is called the low zone system; the model (1) corresponding to the transfer function $g(q_{it};\gamma,\mathrm{c}) = 1$ is called the high zone system. The value of $g(q_{it};\gamma,c)$ varies smoothly from 0 to 1, which shows that the model (1) will be transformed smoothly between the high-regime and the low-regime based on the position parameter c.

Before estimating the parameters, it is necessary to examine whether there is a nonlinear transition effect in the model. The original hypothesis is $H_0 : \mathrm{r} = 0$ and the alternative hypothesis is $H_1 : \mathrm{r} = 1$.Since the unknown parameter c exists in the model (1), the traditional method can't be used to test the model. For this purpose, the first-order Taylor expansion of the transfer function in the model (1) is performed at $\gamma = 0$, and then the following auxiliary regression model is obtained:

$$y_{it} = \mu_i + \beta_0^* \chi_{it} + \beta_1^* \chi_{it} q_{it} + \cdots + \beta_m^* \chi_{it} q_{it}^m + \varepsilon_{it}^* \qquad (2)$$

Among them, $\varepsilon_{\mathrm{it}}^* = \varepsilon_{it} + R_m \beta_1 \chi_{it}$, R_m is the remainder of Taylor's expansion.

The original hypothesis $H_0 : r = 0$ in the test model (1) is equivalent to $H_0 : \beta_1^* = \cdots = \beta_m^* = 0$ in the test model (2). Therefore, two statistics are constructed at the same time:

$$LM = \frac{TN\left(SSR_0 - SSR_1\right)}{SSR_0} \quad LM_F = \frac{\left(SSR_0 - SSR_1\right)}{SSR_1 / (TN - N - 1)}$$

Among them, SSR_0 and SSR_1 respectively represent the sum of squares of residuals under the conditions of the original hypothesis and the alternative hypothesis. If the null hypothesis is rejected in the nonlinear test, the residual nonlinearity test is needed to determine whether there is a single conversion function or two conversion functions. The residual nonlinear effect test is similar to the former method. First, a second-order Taylor expansion of the second transfer function is performed to construct an auxiliary regression model and calculate the corresponding LM and LM_F statistic values. If the original hypothesis H_0 is still unable to be rejected, the residual nonlinear test is continued by analogy until the original hypothesis H_0 can't be rejected. In general, the number of conversion functions is 1 or 2. The general multi-system panel smooth transition model is as follows:

$$y_{it} = \mu_i + \beta_0 \chi_{it} + \beta_{\mathrm{j}} \chi_{it} g(q_{it}; \gamma, c) + \varepsilon_{it} \quad i = 1,2,\cdots,N \quad t = 1,2,\cdots,T \quad j = 1,2,\cdots,r \qquad (3)$$

Nonlinear least square method is mainly used to estimate the parameters of the panel smoothing regression model. Because the nonlinear least square estimation is an iterative operation from the initial value of the position parameter c and the smooth parameter γ, it is necessary to use the grid search method to determine the initial value first.

According to the literature review, this paper selects the level of urbanization (urb), the level of human capital(hum), economic openness (ope) and technology gap (tgap) as transformation variables to construct the following four econometric models. All original data in the model are in logarithmic form to eliminate possible heteroscedasticity of the data.

$$\ln n_{it} = \mu_i + \alpha_0 \ln r\&d_{it} + \alpha_1 \ln fdi_{it} + \beta_0 \ln tr_{it} + \beta_1 \ln tr_{it} * g(\ln urb_{it}; \gamma_j, c_j) + \varepsilon_{it} \qquad (4)$$

$$\ln n_{it} = \mu_i + \alpha_0 \ln r\&d_{it} + \alpha_1 \ln fdi_{it} + \beta_0 \ln tr_{it} + \beta_1 \ln tr_{it} * g(\ln hum_{it}; \gamma_j, c_j) + \varepsilon_{it} \qquad (5)$$

$$\ln n_{it} = \mu_i + \alpha_0 \ln r\&d_{it} + \alpha_1 \ln fdi_{it} + \beta_0 \ln tr_{it} + \beta_1 \ln tr_{it} * g(\ln ope_{it}; \gamma_j, c_j) + \varepsilon_{it} \qquad (6)$$

$$\ln n_{it} = \mu_i + \alpha_0 \ln r\&d_{it} + \alpha_1 \ln fdi_{it} + \beta_0 \ln tr_{it} + \beta_1 \ln tr_{it} * g(\ln tgap_{it}; \gamma_j, c_j) + \varepsilon_{it} \qquad (7)$$

Among them, n_{it} is the explanatory variable, which represents the technological innovation capability of China's i area in t; tr_{it} is the main explanatory variable, which represents the inter-regional industrial transfer of China's i area in t; $r\&d_{it}$ (research and development investment) and fdi_{it} (foreign investment) are control variables; g is the transformation function; μ_i is non-observed individual effect; ε_{it} is the random disturbance term.

3.2 Data Samples and Variable Selection

3.2.1 Data Sources

This paper adopts panel data from 11 provinces (including Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Guangxi, Ningxia, Xinjiang and Inner Mongolia) from 2000 to 2015. The original data are from China

Statistical Yearbook (2001-2016),China Science and Technology Statistics Yearbook (2001-2016) and Provincial Annual Database of the National Bureau of Statistics website. In addition, the inter-regional industrial transfer data is from the relevant provinces' government work report and statistical bulletin from 2000 to 2016.

3.2.2 Variable Selection

The explained variable: Technical innovation capacity (n) is expressed by technological innovation output. This paper chooses the number of patent application to measure technological innovation based on the following two reasons: First, there is a lag time between patent application and authorization, and the amount of patent application can reflect the true level of innovation more than the amount of authorization. Second, the patent authorization may be influenced by external factors such as government patent agency, and it is liable to abnormal changes. In addition, the number of patent applications and the number of patent licenses is generally positively related. Therefore, the number of patent applications as proxy indicators can more reflect the changes in technological innovation ability.

The explanatory variable: the transfer of interregional industry (tr) is represented by the introduction of foreign capital in provinces (regions). Thus we use the fixed asset price index in 2000 as the base period to deflate the data respectively.

Conversion variables: (1)The level of urbanization(urb): It can be expressed as the proportion of urban population to the total population in each region.(2)The level of human capital(hum): it is measured by the years of per capita education. The formula is as follows: the proportion of primary school education personnel*6+ the proportion of junior senior high school education personnel*9+ the proportion of senior high school education personnel*12+ the proportion of college or higher education personnel*16. (3) Economic openness (ope): It is expressed as the ratio of the total imports and exports to the GDP of various regions.(4) Technical gap (tgap): It is expressed as the ratio of the labor productivity of industrial enterprises above designated size in the western provinces to the average labor productivity of industrial enterprises above the designated size in the central and eastern provinces.

Control variables: In addition to the technological spillover effects of industrial transfer, the innovation output of the region is also directly affected by its own r&d investment (r&d) and foreign direct investment (fdi). Therefore, this paper introduces the internal expenditure of r&d funds and the actual utilized fdi in each region as control variables, and uses the fixed asset price index in 2000 as the base period to deflate the data respectively.

3.3 Empirical Results and Analysis

3.3.1 Test of Smoothness of Panel Data

In order to avoid pseudo regression in the model, we use the three methods of LLC, IPS and Breit to test the stability of each variable data. The test results are shown in Table 1. For the horizontal sequence of each variable, most of the test results are not stable. For the first order difference sequence of each variable, the result of the test is shown as a stationary sequence, that is, there is no unit root and all variables are first-order smoothing sequences. Further, in order to determine whether there is a cointegration relationship between variables, the Kao test based on the E-G two step method can be used. The specific test results are shown in Table 2. The results show that the original hypothesis that there is no co-integration relationship between variables is significantly rejected at the 1% level, and the model can be established for regression analysis.

Table 1:Unit Root Test of Panel Data

Variable	LLC test		IPS test		Breit test	
	Horizontal sequence	First order difference sequence	Horizontal sequence	First order difference sequence	Horizontal sequence	First order difference sequence
lnn	16.298	-7.169***	8.833	-5.371***	1.942	-4.454***
	(1.000)	(0.000)	(1.000)	(0.000)	(0.974)	(0.000)
lntr	5.743	-4.075***	3.479	-3.063***	5.242	-2.704***
	(1.000)	(0.000)	(1.000)	(0.001)	(1.000)	(0.003)
lnr&d	8.085	-7.896***	3.650	-3.631***	3.560	-2.988***

	(1.000)	(0.000)	(0.999)	(0.000)	(1.000)	(0.001)
lnfdi	8.937	-5.460***	1.796	-5.457***	3.560	-2.988***
	(1.000)	(0.000)	(0.964)	(0.000)	(1.000)	(0.001)
lnurb	-25.546***	-7.687***	1.583	-6.101***	1.980	-5.994***
	(0.000)	(0.000)	(0.943)	(0.000)	(0.976)	(0.000)
lnhum	6.797	-11.837***	-0.592	-10.847***	-1.715**	-5.368***
	(1.000)	(0.000)	(0.277)	(0.000)	(0.043)	(0.000)
lnope	-1.797**	-8.787***	0.892	-5.063***	1.696	-2.332**
	(0.036)	(0.000)	(0.813)	(0.000)	(0.955)	(0.010)
lntgap	-7.548***	-7.973***	5.221	-7.622***	2.185	-1.288*
	(0.000)	(0.000)	(1.000)	(0.000)	(0.986)	(0.099)
Note: the value in brackets is the corresponding p value; ***, *** and * respectively represent a significant level of 1%, 5%, and 10%.						

Table 2: Kao Test of Panel Data			
Testing method	Hypothesis testing	Statistics	Statistical value
Kao test	H_0: There is no co-integration relationship.	ADF	-2.432（0.008）***
Note: the value in brackets is the corresponding p value; ***, *** and * respectively represent a significant level of 1%, 5%, and 10%.			

3.3.2 Nonlinear Test of Panel Data

Using the practice of Lee and Liu, the nonlinear effects of the above models are tested by constructing LM and LM_F statistics. The results are shown in Table 3. The test statistic of model (4) to model (7) all reject the null hypothesis at 1% significance level, that is to say, there is a nonlinear relationship between the variables, and the threshold effect of the four conversion variables exists. It proves the feasibility of using panel smoothing regression model in this paper. Then the number of optimal conversion functions of the model (4), (5), (6) and (7) is determined by the residual nonlinear test.

Table 3: Results of Nonlinear Test and Residual Nonlinear Test				
Conversion variable	Nonlinear test H_0: r=0;H_1:r=1		Residual nonlinear test H_0: r=1;H_1:r=2	
	LM	LM_F	LM	LM_F
lnurb	63.398***	92.336***	0.017	0.016
	(0.000)	(0.000)	(0.895)	(0.900)
lnhum	48.794***	62.908***	0.005	0.004

	(0.000)	(0.000)	(0.946)	(0.949)
lnope	5.501**	5.291**	0.003	0.003
	(0.019)	(0.023)	(0.955)	(0.957)
lntgap	22.140***	23.599***	0.895	0.818
	(0.000)	(0.000)	(0.344)	(0.367)
Note: the value in brackets is the corresponding p value; ***, *** and * respectively represent a significant level of 1%, 5%, and 10%.				

3.3.3 Determination of the Number of Position Parameters

On the basis of determining the number of conversion functions, the number of position parameters m is also needed to be tested. According to Granger and Terasvirta's method, the AIC and BIC values corresponding to each model are calculated under the condition that the number of conversion functions is 1. According to the minimum rules of AIC and BIC, the optimal number of position parameters is selected. The test results are shown in Table 4. For models (4), (5) and (6), the values of AIC and BIC when m = 1 are both less than the values when m = 2, so that the number of location parameters is 1. For model (7), the BIC value of m=1 is less than the value of m=2, but the value of AIC is greater than m=2, and Colletaz and Hurlin(2008) believe that the less system can fully reflect the characteristics of the PSTR model. Therefore, the position parameters of the model (7) are determined to be 1.

Table 4: Determination of the Number of Position Parameters

Conversion variable	The number of location parameters	AIC	BIC
lnurb	m=1	-2.572	-2.464
	m=2	-2.563	-2.437
lnhum	m=1	-2.399	-2.291
	m=2	-2.388	-2.262
lnope	m=1	-2.105	-1.997
	m=2	-2.093	-1.968
lntgap	m=1	-2.479	-2.371
	m=2	-2.501	-2.375

3.3.4 Analysis of the Empirical Results

The nonlinear least squares estimation of the parameters in the model is carried out, and the results are shown in Table 5.

Table 5: The Results of PSTR Model Estimation

	Variable	Coefficient	(4)	(5)	(6)	(7)
Linear estimation	lnr&d	α_0	-0.590	0.939	2.095	0.111
			(0.597)	(0.431)	(0.128)	(0.924)
	Lnfdi	α_1	2.345**	1.564	2.040	2.418**
			(0.035)	(0.195)	(0.148)	(0.038)
	Lntr	β_0	-0.107**	-0.010	0.173***	-0.451***
			(0.018)	(0.818)	(0.000)	(0.000)
Nonlinear estimation	Lntr	β_1	0.533***	0.450***	0.049***	0.812***
			(0.000)	(0.000)	(0.001)	(0.000)
Conversion slope parameter	γ		4.039	7.009	28.001	3.848
Location parameter	c		-0.883	2.128	-1.918	-1.343
Determination Coefficient	R^2		0.924	0.909	0.878	0.916
Akaike Criteria	AIC		-2.572	-2.399	-2.105	-2.479
Bias rule	BIC		-2.464	-2.291	-1.997	-2.370

Note: the value in brackets is the corresponding p value; ***, *** and * respectively represent a significant level of 1%, 5%, and 10%.

The empirical research shows that model (4) and models (7) both Chinese and foreign direct investment significantly improve the innovation ability in the western region, while foreign direct investment in model (5) and model (6) has no significant connection with the innovation capability in the western region. The research and development input of all four metrology models in the western region has not significantly increased its innovation output., which further indicates that innovation is highly uncertain, and there is no direct relationship between the research and development input and innovation output. However, the results of the nonlinear test part of β_1 in the four models are all significant, which preliminarily validates the research hypotheses proposed in this paper. Here's a detailed explanation of it:

(1) The relationship between the level of urbanization and the innovation effect of inter-regional industrial transfer. In the model (4), the level of urbanization as a conversion variable, and the position parameter c is -0.883. The model has a single threshold, with a value of exp (-0.883) =0.413. When urb is less than or equal to 0.413, the innovation effect tends to be low. When g=0, the elastic coefficient of the inter-regional industrial transfer on the technological innovation capacity of the undertaking area is -0.107, which is significant at 5% level. It indicates that the inter-regional industrial transfer has a significant inhibitory effect on the technological innovation ability of the undertaking area. When urb is greater than or equal to 0.413, the innovation effect tends to be high. When g=1, the elastic coefficient $\beta_0+\beta_1$ of the inter-regional industrial transfer on the technological innovation capacity of the undertaking area is 0.426, which indicates that the inter-regional industrial transfer can promote the upgrading of technological innovation capacity of the undertaking area. As the smoothing parameter is 4.039, it shows that the impact of inter-regional industrial transfer on the technological innovation capacity of the undertaking area presents a steady gradual change with the change of urbanization level. The conversion rate is 4.039. The city is professional and diverse. It can not only bring together professional talents, but also improve the opportunities for people in different fields. Urban development is not only beneficial to the diffusion of innovation between regions, but also conducive to enhancing the capability of independent innovation in the undertaking.

(2) The relationship between human capital and the innovation effect of inter-regional industrial transfer. In the model (5), human capital as a conversion variable, and the position parameter c is 2.128. The model has a single threshold, with a value of exp (2.128) =8.398. When hum is less than or equal to 8.398, the innovation effect tends to be low. When g=0, the elastic coefficient of the inter-regional industrial transfer on the technological innovation capacity of the undertaking area is -0.01.However, the inhibitory effect was not significant due to the small number of coefficients β_0 and the failure to pass the significance test. When hum is greater than or equal to 8.398, the innovation effect tends to be high. When g=1, the elastic coefficient $\beta_0+\beta_1$ of the inter-regional industrial transfer on the technological innovation capacity of the undertaking area is 0.44. In the model, the slope coefficient γ of transformation function is 7.009. It shows that the impact of inter-regional industrial transfer on the technological innovation capacity of the undertaking area presents a gradual change with the change of human capital. The conversion rate is 7.009. In the theory of endogenous growth, the speed and stock of human capital accumulation will play an important role in economic growth. The higher level of human capital in the undertaking is enough to absorb the technology spillovers from the transfer and promote the innovation ability of the whole region.

(3) The relationship between economic openness and the innovation effect of interregional industrial transfer. In the model (6), economic openness as a conversion variable, and the position parameter c is -1.918. The model has a single threshold, with a value of exp (-1.918) =0.147. When ope is less than or equal to 0.147, the innovation effect tends to be low. When g=0, the elastic coefficient of the inter-regional industrial transfer on the technological innovation capacity of the undertaking area is 0.173, which is significant at 1% level. It shows that the inter-regional industrial transfer can significantly promote the upgrading of technological innovation ability of the undertaking area. When ope is greater than or equal to 0.147, the innovation effect tends to be high. When g=1, the elastic coefficient $\beta_0+\beta_1$ of the inter-regional industrial transfer on the technological innovation capacity of the undertaking area is 0.222, which indicates the inter-regional industrial transfer has relatively enhanced the stimulating effect on the technological innovation capability of the undertaking area. In this model, the slope coefficient γ of the transformation function is 28.001, which indicates that the transfer function can be quickly converted from low-regime to high-regime regimes with changes in the degree of openness. The speed of conversion is faster. The higher degree of economic openness means more access to advanced scientific and technological knowledge of other countries in the world. Thus it can enhance its own innovation and absorptive capacity.

(4) The relationship between the technological gap and the innovation effect of the inter-regional industrial transfer. In the model (7), the technological gap as a conversion variable, and the position parameter c is -1.343. The model has a single threshold, with a value of exp (-1.343) =0.261. The technical gap is defined as the ratio of the labor productivity of industrial enterprises above designated size in the western region to the average labor productivity of the central and eastern regions of China, and the value ranges from 0 to 1. Therefore, the greater the value means that the higher the technological level of enterprises in the western region and the smaller the technological gap with the enterprises in the central and eastern regions. When tgap is less than or equal to 0.261, the innovation effect tends to be low. When g=0, the elastic coefficient of the inter-regional industrial transfer on the technological innovation capacity of the undertaking area is -0.451, which is significant at 1% level. It indicates that the inter-regional industrial transfer has a significant inhibitory effect on the technological innovation ability of the undertaking area. When tgap is greater than or equal to 0.261, the innovation effect tends to be high. When g=1, the elastic coefficient $\beta_0+\beta_1$ of the inter-regional industrial transfer on the technological innovation capacity of the undertaking area is 0.361. As the smoothing parameter is 3.848, it shows that the impact of inter-regional industrial transfer on the technological innovation capacity of the undertaking area presents a steady gradual change with the change of the technological gap. The conversion rate is 3.848. If the technological gap between the enterprises in the western region and those in the central and eastern regions is relatively small, the technology brought by inter regional industrial transfer can be easily imitated and studied for the undertaking enterprises, so as to improve the innovation ability of the area. Conversely, when the technological gap is too large, the western region can not only absorb the technological spillover from the transfer industries due to the lack of necessary technological absorptive capacity in the undertaking enterprises. Instead, it will form a more serious technical dependence, which will reduce its own innovation ability.

4. Conclusions

In this paper, we select eleven inter-provincial panel data from 2000 to 2015 in the western region, and take the absorption factors such as urbanization, human capital, economic openness and technology gap as transformation variables. On this basis, we use the PSTR model to analyze the impact of inter-regional industrial transfer on the capacity of technological innovation. The results show that the urbanization, the human capital, the economic openness and technological gap have a significant impact on the capability of technological innovation. When the above variables do not cross the threshold, the influence of regional industrial transfer on technological innovation ability is low or even negative. When the above variables approach or cross the threshold, the impact of regional industrial transfer on technological innovation capability increases.

Based on the research findings, the following suggestions are put forward: Firstly, accelerate the process of urbanization in the west. The increase of the number of cities and the expansion of urban scale can enhance the absorptive capacity of the area to spillover technology and the ability of regional innovation. At present, the level of urbanization in western regions is still far behind that in developed areas. It is one of the effective ways to promote the regional diffusion of innovation by reasonably accelerating the urbanization in the western region. Secondly, enhance the level of human capital in the western region. Only when the human capital is more than a certain threshold, can the western region absorb the spillover technology brought by the industrial transfer. The government should continue to increase the investment in education and training in the western region and take measures to attract talents. Thirdly, expand the level of opening to the outside world. The western region needs to vigorously carry out economic and technological cooperation with foreign countries, explore knowledge horizons, and upgrade knowledge levels so as to enhance its own technological absorptive capacity. Fourthly, the technology of the introduction area should be screened appropriately. The innovation ability of the western region is hard to benefit from the industrial transfer that has great technical gap with itself. Therefore, the western region needs to pay attention to the technical level of the transfer of industry, and choose appropriate industries in which there is not much difference in technical level between the eastern and western regions.

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