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Study on the Effect of International Knowledge Flows on the Industry Innovation Performance in China

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Abstract: From the industrial perspective, absorbing and obtaining external knowledge can save the cost of innovation and accelerate the transformation of knowledge and technology, which plays an important role in promoting industrial innovation. Three industries, namely, computer and communications, drugs and medical, electrical and electronic are taken as the objects of the empirical study. Negative binomial models and related regression models for measuring the effect of international knowledge flow on the industry innovation performance are constructed by collecting and arranging the international knowledge flow data and innovation performance data related to high-tech industry. The empirical analysis results show that patent transnational cooperation demonstrates positive promotion effects on the increase number of industry authorized patents; patent transnational citation makes a significant role in promoting the future patent citation frequency; the technical innovation brought by technology introduction funds plays an important role in the development and industrialization of new products.

Key words: Algorithmsknowledge flow, industry innovation performance, negative binomial models

INTRODUCTION

Technology innovation is widely regarded as one of the important sources of economic development. Technology innovation system consists of a series of interactions between innovation subjects and innovation schemes (Nooy *et al*., 2005), which are used to promote the generation, diffusion and utilization of innovation, simulate industrial upgrading and enhance the core competitiveness of the industry. In the process of industrial innovation, innovative subjects improve their knowledge reserves and innovation abilities through learning, collaboration on a global scale, so as to face the increasingly competitive environment.

In the context of global economic, scientific and technical integration, the internationalization of technological innovation is bound to arouse the international of knowledge flow (Van looy *et al*., 2003) the interaction of knowledge is no longer confined to local innovation networks. With the international spread of technology, the international movement of personnel, the international transfer of capital, the knowledge flows effectively within the global network and this international knowledge flow pan obvious role in improving the quality and effectiveness of industrial innovation. Some researchers raised a series of studies to prove that patent citation analysis is an effective method for mesuring the knowledge flow (Criscuoloa and Verspagen, 2008; Cho and Shih, 2011; Erdi *et al*., 2013; Li and Lin, 2013) To achieve the target of technological innovation, extensively absorb external knowledge, accelerate industrial technology innovation and promote the change in the way of production, enhance industrial upgrading, promote the formation of the international system of industrial innovation, are of great significance for improving the core competitiveness of the industry.

In general, international knowledge flow mainly includes patent transnational cooperation and citation, personnel international movement, international mobility of financial capital, international professional consulting, international technology licensing and technology transfer and international training. Due to the availability and applicability of data, the paper takes patent transnational cooperation, patent transnational citation and technology introduction as empirical study objects to investigate the effect of three international knowledge flows on the industry innovation performance in China.

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MODEL CONSTRUCTION

Data acquisition and processing: For the purpose of analyzing the effect of three international knowledge flows: patent transnational cooperation, patent transnational citation and technology introduction on the industry innovation performance in China, we collect data of computer and communications industry, drugs and medical industry, electrical and electronic industry as study objects. The data of patent transnational cooperation and patent transnational citation are obtained from National Bureau of Economic Research (7) (short for NBER) statistical database of the United States Patent and Trademark Office(short for USPTO) patent. We adopt technology introduction funds and technology digestion and absorption funds to measure the index of technology introduction. In order to ensure the completeness and applicability of data, the research pairs USPTO patent technology classification and the high-tech industries classification in China. The specific pairings are shown in Table 1.

The construction of the research model: The concept "industry absorption capacity" was first proposed by Cohen and Levinthal (1990) in the early 1990s. The formation of absorption capacity are associated with innovation subject's knowledge stock, education level, ceeusro contact degree, basic research input, human capital and cultural features. In the empirical analysis, subject to the constraints of the data acquisition, most studies use the knowledge stock to approximately measure absorptive capacity. The paper utilized different industries and R and D personnel per capital output as the knowledge stock of the industry, more representative of the absorptive capacity.

In this research, dependent variable "new products output" is continuous data, a general regression model is used for analysis; dependent variables "authorized patents number" and "patent transnational cited number" are count data, a counting model is used for analyzing. Scholars (Long, 1997) often adopt Poisson model to analyze the count data, however, the model requires the variable mean is equal to the variance. So here, we assume that under the same remarkable level 0.001, null hypothesis is rejected and means Poisson model is rejected. Further observed that the variance of patent licensing number and patent transnational citation number are much larger than the mean, thus the negative binomial model is an appropriate analytical model (Hausman *et al*., 1984).

Table 1: USPTO technology classification and the corresponding high-tech industries classification

USPTO technology classification	Corresponding high-tech industries classification
Computer and communications	Communication equipment manufacturing
	Radar and related equipment manufacturing
	Broadcasting and TV equipment manufacturing
	Electronic computer machine manufacturing
	Electronic computer peripheral equipment Manufacturing
Drugs and medical	Pharmaceutical manufacturing
	Medical equipment and instruments manufacturing
Electrical and electronics	Electronic devices manufacturing
	Electronic component manufacturing
	Household audio-visual equipment manufacturing
	Other electronic equipment manufacturing

Basic Poisson model is shown in (1), which is used to calculate a given a set of independent variables x_i, the probability of the dependent variable values y_i. In order to avoid the mean of λ_i is negative; take the values of λ_i as exponential form of the dependent variable, such as Eq. 2 below:

$$p(y_i \mid x_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i\,!} \tag{1}$$

$$\lambda_i = E(y_i \mid x_i) = \exp(x_i\,\beta) \tag{2}$$

In order to adjust the predicted mean with the variance, we replace the mean value λ_i in the above model by the gamma distribution as shown in Eq. 3. Then the probability density function of the dependent variable observations is negative binomial distribution for the parameters γ_i and δ, shown in Eq. 4, the constitute form of γ_i is the same as λ_i:

$$\lambda_i \sim \Gamma(\lambda_i, \delta) \tag{3}$$

$$\begin{aligned} p(y_i) &= \int_0^\infty \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i\,!} f(\lambda_i)\, d\lambda_i \\ &= \frac{\Gamma(\gamma_i + y_i)}{\Gamma(\gamma_i)\Gamma(y_i+1)}\left(\frac{\delta}{\delta+1}\right)^{\gamma_i}\left(\frac{\delta}{\delta+1}\right)^{y_i} \sim BN(\gamma_i, \delta) \end{aligned} \tag{4}$$

Previous research results show the fixed effect negative binomial model is superior to the random effect negative binomial model, for the former model only considers the variance of the intra-industry and controls some factors specific to various industries which are not included in the model and does not change over time. Hausman test rejected the random effects model at the 0.001 significance level. Therefore, the study utilized fixed effects negative binomial model to analyze the authorized patent number and patent transnational cited number.

Due to the certain delay between innovation input and output, so the study applies α to represent this time delay. While considering the output delay, the mean value of authorized patents number γ and patent transnational cited number γ' are shown as Eqs. 5 and 6:

$$\begin{aligned}\gamma_{i,t+\alpha} &= E(\text{Patent} \mid \text{ERDPC}, \ln \text{FTP}, \text{IOPC}, \ln \text{ETI}, \ln \text{ETA}, \ln \text{Citing}, \ln \text{Coop},) \\ &= \exp(\beta_0 + \beta_1 \text{ERDPC}_{i,t} + \beta_2 \ln \text{FTP}_{i,t} + \beta_3 \ln \text{IOPC}_{i,t} \\ &\quad + \beta_4 \ln \text{ETI}_{i,t} + \beta_5 \ln \text{ETA}_{i,t} + \beta_6 \ln \text{Citing}_{i,t} + \beta_7 \ln \text{Coop}_{i,t})\end{aligned} \tag{5}$$

$$\begin{aligned}\gamma'_{i,t+\alpha} &= E(\text{Cited}_{i+\alpha} \mid \text{ERDPC}, \ln \text{FTP}, \text{IOPC}, \ln \text{ETI}, \ln \text{ETA}, \ln \text{Citing}, \ln \text{Coop},) \\ &= \exp(\beta_0 + \beta_1 \text{ERDPC}_{i,t} + \beta_2 \ln \text{FTP}_{i,t} + \beta_3 \ln \text{IOPC}_{i,t} \\ &\quad + \beta_4 \ln \text{ETI}_{i,t} + \beta_5 \ln \text{ETA}_{i,t} + \beta_6 \ln \text{Citing}_{i,t} + \beta_7 \ln \text{Coop}_{i,t})\end{aligned} \tag{6}$$

Here i represents the industry, t represents the year, α represents the delay. The meaning of each variable in the model is introduced below.

The dependent variables include authorized patent number Patents, patent transnational cited number Cited and new product output IOVNP.

The independent variables include technical introduction funds InETI, technology digestion and absorption funds InETA, patent transnational citation number InCiting and patent transnational cooperation number $\text{Coop}_{i,t}$.The control variables include R and D funds input ERDPC, R and D Personnel input In FTP and absorptive capacity IOPC.

Since the new product output values are not count data, they couldn't be analyzed by negative binomial model, however, considering the technology will arouse technological change to a large extend and enable enterprises to improve and innovate the product, therefore, this study establishes a general regression model to analyze the impact of the independent variable on the new products output. The model is shown as Eq. 7.

$$\begin{aligned}\ln \text{IOVPN}_{i,t+\alpha} &= \beta_0 + \beta_1 \text{ERDPC}_{i,t} + \beta_2 \ln \text{FTP}_{i,t} + \beta_3 \ln \text{IOPC}_{i,t} \\ &\quad + \beta_4 \ln \text{ETI}_{i,t} + \beta_5 \ln \text{ETA}_{i,t} + \beta_6 \ln \text{Citing}_{i,t} + \beta_7 \ln \text{Coop}_{i,t}\end{aligned} \tag{7}$$

EMPIRICAL STUDY

By adopting the regression model established above, we carry out the study about the effect of international knowledge flow of different industries on the industrial innovation performance.

Since there is a certain delay between knowledge input and output, thus if only one delay is chosen for analysis, then analysis results distortion will be caused to a certain extent. Therefore, for the three dependent variables in this study, we choose different length of time delay to carry out the analysis. Specifically, we consider the time delay of 1 year, 2 years and 3 years to study effect of independent variables on the dependent variable. That means $\alpha = 1$, $\alpha = 2$ and $\alpha = 3$, respectively.

The analysis results of three dependent variables affected by the independent variables are shown in tables 2 to 10 and models 1-16 are explained as follows:

- Model 1 measures the condition that only control variables are included in the regression model
- Models 2-5 measures the condition that single independent variable is included in the regression model, respectively
- Model 6-11 measures the condition that random two independent variables are included in the regression model simultaneously
- Model 12-15 measures the condition that random three independent variables are included in the regression model simultaneously
- Model 16 measures the condition that the four independent variables are all included in the regression model simultaneously

Determination coefficient R^2 and adjusted R^2 describes the goodness of fit of the model. When the values are closer to 1, the fitting effect is much better. For the whole analysis process, the control variables are always in all regression models.

Efect of international knowledge flow on the patent output:

- When $\alpha = 1$, the delay period is one year

We can see from Table 2, for the authorized patents output, Coop is the most important and continuously significant explanatory variable. As long as the variables are included in the model, the model has been well fitted. The coefficient estimation values are significantly positive at the 0.001 test level in model 5, 8, 10, 13, 14 and are significantly positive at the 0.01 test level in model 11, 15, 16. The results indicate that patent transnational cooperation has a positive impact on the industrial authorized patent output number; more international cooperation will inspire more patent output. Observe the p-value of InETI, the index is not significant in all models, that means the technology introduction funds doesn't obviously affect the industrial patents output. InETA and InCiting are only of significance when they are left alone in the model, that means the effects of the introduction of

Table 2: The regression results of authorized patent numbers ($\alpha = 1$)

Model	(n = 2)	lnETI	lnETA	lnCiting	lnCoop	R^2	Adjust-R^2
1	Coe-est					0.2946	0.2026
	p-value						
2	Coe-est	0.2889				0.3526	0.2349
	p-value	0.1744					
3	Coe-est		0.7759			0.5243	0.4378
	p-value		0.0036				
4	Coe-est			0.4091		0.5376	0.4535
	p-value			0.0026			
5	Coe-est			0.7121		0.6711	0.6113
	p-value			<0.0001			
6	Coe-est	-0.0810	0.8407			0.5272	0.4147
	p-value	0.7214	0.0111				
7	Coe-est	0.1365		0.3831		0.5495	0.4423
	p-value	0.4635		0.0064			
8	Coe-est	0.2535			0.7001	0.7156	0.6479
	p-value	0.0841			<0.0001		
9	Coe-est		0.5595	0.3046		0.6411	0.5557
	p-value		0.0226	0.0162			
10	Coe-est		0.4739		0.5868	0.7451	0.6844
	p-value		0.0222		0.0003		
11	Coe-est			0.2125	0.5684	0.7213	0.6549
	p-value			0.0653	0.0013		
12	Coe-est	-0.1220	0.6529	0.3104		0.6478	0.5421
	p-value	0.5467	0.0285	0.0165			
13	Coe-est	0.0827	0.3995		0.6025	0.7480	0.6724
	p-value	0.6354	0.1246		0.0005		
14	Coe-est	0.1919		0.1689	0.5888	0.7447	0.6681
	p-value	0.1907		0.1468	0.0009		
15	Coe-est		0.4059	0.1620	0.4951	0.7728	0.7046
	p-value		0.0460	0.1343	0.0028		
16	Coe-est	0.0353	0.3760	0.1577	0.5043	0.7733	0.6897
	p-value	0.8380	0.1384	0.1620	0.0043		

digestion and absorption funds and patent transnational citation frequency on the industrial patents output are limited.

- When $\alpha = 2$, the delay periods are two years

We can see from Table 3, InCoop is still the most important and continuously significant explanatory variable. As long as the variable is contained in the mode, the fitting effects are look well and are significantly positive at the 0.001 test level. And at this stage InETI, InETA, InCiting are of no significance:

- When $\alpha = 3$, the delay periods are three years

From Table 4, InCoop is still the most important and continuously significant explanatory variable. As long as the variable is contained in the mode, the fitting effects are look well. Here in model 5, 8, 10, 13, 14, the coefficients are significantly positive at the 0.001 test level and in model 11, 15, 16 the coefficients are significantly positive at the 0.01 test level. And at this stage InETI, InETA, InCiting are almost of no significance.

The effect of International knowledge flow on patent transnational cited number:

- When $\alpha = 1$ the delay period is one year

Table 3: The regression results of authorized patent numbers ($\alpha = 1$)

Model	(n = 2)	lnETI	lnETA	lnCiting	lnCoop	R^2	Adjust-R^2
1	Coe-est					0.3432	0.2575
	p-value						
2	Coe-est	0.2176				0.3801	0.2673
	p-value	0.2649					
3	Coe-est		0.3755			0.4035	0.2950
	p-value		0.1501				
4	Coe-est			0.2372		0.4347	0.3319
	p-value			0.0724			
5	Coe-est				0.7000	0.7501	0.7057
	p-value				<.0001		
6	Coe-est	0.0810	0.3106			0.4068	0.2655
	p-value	0.7354	0.3418				
7	Coe-est	0.1334		0.2118		0.4475	0.3160
	p-value	0.4930		0.1243			
8	Coe-est	0.1827			0.6914	0.7769	0.7238
	p-value	0.1332			<0.0001		
9	Coe-est		0.2387	0.1926		0.4558	0.3262
	p-value		0.3768	0.1699			
10	Coe-est		0.0175		0.6954	0.7511	0.6918
	p-value		0.9231		<0.0001		
11	Coe-est			-0.0065	0.7044	0.7510	0.6917
	p-value			0.9474	<0.0001		
12	Coe-est	0.0560	0.1957	0.1900		0.4574	0.2946
	p-value	0.8121	0.5528	0.1871			
13	Coe-est	0.2845	-0.2383		0.7496	0.7898	0.7267
	p-value	0.0693	0.2808		<0.0001		
14	Coe-est	0.2018		-0.0523	0.7259	0.7800	0.7140
	p-value	0.1201		0.5995	<0.0001		
15	Coe-est		0.0213	-0.0092	0.7006	0.7512	0.6765
	p-value		0.9110	0.9297	<0.0001		
16	Coe-est	0.2982	-0.2315	-0.0455	0.7779	0.7922	0.7156
	p-value	0.0679	0.3054	0.6480	<0.0001		

We can see from Table 5, for the patent transnational cited number, explanatory variable InETI has always been positive significant at the 0.01 test level and is the most important variable which affects InCited. That means technology introduction funds have a positive impact on the patent transnational cited number. In contrast, InETA has been of no significance. For the variable InCiting, it is obvious significant only when it is alone in the model (see in model 5, $p<0.01$) but the model fit is poor here. The variable InCoop is almost of no significance except in model 15 and 16. Overall, for the patent cited number, other variables are of lower significance in addition to InETI.

- When $\alpha = 2$, the delay periods are two years

We can see from Table 6, the result is similar to condition while $\alpha = 1$. For the patent transnational cited number, explanatory variable InETI has always been positive significant at the 0.01 test level and is the most important variable which affects In Cited. In contrast, InETA has been of no significance. For the variable InCiting, it is obvious significant except for model 15 and 16. The variable InCoop is almost of no significance except in model 15 and 16 at the test level 0.001:

Table 4: The regression results of authorized patent numbers ($\alpha = 1$)

Model	(n = 2)	lnETI	lnETA	lnCiting	lnCoop	R^2	Adjust-R^2
1	Coe-est					0.3129	0.2233
	p-value						
2	Coe-est	0.2977				0.3751	0.2615
	p-value	0.1530					
3	Coe-est		0.5161			0.4156	0.3093
	p-value		0.0620				
4	Coe-est			0.3521		0.4948	0.4029
	p-value			0.0101			
5	Coe-est				0.6888	0.6688	0.6086
	p-value				<0.0001		
6	Coe-est	0.1092	0.4287			0.4210	0.2831
	p-value	0.6618	0.2111				
7	Coe-est	0.1706		0.3197		0.5137	0.3979
	p-value	0.3767		0.0233			
8	Coe-est	0.2636			0.6763	0.7175	0.6502
	p-value	0.0710			<0.0001		
9	Coe-est		0.3066	0.2949		0.5262	0.4134
	p-value		0.2510	0.0380			
10	Coe-est		0.1870		0.6393	0.6805	0.6044
	p-value		0.3915		0.0004		
11	Coe-est			0.1486	0.5883	0.6937	0.6207
	p-value			0.2062	0.0014		
12	Coe-est	0.0709	0.2523	0.2915		0.5285	0.3870
	p-value	0.7596	0.4372	0.0453			
13	Coe-est	0.2982	-0.0811		0.6961	0.7188	0.6345
	p-value	0.1142	0.7600		0.0002		
14	Coe-est	0.2283		0.0968	0.6125	0.7272	0.6458
	p-value	0.1329		0.4101	0.0008		
15	Coe-est		0.1315	0.1323	0.5645	0.6991	0.6089
	p-value		0.5536	0.2788	0.0029		
16	Coe-est	0.2683	-0.0959	0.0996	0.6341	0.7290	0.6292
	p-value	0.1639	0.7206	0.4086	0.0014		

Table 5: Regression results of patent transnational cited numbers ($\alpha = 1$)

Model	(n = 2)	lnETI	lnETA	lnCiting	lnCoop	R^2	Adjust-R^2
1	Coe-est					0.4116	0.3349
	p-value						
2	Coe-est	0.6176				0.6318	0.5648
	p-value	0.0015					
3	Coe-est		0.4594			0.4785	0.3837
	p-value		0.1071				
4	Coe-est			0.3767		0.5828	0.5069
	p-value			0.0065			
5	Coe-est				0.3752	0.4985	0.4073
	p-value				0.0638		
6	Coe-est	0.6415	-0.0543			0.6324	0.5448
	p-value	0.0074	0.8542				
7	Coe-est	0.5061		0.2804		0.7194	0.6526
	p-value	0.0043		0.0182			
8	Coe-est	0.6001			0.3468	0.7058	0.6358
	p-value	0.0009			0.0319		
9	Coe-est		0.2211	0.3354		0.5962	0.5001
	p-value		0.4125	0.0220			
10	Coe-est		0.3083		0.2937	0.5245	0.4112
	p-value		0.2960		0.1690		
11	Coe-est			0.3223	0.1572	0.5944	0.4979
	p-value			0.0368	0.4456		
12	Coe-est	0.6011	-0.2402	0.3071		0.7304	0.6496
	p-value	0.0050	0.3761	0.0139			
13	Coe-est	0.7605	-0.3755		0.4386	0.7295	0.6484
	p-value	0.0009	0.1999		0.0144		
14	Coe-est	0.5262		0.2028	0.2131	0.7406	0.6628
	p-value	0.0031		0.1167	0.2152		
15	Coe-est		0.4059	0.1620	0.4951	0.7728	0.7046
	p-value		0.0460	0.1343	0.0028		
16	Coe-est	0.0353	0.3760	0.1577	0.5043	0.7738	0.6897
	p-value	0.8380	0.1384	0.1620	0.0043		

- When $\alpha = 3$, the delay period are three years

We can see from Table 7, for the patent transnational cited number, explanatory variable InETI has always been positive significant and is the most important variable which affects InCited. In contrast, InETA has been of no significance. The significant of the variable InCiting is lower than the condition while $\alpha = 2$. The variable InCoop is almost of no significance except for the model 15 and 16 at the test level 0.01:

The effect of international knowledge flow on new product output:

- When $\alpha = 1$, the delay period is one year

We can see from Table 8, for the new product output, explanatory variable InETI has always been significant at the 0.001 test level and is the most important variable which affects InIOVNP. As long as the variable is included in the model, the model fits well (R^2 is close to 1), that means the input of technology Introduction funding has a positive effect on the increase of new product output. For explanatory variables InCiting and InCoop, though they seems to be not significant while they are single in the model (see in model 4 and 5), however, they are significant when they both appear in the model (see in model 11, 14and 15). InETA is not significant when it is alone in the model (see in model 3) and the Model fitting effect level even declines when it exists:

- When $\alpha = 2$, the delay periods are two years

We can see from Table 9, explanatory variable InETI has always been significant and is the most important variable which affects InIOVNP As long as the variable is included in the model; the model fit well (R^2 is close to 1). For explanatory variables InCoop, as long as InETI is included in the model then InCoop is significant (see in model 8, 13, 14, 15, 16) and the models fit well. Only the model contains variable InCoop and the variable InCiting is significant (see in model 11, 14, 15, 16). By comparison, InETI is still not significant except for the other three independent variables appear in the model at the same time:

- When $\alpha = 3$, the delay periods are three years

We can see from Table 10, explanatory variable InETI has always been significant and is the most important variable which affects InIOVNP. As long as the variable

Table 6: Regression results of patent transnational cited numbers ($\alpha = 1$)

Model	(n = 2)	lnETI	lnETA	lnCiting	lnCoop	R^2	Adjust-R^2
1	Coe-est					0.3841	0.3037
	p-value						
2	Coe-est	0.6739				0.6888	0.6322
	p-value	0.0001					
3	Coe-est		0.6509			0.5402	0.4566
	p-value		0.0121				
4	Coe-est			0.3952		0.6030	0.5308
	p-value			0.0021			
5	Coe-est				0.2685	0.4358	0.3332
	p-value				0.1697		
6	Coe-est	0.5984	0.1717			0.6958	0.6234
	p-value	0.0036	0.4935				
7	Coe-est	0.5590		0.2888		0.7968	0.7485
	p-value	0.0002		0.0031			
8	Coe-est	0.6619			0.2372	0.7290	0.6645
	p-value	0.0001			0.0919		
9	Coe-est		0.4268	0.3155		0.6612	0.5806
	p-value		0.0713	0.0123			
10	Coe-est		0.5935		0.1115	0.5479	0.4402
	p-value		0.0330		0.5561		
11	Coe-est			0.3946	0.0016	0.6030	0.5085
	p-value			0.0072	0.9932		
12	Coe-est	0.5603	-0.0033	0.2892		0.7968	0.7359
	p-value	0.0016	0.9880	0.0050			
13	Coe-est	0.6629	-0.0025		0.2378	0.7290	0.6477
	p-value	0.0016	0.9926		0.1331		
14	Coe-est	0.5648		0.2664	0.0617	0.7989	0.7368
	p-value	0.0003		0.0158	0.6551		
15	Coe-est		0.0213	-0.0092	0.7006	0.7512	0.6765
	p-value		0.9110	0.9297	<0.0001		
16	Coe-est	0.2982	-0.2315	-0.0455	0.7779	0.7922	0.7156
	p-value	0.0679	0.3054	0.648	<0.0001		

Table 7: Regression results of patent transnational cited numbers ($\alpha = 1$)

Model	(n = 2)	lnETI	lnETA	lnCiting	lnCoop	R^2	Adjust-R^2
1	Coe-est					0.454	0.3828
	p-value						
2	Coe-est	0.5628				0.6638	0.6027
	p-value	0.0012					
3	Coe-est		0.2885			0.4838	0.3905
	p-value		0.2681				
4	Coe-est			0.2815		0.5637	0.4843
	p-value			0.0281			
5	Coe-est				0.1096	0.4625	0.3648
	p-value				0.5612		
6	Coe-est	0.6730	-0.2505			0.6786	0.6021
	p-value	0.0018	0.3368				
7	Coe-est	0.4878		0.1886		0.7093	0.6401
	p-value	0.0039		0.0840			
8	Coe-est	0.5586			0.0832	0.6687	0.5898
	p-value	0.0016			0.5836		
9	Coe-est		0.1020	0.2624		0.5669	0.4638
	p-value		0.6939	0.0583			
10	Coe-est		0.2686			0.4852	0.3636
	p-value		0.3472				
11	Coe-est		0.3180	-0.1055		0.5697	0.4672
	p-value		0.0327	0.5932			
12	Coe-est	0.6424	-0.3910	0.2322		0.7429	0.6658
	p-value	0.0014	0.1216	0.0368			
13	Coe-est	0.7207	-0.3793		0.1759	0.6965	0.6055
	p-value	0.0013	0.1907		0.2899		
14	Coe-est	0.4827		0.2083	-0.0541	0.7109	0.6242
	p-value	0.0053		0.1029	0.7449		
15	Coe-est		0.1315	0.1323	0.5645	0.6991	0.6089
	p-value		0.5536	0.2788	0.0029		
16	Coe-est	0.2683	-0.0959	0.0996	0.6341	0.7290	0.6292
	p-value	0.1639	0.7206	0.4086	0.0014		

Table 8: Regression results of new product output ($\alpha = 1$)

Model	(n = 2)	lnETI	lnETA	lnCiting	lnCoop	R^2	Adjust-R^2
1	Coe-est					0.6616	0.6174
	p-value						
2	Coe-est	0.5702				0.8547	0.8283
	p-value	<0.0001					
3	Coe-est		0.2292			0.6787	0.6203
	p-value		0.2904				
4	Coe-est			0.1995		0.711	0.6584
	p-value			0.0654			
5	Coe-est				-0.2258	0.6939	0.6383
	p-value				0.1414		
6	Coe-est	0.7246	-0.3512			0.8808	0.8524
	p-value	<0.0001	0.0440				
7	Coe-est	0.5311		0.0984		0.8658	0.8339
	p-value	<0.0001		0.2015			
8	Coe-est	0.5830			-0.2534	0.8954	0.8705
	p-value	<0.0001			0.0094		
9	Coe-est		0.1009	0.1807		0.7138	0.6457
	p-value		0.6505	0.1233			
10	Coe-est		0.3999		-0.3316	0.739	0.6769
	p-value		0.0707		0.0389		
11	Coe-est			0.3624	-0.4709	0.8188	0.7757
	p-value			0.0010	0.0020		
12	Coe-est	0.7052	-0.4404	0.1475		0.9041	0.8753
	p-value	<0.0001	0.0105	0.0395			
13	Coe-est	0.6692	-0.2017		-0.2041	0.9025	0.8732
	p-value	<0.0001	0.2430		0.0479		
14	Coe-est	0.4917		0.2507	-0.4186	0.9502	0.9353
	p-value	<0.0001		0.0001	<0.0001		
15	Coe-est		0.2616	0.3299	-0.5181	0.8371	0.7882
	p-value		0.1498	0.0024	0.0009		
16	Coe-est	0.5917	-0.2401	0.2578	-0.3647	0.9602	0.9455
	p-value	<0.0001	0.0420	<0.0001	<0.0001		

Table 9: Regression results of new product output ($\alpha = 1$)

Model	(n = 2)	lnETI	lnETA	lnCiting	lnCoop	R^2	Adjust-R^2
1	Coe-est					0.6734	0.6308
	p-value						
2	Coe-est	0.5699				0.8659	0.8416
	p-value	<0.0001					
3	Coe-est		0.1860			0.6846	0.6273
	p-value		0.3850				
4	Coe-est			0.1712		0.7097	0.6569
	p-value			0.1113			
5	Coe-est				-0.2756	0.7215	0.6708
	p-value				0.0641		
6	Coe-est	0.7535	-0.4175			0.9027	0.8795
	p-value	<0.0001	0.0103				
7	Coe-est	0.5429		0.0679		0.8712	0.8406
	p-value	<0.0001		0.3641			
8	Coe-est	0.5852			-0.3033	0.9241	0.9060
	p-value	<0.0001			0.0006		
9	Coe-est		0.0742	0.1574		0.7112	0.6425
	p-value		0.7400	0.1787			
10	Coe-est		0.3796		-0.3760	0.7620	0.7053
	p-value		0.0725		0.0163		
11	Coe-est			0.348	-0.5109	0.8364	0.7974
	p-value			0.001	0.0006		
12	Coe-est	0.7374	-0.4917	0.1227		0.9188	0.8944
	p-value	<0.0001	0.0027	0.0605			
13	Coe-est	0.6870	-0.2380		-0.2451	0.9339	0.9140
	p-value	<0.0001	0.1004		0.0060		
14	Coe-est	0.4998		0.2345	-0.4578	0.9719	0.9635
	p-value	<0.0001		<0.0001	<0.0001		
15	Coe-est		0.2465	0.3173	-0.5554	0.8526	0.8084
	p-value		0.1538	0.0022	0.0003		
16	Coe-est	0.6140	-0.2741	0.2426	-0.3962	0.9849	0.9793
	p-value	<0.0001	0.0007	<0.0001	<0.0001		

Table 10: Regression results of new product output ($\alpha = 1$)

Model	(n = 2)	lnETI	lnETA	lnCiting	lnCoop	R^2	Adjust-R^2
1	Coe-est					0.6718	0.6290
	p-value						
2	Coe-est	0.5126				0.8285	0.7973
	p-value	0.0002					
3	Coe-est		0.1108			0.6759	0.6169
	p-value		0.6068				
4	Coe-est			0.1196		0.6897	0.6332
	p-value			0.2732			
5	Coe-est				-0.3462	0.7482	0.7024
	p-value				0.0170		
6	Coe-est	0.7162	-0.4628			0.8739	0.8439
	p-value	<0.0001	0.0120				
7	Coe-est	0.5032		0.0238		0.8292	0.7885
	p-value	0.0005		0.7795			
8	Coe-est	0.5314			-0.3713	0.9161	0.8962
	p-value	<0.0001			0.0001		
9	Coe-est		0.0297	0.1141		0.6899	0.6161
	p-value		0.8975	0.3404			
10	Coe-est		0.3345		-0.4347	0.7798	0.7274
	p-value		0.0970		0.0048		
11	Coe-est			0.3125	-0.5575	0.8414	0.8036
	p-value			0.0021	0.0002		
12	Coe-est	0.7055	-0.5118	0.0809		0.8809	0.8452
	p-value	<0.0001	0.0079	0.2904			
13	Coe-est	00.6308	-0.2325		-0.3145	0.9255	0.9032
	p-value	<0.0001	0.1275		0.0013		
14	Coe-est	0.4552		0.2091	-0.5091	0.9544	0.9407
	p-value	<0.0001		0.0006	<0.0001		
15	Coe-est		0.2147	0.2858	-0.5963	0.8537	0.8098
	p-value		0.2085	0.0047	0.0001		
16	Coe-est	0.5656	-0.2649	0.2169	-0.4496	0.9665	0.9542
	p-value	<0.0001	0.0166	0.0001	<0.0001		

is included in the model, the model fits well. Explanatory variable InCoop is always significant though the influence of it on dependent InIOVNP is smaller than InETI (see in model 5,8,10,11,13,14,15,16). Only the model contains variable InCoop and then the variable InCiting is significant (see in model 11, 14, 15, 16). InETA has not been significant.

CONCLUSION

After the above quantitative analysis, we get the following main conclusions:

- Firstly, from the analysis of our three industries, patent transnational cooperation has a significant effect on promoting the industry authorized patents, It is considered that more transnational cooperation can inspire national patent output. In general, transnational cooperation is a long-distance cooperation, such cooperation is conducive for the main part of industrial innovation to acquire advanced external knowledge, breakthrough the current technological paradigm, make technological change and obtain more patent output. According to the results of data analysis, the positive promoting effects have a certain delay extension, compared to 1-year time delay, as the increase of delay, the positive promoting effect is more obvious. Overall, patent transnational citation and technical introduction have a limited effect on the increase of authorized patent number
- Secondly, from the analysis of our three industries, patent transnational cooperation and the input of technology digestion and absorption input funds do not have a significant effect on the increase of patent cited frequency. For patent cited frequency has an obvious delay, when the delay increases, patent transnational cooperation has a significant effect on patent cited frequency in the future. By learning patent literature of other countries, the part of industrial innovations access, digest and obsorb new technological achievements and make them to be their own knowledge and technology outputs. Similarly, the inputs of technology introduction funds have a significant positive effect on the future cited number of patent. The introduction of foreign advanced technology has a positive role in promoting their own technological innovations
- Thirdly, from the analysis of our three industries, patent transnational citation and the input of technology digest funds do not have significant effect on the increase of new product output. Among the three delayed stage, the input of technical introduction funds have a significant effect on the increase of new product output, which means that the technological innovations brought by technical introduction play an important role on the development and the industrialization of new products. When the time delay increases, patent transnational cooperation has a positive promotion effect on the increase of new product output, that means by learning other countries' advanced technologies and transform those into their own productivity and knowledge and technologies, which will be conducive to the development and industrialization of new products

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