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Research on innovation Mode Selection of high-tech Industry from the perspective of knowledge potential difference

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Abstract. This paper puts the supply and demand of external technology into the scope of knowledge potential difference and discusses the choice of innovation mode in high-tech industry from the perspective of knowledge potential difference. And based on high technology industry in 2009-2016 provincial panel data, the relative difference between the human capital of universities and the human capital of high-tech industries is used to measure the regional knowledge potential difference. The threshold regression method is used to empirically test the nonlinear effect of innovation mode on innovation performance of high-tech industry under different knowledge potential differences and identify the "Inverted U" mechanism of knowledge potential difference on external technology transfer of high-tech industry. The results show that there are two thresholds for knowledge potential difference in Chinese provinces, and with the increase of knowledge potential difference, the efficiency of independent R&D in high-tech industries decreases. When the knowledge potential difference is moderate, the innovation mode of domestic technology transformation can significantly promote the high-tech industry. According to the two threshold values, the knowledge potential difference of each jurisdiction presents typical three-stage regular changes. The conclusion of this paper provides theoretical support for the innovation mode selection of high-tech industry.

1 Introduction

The transformation and upgrading of enterprises driven by technological innovation has become the consensus of the whole society. As a knowledge-intensive industry, high-tech industry needs to gain market advantages through continuous innovation. Its innovation mode and innovation performance are of great significance to the high-quality development of China's economy. According to statistics, from 1995 to 2016, the number of high-tech enterprises has exceeded 300, with their main business revenue reaching 15.379633 billion yuan, with an average annual growth rate of 21.32%, strongly supporting the steady and rapid growth of the Chinese economy. With the transformation of China's high-tech industry from the stage of following the lead to the stage of parallel and leading, it is more necessary to enhance industrial competitiveness through continuous innovation and accelerate the transformation of Chinese manufacturing into "Intelligent Manufacturing in China" [1]. In this sense, it is of great practical value to deepen the research on innovation behavior of high-tech industry.

This paper focuses on the innovation mode selection of high-tech industry. Existing studies believe that the innovation mode of high-tech industry can be divided into internal technology acquisition mode dominated by independent R&D and external technology acquisition mode dominated by transformation of scientific and technological achievements[2]. There is no doubt that high-tech enterprises have certain rules in the choice of innovation mode, but many scholars' research conclusions are contrary to each other. On one hand, Fu Yuanhai et al.[3] found that the influences of the two technology acquisition modes on the innovation ability of enterprises were complementary, and Cui Miao et al.[4]also confirmed this conclusion through theoretical and case studies. On the other hand, Xu Xin[5] and Yu Liping[6] believe that the two technology acquisition modes are substitution relations. In addition, there is a view that the relationship between the two is dynamic. Xu Bin[7] believes that in the early stage of the development of high-tech industry, it is particularly important to adopt an innovation mode dominated by external technology acquisition due to its low R&D level. However, as high-tech industry enters the mature stage, the primary and secondary relationship between the two will change and the innovation mode dominated by independent R&D will be adopted instead. According to statistics, Chinese enterprises mainly choose the innovation mode of independent R&D, and the input of external technology introduction only accounts for 13% of the innovation expenditure[8]. However, the key supply role of universities in the technology innovation system cannot be ignored: on one hand, universities occupy the "high value" of R&D resources; on the other hand, they play the role of "leading" in scientific and technological innovation. The constantly emerging scientific and technological achievements seem to be incompatible with

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the current innovation mode choice of high-tech industry. As the main demand side of the university technology transfer(UTT)[9], the low demand for the technological achievements of universities undoubtedly leads to a low equilibrium level of the conversion rate of China's UTT. However, western developed countries have high UTT levels, because their universities have a high level of R&D[10]. Based on this, the question raised in this paper is that: Is the innovation mode of high-tech industry affected by the knowledge level of universities? Whether the scientific and technological achievements of universities have enough value to the high-tech industry? Under what technological conditions will the high-tech industry choose the innovation mode of external technology acquisition?

There are two types of paper that are most relevant to this study. The first is to explore the relationship between independent innovation and external technology acquisition from the perspective of relevance. For example, The research of Liu Xiaolu et al. [11] points out that independent innovation plays a dominant role in the accumulation of enterprises' innovation ability. Chen[12] believes that the way enterprises choose to introduce technologies is affected by their own technological capabilities. The research of Pang Changwei[13] shows that cooperation efficiency may promote enterprises to shift from the innovation mode dominated by independent R&D to introduced innovation. Second, the threshold effect of technology acquisition mode is discussed from the perspective of human capital. For example, Sun Luyun[14] tested the threshold effect of internal and external technology on regional innovation ability based on human capital. Drew the conclusion that both internal and external technologies can promote regional innovation ability when the human capital is greater than the threshold value. Bao Yongwen[15] further proposed that the level of enterprise innovation cannot be improved when human capital is lower than the threshold value. The above papers only focus the research perspective technology on the demand side, but do not include the external technology supplier into the analysis framework of supply and demand. In order to bring the external technology suppliers into the research framework of high-tech industry innovation model. This paper introduces the knowledge potential difference theory which measures the knowledge level difference in the process of technology transfer into the analysis category. The reason is that the difference in knowledge level affects the difficulty of technology transfer, which will determine whether the high-tech industry will choose the innovation mode dominated by technology transfer. In terms of research ideas, this paper firstly analyzes the knowledge potential difference theory in detail, quantifies the knowledge potential difference of China's high-tech industry according to the theory, and analyzes the current situation of knowledge potential difference in China's provincial regions. Furthermore, in order to identify the influence mechanism of knowledge potential difference on high-tech industry innovation pattern, the panel threshold model is used for testing. The conclusion of this paper not only has some enlightening significance for the innovation mode selection of high-tech industry, but also provides a new explanation for the technology transfer in China.

There may be two marginal contributions in this paper. First, from the perspective of research, the knowledge potential difference theory describing technology transfer is introduced into the research framework of high-tech industry innovation mode, and the context of knowledge potential difference between high-tech industry and universities in China is analyzed to broaden the research horizon of high-tech industry innovation mode. Second, in terms of research content, the empirical test of the "inverted U-shaped" mechanism of knowledge potential difference on technology transfer based on relevant data of China's high-tech industry has enriched the empirical paper on knowledge potential difference. The remaining content is arranged as follows: the second part is the theoretical framework and research hypothesis, the third part is the research setting, the fourth part is the empirical analysis, and the last part is the conclusion and enlightenment.

2 Theoretical framework and research hypothesis

2.1 Theoretical framework of knowledge potential difference

The efficiency of external technology transformation of high-tech industry is affected by knowledge potential difference. Chen Feixiang et al.[16] constructed a knowledge diffusion field model to explain the role of knowledge potential difference, and found that it was easy for the high knowledge potential to spread technology to the low knowledge potential through technology output and other means. Based on the research on public platforms, Li Liusheng [17] believed that the party with a high knowledge potential (source of knowledge) would form a knowledge potential difference with the party with a low knowledge potential (receiver of knowledge). In this case, the former has a high transformation value and the latter has a high demand for the former, and knowledge transfer often occurs here. The research results of Ensign[18] show that the knowledge potential difference has a significant impact on the performance of knowledge transfer and the choice of enterprise partners. In addition, Marjolein[19] pointed out that the effective transfer of knowledge is based on the moderate knowledge potential difference. On this basis, Li Yongzhou [20] proposed that there is an "inverted U-shaped" relationship between knowledge potential difference and knowledge transfer. This paper believes when the knowledge potential difference is too low, the innovation efficiency of technology introduction in high-tech industries is low, and the innovation mode of independent R&D is mainly adopted for high-tech industries. When the knowledge potential difference is moderate, the innovation efficiency of the independent R&D mode of high-tech industry is low, so it needs to adopt the external technology introduction mode instead. When the knowledge potential difference is too high, it is difficult for the high-tech industry to absorb the technology from the technology supplier, and the innovation efficiency of external technology introduction mode is low. At the same time, the role of independent R&D will also be weakened because of the low level of knowledge in high-tech industries.

This paper focuses on external technology suppliers in universities. On one hand, universities are the main channels for obtaining external technology in high-tech industries[9], so it is undoubtedly reasonable to take universities as technology suppliers. On the other hand, from the perspective of operability, external technology suppliers such as domestic and foreign enterprises and public R&D institutions are relatively deficient, while relevant data of universities are relatively sufficient. However, it should be pointed out that the influence of geographical distance on the external technology introduction of high-tech industry cannot be ignored. Mukherji[21] showed that knowledge flow has localization effect. Being in the same province can greatly promote knowledge spillover between universities and enterprises, but once they are not in the same province, distance has insignificant effect on knowledge spillover. This indicates that the technical connection between universities and high-tech industries is often constrained by the inter-provincial geographical distance, so the knowledge potential difference defined in this paper takes the provinces as the unit. In other words, the knowledge potential difference is defined as the knowledge potential of universities (measured by the stock of human capital) minus the knowledge potential of high-tech industries (measured by the stock of human capital) divided by the sum of the two. The selection of human capital stock as the measurement basis comes from the empirical research experience of Sun Luyun[14] on technology introduction and innovation development.

2.2 Research hypothesis on innovation model of high-tech industry

According to the above theoretical framework of knowledge potential difference, this paper calculates the knowledge potential difference of the selected samples in 2016. The specific results are reported in the form of map visualization, as shown in Figure 1:

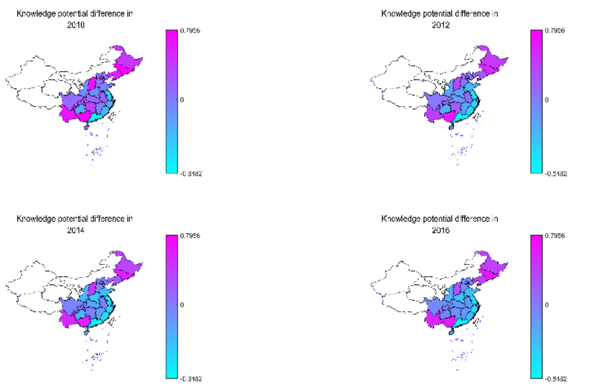

Fig1. Knowledge potential difference of high-tech industries in provinces

According to Figure 1, it can be found that the knowledge potential difference of high-tech industries in various provinces is generally low. Based on the knowledge potential difference theory, the innovation mode of domestic technology transformation in high-tech industry is inefficient, and independent R&D is the preferred innovation mode of high-tech industry. In existing studies, due to different time span of data adoption, technology introduction and independent R&D have different effects on technological innovation in high-tech industries, such as Li Guangsi and Chen Heng[22, 23]. Therefore, it is still necessary to test whether the high-tech industry will prefer independent R&D rather than domestic technology introduction in the context of low knowledge potential difference.

Furthermore, it is necessary to identify the basis for high-tech industry to select innovation mode under the action of knowledge potential difference. That is, verifying the "inverted U-shaped" action mechanism of knowledge potential difference. The effect of different technology acquisition modes on technological innovation has been explored in previous paper: First, there is uncertainty about the effect of technology introduction on technological innovation in high-tech industries[22,23]. Secondly, Luca Berhicci[24] shows that opportunity cost caused by R&D boundary increases and external technology acquisition has a significant negative impact on technological innovation of enterprises with the increase of internal knowledge stock. According to the theory of knowledge potential difference, the potential difference of the nonlinear effect of the innovation behavior and knowledge about: due to the high technology industry knowledge potential is high in low potential difference provinces, universities are less likely to produce relatively high-quality scientific and technological achievements. The opportunity cost of adopting the innovation mode of domestic technology introduction in high-tech industry is too high, so it has a negative effect on technological innovation. The province with appropriate knowledge potential difference has a higher knowledge potential and a higher probability of technological achievements. Therefore, the adoption of innovation mode of domestic technology introduction in high-tech industry can promote technological innovation. However, when the knowledge potential difference is too high, the high-tech industry cannot absorb the scientific and technological achievements from universities. On the contrary, the innovation mode of domestic technology introduction has no significant effect on its technological innovation.

At present, the inter-provincial knowledge potential difference has heterogeneity, which provides a condition for this paper to examine the mechanism of knowledge potential difference. Specifically, the knowledge potential difference between high-tech industries and universities in different regions is different, so the high-tech industries in different provinces choose the same innovation mode to have different effects on technological innovation. Therefore, it is necessary to test whether there is an significant threshold effect in the knowledge potential difference among provinces. Based on this, the following hypotheses to be tested are proposed:

H.a: The knowledge potential difference has a non-linear effect on the independent R&D mode of high-tech industry, and shows an "inverted U shape" with the innovation mode of domestic technology introduction.

3 Study design

3.1 Model specification

In terms of model setting, this paper draws on the thought of Fu Yuanhai[3] and studies the innovation mode selection of high-tech industry based on the influence of innovation mode on the innovation performance of high-tech industry. Therefore, innovation performance is adopted as the explained variable. In order to test the action mechanism of knowledge potential difference, knowledge potential difference is adopted as the threshold variable, technology introduction and independent R&D as the threshold dependent variable. However, the effect of technology introduction on innovation performance is often affected by the absorption capacity of high-tech industries[25], which is represented by the cross term of technology introduction and absorption capacity. Based on Hansen's fixed effect panel threshold regression model, this paper sets the estimation equation as:

$$IP_{it} = \beta_0 + \beta_1 DT_{it} * Ab_{it} * I_{it} + \beta_2 Te_{it} * I_{it} + \beta_3 DT_{it} * Ab_{it} * (1 - I_{it}) + \beta_4 Te_{it} * (1 - I_{it}) + \sum Ctrl + \mu_i + \varepsilon_{it} \quad (1)$$ [1]①

Where, *IP* represents innovation performance, *DT* represents domestic technology introduction, *Ab* represents absorption capacity, *Te* represents investment in independent R&D, *Ctrl* is the control variable, including foreign technology purchase(*OT*) and export(*Ex*), μ is the individual effect of the province, ε is the random disturbance term, and the value of the dummy variable is:

$$I = \begin{cases} 1, Know\_PD_{it} < \gamma \\ 0, Know\_PD_{it} \geq \gamma \end{cases} \quad (2)$$

Know_PD is the knowledge potential difference defined in this paper as a threshold variable; γ is the threshold value. The value of the dummy variable depends on whether the knowledge potential difference is higher than the threshold value.

3.2 Variable selection and data

- **Explained variable**. Referring to Chen Heng[22], this paper selects sales revenue of new products to measure innovation performance of high-tech industry. On one hand, the sales revenue of new products is the representation of innovation results of high-tech industries, which directly reflects the innovation performance. On the other hand, universities are selected as external technology suppliers, so it will inevitably cause endogenous problems if we choose patents as explained variable.
- **Threshold variable**. The threshold variable is the knowledge potential difference. According to the theoretical framework above, the knowledge potential difference index is defined as follows:

$$Know\_PD = (GH - IH)/(GH + IH) \quad (3)$$

Know_PD is the knowledge potential difference, *GH* is the knowledge potential of universities, is measured by the equivalent of R&D full time equivalent of college personnel, *IH* is the knowledge potential of high-tech industries, is measured by the equivalent of R&D full time equivalent of its personnel.

- **Threshold dependent variables**. The independent R&D is measured by the R&D expenditure within the high-tech industry, and the domestic technology introduction is measured by the technical expenditure purchased within the territory of each industry as a proxy variable.
- **The moderator variable** was absorption capacity. Referring to Li [26], this paper measures the absorption capacity of an industry by R&D stock. Using the perpetual inventory method to calculate the R&D stock:

$$R_{t_0} = \frac{E_{t_0}}{k + \delta}, t_0 = 2009$$
$$R_t = R_{t-1}(1 - \delta) + E_t, t = 2009, 2000 \cdots 2016$$
(4)

R is R&D Stock, E is R&D expenditure, k is the average annual growth rate of R&D expenditure. δ is the annual depreciation rate of stock. According to the research of Liu Hui[2], 15% is selected as the annual depreciation rate.

- **Control variables**. Including foreign technology purchase and export[27]. The former is measured by the foreign technology purchase amount of the high-tech industry, while the latter is measured by the export amount of the high-tech industry.

3.3 Dataset

This paper collected data of 25 provinces and cities in 2009-2016 provincial panel data (Too many missing values of data before 2009, part of the data in 2017 is not available.) as the research sample, data from the China statistical yearbook of science and technology, China statistics yearbook on high technology industry and China statistical yearbook. Among them, innovation performance, independent research and development, absorption capacity, domestic technology introduction, foreign technology purchase and export are all reduced accordingly and the natural logarithm is taken. Descriptive statistics of variables are shown in Table 1. The average value of domestic technology introduction is significantly lower than the average value of independent R&D. Indicating that the high-tech industry has a low demand for domestic technology, which is consistent with the intuition of theoretical analysis.

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[1] ①This is the panel threshold regression model of single threshold effect, and the panel regression model of double threshold effect is similar, which will not be repeated.

Table1. Descriptive statistics of variables

Variable	Mean	St	Min	Max	Obs
IP	15.05	1.71	9.64	18.86	200
OT	8.25	2.36	1.61	13.44	200
Ex	5.85	2.23	0.64	11.31	200
DT	8.42	1.64	2.08	13.23	200
Te	12.59	1.41	9.18	16.03	200
Know_PD	-0.03	0.40	-0.85	0.80	200
Ab	13.73	1.48	10.27	17.37	200

4 Empirical analysis

4.1 Basic regression results and analysis

First we use the fixed effect panel model to estimate the model. Through the Hausman test, the chi-square statistic is 17.92 and the p-value is 0.006. Therefore, a fixed-effect model is used. The estimated results are shown in Table 2.

Table2. Estimation of fixed effect panel model

Variable	Coefficient	Standard	T-Statistic
*OT*Ab*	-0.005**	0.002	-2.20
Ex	0.110***	0.037	3.03
*DT*Ab*	0.002	0.002	0.81
Te	0.745***	0.229	3.25
Ab	0.147	0.180	0.82
Know_PD	0.006	0.392	0.02
C	3.296***	1.152	2.86

It can be seen from Table 2 that foreign technology purchase (*OT*Ab*) is significantly negative at the 5% level, and the introduction of technology in the high-tech industry with strong absorption capacity has a negative impact on innovation performance. The explanation is: With the development of the high-tech industry, its independent R&D has been significantly improved, and the "ceiling" effect has led to the negative effect of foreign technology purchases on innovation performance[28]. Exports are significantly positive at the 1% level, indicating that exports of high-tech industries often have a significant effect on innovation performance. This is because the products exported by high-tech industries are mostly technology-intensive products, and the increase in exports has a direct effect on innovation performance. Independent R&D in the high-tech industry is significant at the 1% level, with an estimated coefficient of 0.745, and the domestic technology introduction (*DT*Ab*) coefficient is estimated to be 0.002 and not significant. It shows that the current main means of improving innovation performance of high-tech industries are exports and independent R&D. Domestic technology introduction still cannot significantly promote the innovation performance of high-tech industries.

4.2 Testing of Threshold Effect of Knowledge Potential Difference and Estimation of Threshold Value

Next, a non-linear panel model with knowledge potential difference as the threshold variable is used for testing. Through the single-threshold and double-threshold effect tests of formula (1), the results are shown in Table 3.

Table3. Testing of threshold effect

Hypothesis testing	P-value	Critical Value		
		10%	5%	1%
Single Threshold***	0.003	4.557	6.432	10.251
Double Threshold**	0.023	4.801	6.483	9.654

It can be seen from Table 3 that the single-threshold effect is significant at the 1% level, and the double-threshold effect is significant at the 5% level, indicating that there is a significant knowledge potential difference for the impact of high-tech industry R&D expenditure and technology introduction affected by absorptive capacity on innovation performance. Correspondingly, the thresholds under the two thresholds are estimated in Table 4.

Table4. Estimation of threshold effect

	Estimate	95% Confidence interval
Single Threshold***	-0.405	[-0.436, -0.360]
Double Threshold**	-0.405, 0.110	[-0.436, -0.375], [0.050,0.141]

The results show that the single threshold estimation value of the single threshold model is -0.405, which is within the 95% confidence interval [-0.436, -0.360]. And it can be considered that the estimated value is equal to the true value. At the same time, the confidence interval is narrow, indicating that the threshold interval is reasonable. In addition, the lower threshold of the double-threshold model is also estimated to be -0.405, which proves that the single-threshold model is accurate. The two thresholds fall within the 95% confidence intervals [-0.436, -0.375], [0.050, 0.141] of the double threshold model respectively. It can be considered that the estimated value is equal to the true value at this stage.

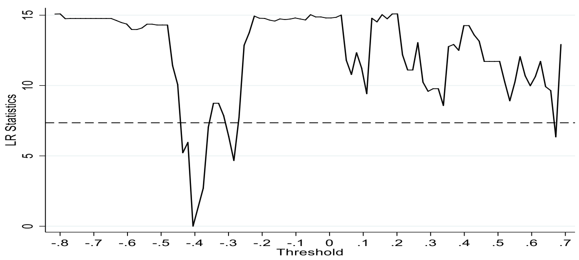

Fig2. LR statistics graph of threshold effect

Figure 2 reports the LR statistics of the threshold effect, indicating that there is a non-linear knowledge potential threshold effect on the impact of domestic R&D expenditure on high-tech industries and domestic technology purchases affected by absorptive capacity on innovation performance. There are different mechanisms of action in different intervals. Due to the need to verify the "inverted U" mechanism of knowledge potential difference, the following mainly analyzes the double threshold model.

4.3 Empirical results of knowledge threshold panel model

Parameter estimation is performed on the nonlinear threshold model expressed by equation (3.1), and the obtained estimation results are shown in Table 5. The results show that the estimated values, standard errors, and significance of the control variables of the nonlinear threshold model are almost consistent with the fixed-effect model estimates. It is important to note that the estimated value of the coefficient of absorptive capacity is positive, and it is significant at the 10% level, indicating that high-absorptive high-tech industries have a greater role in promoting innovation performance from the perspective of knowledge potential difference. This reveals the importance of industrial absorptive capacity from the perspective of knowledge potential difference. At the same time, it also can indicate that the regression result of the threshold model of knowledge potential difference is more robust.

Table5. Threshold effect model parameter estimation

Variable	Coefficient	Std(rob)	T-test
*OT*Ab*	-0.004**	0.002	-2.454
Ex	0.090***	0.033	2.743
Ab	0.245*	0.147	1.664
*DT*Ab*($Know\_PD<\gamma_1$)	-0.002	0.004	-0.360
*DT*Ab*($\gamma_1<Know\_PD<\gamma_2$)	0.004*	0.002	1.746
*DT*Ab*($Know\_PD>\gamma_2$)	0.002	0.004	0.444
Te($Know\_PD<\gamma_1$)	0.607***	0.179	3.402
Te($\gamma_1<Know\_PD<\gamma_2$)	0.505***	0.180	2.805
Te($Know\_PD>\gamma_2$)	0.491***	0.184	2.674

It can be seen from Table 5 that the double threshold model divides the entire sample into three intervals according to the threshold value of the threshold variable, namely [-1, -0.405), [-0.405,0.110), [0.110,1]. The specific analysis is as follows:

The first stage of knowledge potential difference is when the knowledge potential difference is less than the lower threshold. Domestic technology import (*DT*Ab*) is not significant and the coefficient is negative. Indicating that when the knowledge potential of universities is significantly lower than that of high-tech industries, the adoption of technology import mode by high-tech industries with high absorption capacity will adversely affect innovation performance, but the role not significant. The coefficient of independent R&D is positive and the estimated value of the coefficient is 0.607, which is significant at the level of 1%. On the one hand, the universities in this area have a relatively low knowledge relative to the high-tech industry, and they are unable to provide high-quality technology for transfer. On the other hand, the independent R&D capabilities of the high-tech industry in this area are very strong. The willingness to introduce technology is weak. In short, when the knowledge potential difference is small, the innovation model of the high-tech industry tends to be mainly independent R&D, and the amount of domestic technology introduction are relatively small.

The second stage of knowledge potential difference is when the knowledge potential difference is between the upper and lower thresholds. The domestic technology introduction coefficient is 0.004, which is significant at the 10% level. In addition, the coefficient of independent R&D is still positive but reduced from 0.672 to 0.505, which is significant at the level of 1%. The reason is that the knowledge potential difference between universities and high-tech industries has increased, the efficiency of independent R&D has been relatively reduced, and the efficiency of technology transfer has been relatively improved. At the same time, the proportion of domestic technology imports has increased, indicating that the demand for scientific and technological achievements has improved. But for the high-tech industry that belongs to this interval of knowledge potential difference, the technology introduction mode is still not its main choice of innovation. The reason may be that the relevant issues on the supply side of the transformation of scientific and technological achievements have not been effectively resolved. Such as: low efficiency of the intermediary in the transformation of scientific and technological achievements, immature transformation system, etc. [29].

The third stage of knowledge potential difference is when the knowledge potential difference is higher than the upper threshold. The conversion coefficient of domestic results adjusted for absorptive capacity is positive, but not significant. The coefficient of independent R&D is positive but the estimated value is reduced from 0.505 to 0.491, which is significant at the level of 1%. The high-tech industry in this range still adopts an innovation model based on independent R&D, but the coefficient of independent R&D and domestic technology introduction (*DT*Ab*) both are significantly smaller than the second stage of knowledge potential difference. Based on the knowledge potential difference theory, if the knowledge potential difference is too high, the high-tech industries belonging to this range cannot absorb domestic technology well, resulting in a low level of technology transfer. Explained by the actual situation: China has few provinces with high level of high-tech industry development and higher levels of university development. At present, most of the provinces in this area are those with high level of university development and low level of high-tech industry development. The development situation does not support the huge amount of high-risk technology introduction or independent R&D. Even if the technology introduction method is adopted, it cannot be well digested and absorbed. In general: too high a knowledge potential difference may lead to "indigestion" in the high-tech industry, which inhibits the external technology conversion efficiency of the high-tech industry in turn. Overall, the hypothesis H.a is confirmed.

4.4 Variation Trend and Realistic Basis of Knowledge Potential Difference Based on Double Threshold Model

By summarizing the changes in the knowledge potential differences of the provinces during the sample period, this paper finds a typical three-stage change law of knowledge potential difference as shown in Figure 3:

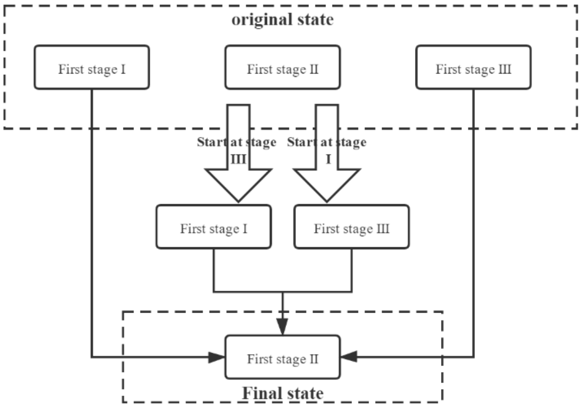

Fig3. Three-stage change law of knowledge potential difference

The explanation of Figure 3 is as follows: With the continuous development of the high-tech industry, due to the rational employment of college graduates based on wages and benefits, coupled with the restrictions on the ability of high-tech industry talent absorption. In areas currently in the first stage, the knowledge potential difference will continue to shift to the second stage due to the development of local universities and the saturation of high-tech industry talents. There are two situations in the region currently in the second stage. The regional knowledge potential difference starting from the first stage will continue to be transferred to the third stage and approaching the second stage; the regional knowledge potential difference starting from the third stage will continue to be moved to the first stage and then approaching the second stage. In areas currently in the third stage, the knowledge potential difference will eventually be transferred to the second stage.

The internal mechanism that caused this phenomenon is that the core talents of universities have been lost in the past ten years[30], while the high-tech industry has rapidly accumulated talent capital[31]. As a result, the knowledge potential differences in most provinces is currently negative, and the knowledge potential difference in provinces with high levels of economic development is even lower. However, the high-tech industry cannot accept human capital without restrictions, and the threshold for accepting human capital will become higher when it reaches a peak. Coupled with the "double first-class" construction background, universities set salary independently to attract talents to stay in school[32]. Therefore, the knowledge potential of universities have a tendency to catch up and surpass the high-tech industry. Specifically, the high-tech industries in the provinces that are currently in the first stage are more mature, and as the human capital accumulation of universities accumulate, the knowledge potential difference will become smaller. For provinces transferred from the first stage to the second stage, the knowledge potential difference may oscillate near the upper threshold but eventually stabilize in the second stage. For provinces transferred from the third stage to the second stage, the knowledge potential difference may oscillate around the lower threshold but eventually stabilize in the second stage. The high-tech industries in the provinces currently in the third stage are developing slowly, and the knowledge potential difference will eventually stabilize in the second stage due to the accumulation of human capital in the high-tech industries.

In addition, analysis of Table 6 shows that Tianjin, Hunan, Anhui, and Chongqing in the third stage have moved to the second stage; Henan and Shandong in the second stage have moved to the first stage; Guizhou, which is more representative moved from the second stage to the first stage and moved to the second stage again. Through Matlab programming and drawing, you can see this change more intuitively. At present, the provinces with knowledge potential difference below the lower threshold gradually decrease. And the levels of knowledge potential differences between provinces significantly lower than the lower threshold are close to the trend of the lower threshold as the year increases. Some of the provinces where the current knowledge potential difference level is greater than the upper threshold are gradually increasing, and the other part of the knowledge potential difference level has a tendency to fall below the upper threshold. The provinces currently between the upper and lower thresholds are very complicated. There are both provinces that have broken down the lower threshold trend and those that have broken up the upper threshold trend. This all coincides with the three-stage change rule of the knowledge potential difference proposed earlier, as shown in Figures 4.

Table6. Change of knowledge potential of each province

group	2009	2016
Above the upper threshold	Beijing, Tianjin, Shanxi, Liaoning Jilin, Chongqing, Hunan, Guangxi, Anhui, Yunnan, Heilongjiang	Beijing, Shanxi, Liaoning, Jilin, Guangxi, Yunnan, Heilongjiang
Between the two thresholds	Hebei, Shanghai, Jiangxi, Shandong, Henan, Hubei, Hainan, Sichuan, Guizhou, Shanxi	Tianjin, Hebei, Shanghai, Jiangxi, Anhui, Hunan, Chongqing, Hubei, Sichuan, Guizhou, Shaanxi, Hainan
Below the lower threshold	Guangdong, Jiangsu, Zhejiang, Fujian	Jiangsu, Guangdong, Fujian, Zhejiang, Henan, Shandong

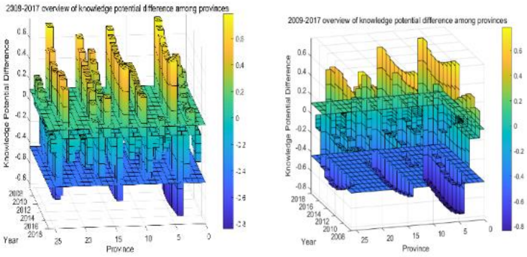

Fig4. Overview of Knowledge Potential difference in each province over the years (Top view and up view)

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