Technological Innovation Effect of China's High-Tech Intermediate Goods Import--Evidence From WIOT(2000-2014)

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Abstract: Combined with the global Input-Output Table (WIOT) and panel data of China's high-tech industry from 2004 to 2014, the least square regression model and panel threshold regression model are used to empirically study the impact of intermediate imports on technological innovation in high-tech industries.The results show that the output of technological innovation in China's high-tech industry shows a trend of fluctuation and rise during the survey period.The import of intermediate products has a positive lag effect on technological innovation output of high-tech industry.Knowledge stock accumulation has a positive moderating effect on the technological innovation effect of imported intermediate products

Keywords: import of intermediate products; knowledge stock; technological innovation

1 Introduction

Internationalization is an effective means to pursue innovation prospects and activities[1] (Dig A,2021). Import of high-tech intermediate goods is an important measure to deepen supply-side structural reform and promote the "dual circulation" strategy.Since China's entry into WTO, China has gained considerable trade volume by undertaking a large number of processing and assembly activities of imported intermediate products. On the other hand, foreign intermediate products have brought a significant impact on China's technological development.Therefore, it is doubtful whether the introduction of foreign intermediate products is an effective means to drive technological innovation by optimizing the supply side in China, and whether it will definitely play a positive role in the technological innovation of China's high-tech industry.What is the mechanism of action? Therefore, answering the above questions will help to objectively evaluate the technical performance of China's use of imports to allocate foreign resources, and on the other hand, provide ideas for correctly exerting the technical effect of domestic resource allocation.This is of great significance for China to get out of the passive situation of core technology being controlled by others, and for China to adapt to the new international environment and win new competitive advantages.

1.1 Influence mechanism analysis

The effect mechanism of imported intermediate products on technological innovation is mainly the mechanism of "learning by doing".The innovation and quality improvement of intermediate

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products are the driving force and inner form of Schumpeter's innovation. Intermediate products embody the international competitiveness of upstream manufacturers while imported intermediate products provide direct learning opportunities for importers.It is not only conducive to follow the enterprises to learn, digest and absorb the innovation content contained in imported products[2](He H L,2021),but also to carry out imitation production and upgrade creation in China to improve labor productivity[3](Hml A， 2020).The more innovation content contained in intermediate products, the more dynamic effect it has on importers.The more innovative content of intermediate products, the greater the dynamic effect on importing enterprises[4](Huang X H，2022). The empirical results of Singapore show that the import of intermediate inputs will greatly improve the labor productivity of the domestic manufacturing industry[5、6](Javed S A , ,2021；Kumar R ,2021).Enterprises engaged in processing trade can learn and absorb the knowledge and information contained in these imported products by importing core parts or components from abroad in the process of processing and assembly. At the same time, it will be internalized into the enterprise's own ability, so as to improve the domestic production efficiency, and cultivate and accumulate the human capital to master these advanced knowledge.

However, the technological innovation effect brought by importing intermediate products strongly depends on the accumulation of knowledge stock of Chinese enterprises themselves，and there is a time lag phenomenon. Enterprises with different technical levels have different motivations for learning and absorbing imported intermediate products. Enterprises with a higher technical level are more inclined to learn advanced technologies in imported intermediate products, and can digest and absorb external knowledge well, and convert external knowledge into technologies that match the internal technical processes of the enterprise, thereby enhancing technological innovation capabilities[7,8](Nh A ,2021；Suwal N，2020).

2 Research design

2.1 The empirical study of intermediate goods import and technological innovation in China's high-tech industry

2.1.1 Model settings

In terms of research methods, this paper adopts industry-level panel data and based on panel regression model to explore the linear and nonlinear mechanism of the interaction between imported intermediate products and knowledge stock accumulation on technological innovation[9](Sun H ,2021). The model is set to:

$$\begin{aligned}\ln(Y)_{it} &= \alpha_i + \alpha_1 \ln(imp)_{i,t} + \alpha_2 \ln(ks)_{i,t} + \alpha_3 \ln(imp)_{i,t} * \ln(ks)_{i,t} \\ &+ \alpha_4 \ln(k)_{i,t} + \alpha_5 \ln(l)_{i,t} + \alpha_6 \ln(gf)_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{1}$$

In formula (2), Y represents the comprehensive index of technological innovation output of industry i in period t , imp represents imported intermediate products, ks represents knowledge stock, k represents R&D investment, l represents R&D human capital investment, and gf represents government funding , α_1, α_2, α_3, α_4 , α_5, α_6 represent the

corresponding elastic coefficients. α_i represents the intercept term of individual heterogeneity, indicating the influence of individuals, that is, the influence of variables that are ignored in the response model and can reflect the differences between individuals. Therefore, the above equation can also be called "unobservable effect model". ε represents the random error term, also known as white noise.

2.1.2 Variable selection and data sources

(1) Variable selection and processing

Explained variable: Technological innovation (Y). This paper uses the comprehensive index of technological innovation output derived from the output of scientific research results and product output to measure the technological innovation level of China's high-tech industries.

Explanatory variables:

(1) Intermediate imports (imp).

The import of intermediate goods is measured by the import value of intermediate goods of China's high-tech industry from 43 other major countries in the world, and the original data is deflated using the price index of 2003 as the base period.

(2) knowledge stock (ks).

This paper uses the perpetual inventory method to calculate the knowledge stock.

(2)Data source

Since WIOD's global input-output table is currently only updated to 2014， data on imports of intermediate goods comes from the World Input-Output Table (WIOT) from 2004 to 2014 in the WIOD database.

3 Empirical Research

3.1 Measurement of technological innovation output based on projection pursuit modelPreliminary

According to the steps of the projection pursuit model, the optimal projection direction of the technological innovation output of 16 high-tech industries in China from 2004 to 2014 is globally optimized through MatlabR2014a software, and then the comprehensive index of technological innovation output of each industry is calculated (See Figure 1).

As can be seen from Table 2 and Figure 1, the comprehensive output of technological innovation in China's high-tech industry sub-sectors generally shows a fluctuating upward trend, and the level of technological innovation output is generally low. There is a large gap in the technological innovation output among various sub-sectors. From 2008 to 2014, the technological innovation output of high-tech industries did not increase significantly, and even declined to varying degrees. Among the sub-sectors, the industry with the highest level of technological innovation output is the communication equipment manufacturing industry,

followed by the electronic computer manufacturing, electronic device manufacturing, etc., and the aerospace manufacturing industry with the least technological innovation output.

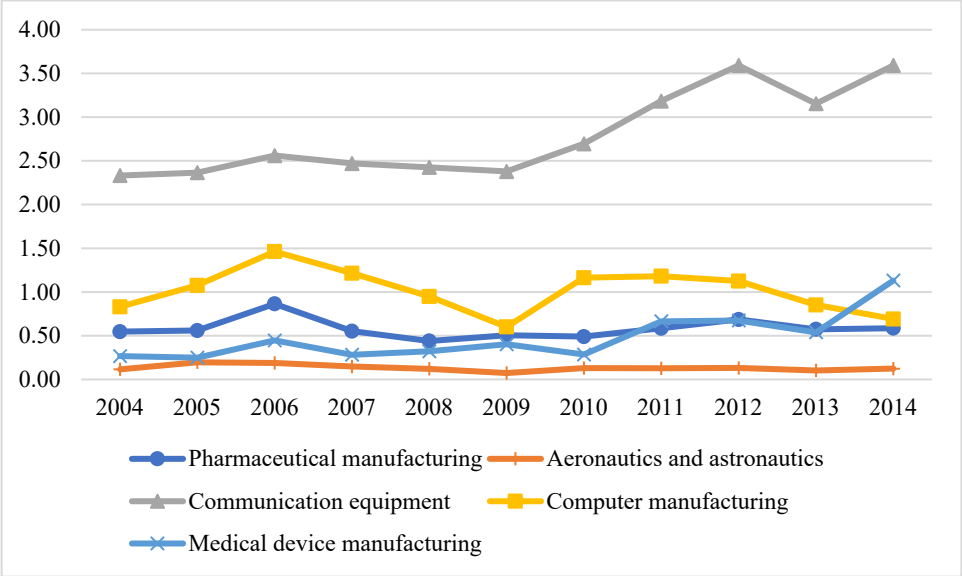

Figure 1. The five major industries of high-tech industry technological innovation output over the years

3.2 Regression Estimation of Imported Intermediate Goods and Technological Innovation of High-tech Industries

In this paper, Stata14.0 software is used to estimate the model by least squares. The model estimation results are shown in Table1.

Table 1 Estimated results of patent application as the dependent variable

					Robust	
F.pa	Coef.	Std. Err.	t	P>|t|	[95% Conf.Interval]	
imp	1.313***	0.288	4.550	0.000	0.728	1.899
ks	3.105 ***	0.508	6.120	0.000	2.074	4.136
imp*ks	0.170 ***	0.040	4.270	0.000	0.089	0.251
k	-0.025	0.239	-0.110	0.917	-0.511	0.461
l	-0.086	0.331	-0.260	0.797	-0.757	0.585
soe	-0.504*	0.286	-1.760	0.087	-1.085	0.077
gz	-1.382***	0.189	-7.300	0.000	-1.766	-0.998
gf	1.411***	0.175	8.080	0.000	1.057	1.766
_cons	-16.324***	4.963	-3.290	0.002	-26.399	-6.250

(Note: Calculated using Stata 14.0, _cons represents a constant, ***, **, * represent the significant levels of 1%, 5%, and 10%, respectively)

Table 2 The estimation results of imported intermediate products lagging in the first period and technological innovation of high-tech industry

			Robust			
y	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
L1.imp	-1.224***	0.399	-3.070	0.004	-2.030	-0.419
ks	0.286	0.187	1.530	0.134	-0.091	0.664
k	0.864***	0.266	3.240	0.002	0.326	1.402
l	0.487*	0.253	1.920	0.061	-0.024	0.998
soe	0.015	0.396	0.040	0.969	-0.784	0.815
gz	-0.786***	0.194	-4.060	0.000	-1.177	-0.395
imp*ks	0.095***	0.033	2.910	0.006	0.029	0.162
gf	-0.678***	0.138	-4.900	0.000	-0.958	-0.399
_cons	-5.634	4.400	-1.280	0.208	-14.521	3.252

(Note: Calculated using Stata 14.0, _cons represents a constant, ***, **, * represent the significant levels of 1%, 5%, and 10%, respectively)

The goodness of fit of the model was 0.907, indicating that the model fitting effect was good. It can be seen from Table 2 that the estimation results of all variables with a one-period lag are significantly different from the two previous estimation results. The most significant one is that the impact of imported intermediate products on technological innovation has changed from a negative effect to a positive effect, with a significant level of 10%. This result shows that when all the other independent variables and imported intermediates are configured at the same time, the possible innovation "crowding out" effect of imported intermediates turns into a "driving" effect. This mechanism of action is in line with the "learning by doing" mechanism of imported intermediate products: enterprises gradually absorb the technical elements contained in the intermediate products in the production process, and then combine their own knowledge accumulation to transform them into independent innovation achievements. At the same time, knowledge stock plays a positive role in promoting technological innovation, with a significant level of 1%. The intersection of imported intermediate products and knowledge stock also has a significant role in promoting technological innovation. This shows that knowledge stock can improve the technological innovation effect of imported intermediate products. Explain that assumptions 1.

In order to further prove the robustness of this result, the imported intermediate products in the model are delayed by one period to verify their effect on technological innovation. The specific results are shown in Table 2:

4 Discussion

The empirical results show that the import of intermediate products has a lagging positive effect on the technological innovation level of high-tech industries, and the lagging supporting resource input has a positive effect on technological innovation.When imported products and other important resources are allocated at the same time, there is a time-lag driving effect on

technological innovation. This mechanism reflects the innovation mechanism of “learning by doing” [10、11](Vafadar A ,et al., 2021; Wang R ,et al., 2020).At the same time, it highlights the importance of internal circulation of resources.

5 Conclusion

Based on the 2004-2014 Global Input-Output Database (WIOD) and the China High-tech Industry Statistical Yearbook, this paper uses least squares regression to empirically study the mechanism of imported intermediate goods and technological innovation in high-tech industries.On the one hand, it explores the technological innovation delay effect of intermediate goods import based on the theory of “learning by doing”. On the other hand, it explores the role of knowledge stock accumulation in the technological innovation effect of intermediate goods import.Furthermore, the threshold effect of knowledge stock is investigated based on the subjective ability to explore tacit knowledge.The empirical results provide policy ideas for my country’s high-tech industry to base itself on the national knowledge stock, implement the structural adjustment of the knowledge supply side, and treat imported intermediate products reasonably and appropriately, so as to help achieve breakthroughs in technological innovation in my country’s high-tech industry.

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