Analysis of the Dynamic Relationship Between Foreign Trade and Technological Innovation Based on VAR Model

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Abstract. Since the reform and opening up, foreign trade has played a significant role in China's economic growth. Based on the relevant data of China from 1995 to 2019, this paper systematically analyses the dynamic relationship between foreign trade and technological innovation by using the vector auto regression model (VAR). The results show that technological progress can significantly promote the export of high-tech products, and high-tech product exports also have a positive impact on technological progress; Technological progress also has a significant role in promoting the export of low technology products. Obviously, the superposition effect of technological progress in different periods will have a profound positive effect on the growth of foreign trade; The impact of foreign trade growth on technology input and output is short-term, weak and unsustainable.

Keywords: foreign trade · technological innovation · dynamic relationship · entropy weight method · VAR model

1 Introduction

Since 2020, the global economy has been hit by the new pneumonia. The contribution of exports to China's economic growth is weak, the traditional industries have excess capacity, the industrial structure needs to be further optimized and upgraded, and the pace of technological innovation needs to be accelerated.

Many scholars' relevant researches mainly focus on the theoretical description of the relationship between foreign trade and technological innovation, and rarely involve empirical analysis. Even if empirical analysis is carried out, regression method is often used for analysis. This cannot reflect the dynamic correlation between variables. This paper makes an empirical analysis of China's economic data in the past 25 years using VAR model. Through impulse response function and variance decomposition analysis, the interaction process between foreign trade and technological innovation is deeply analyzed.

This paper is divided into three steps to carry out empirical research: the first step is to use entropy weight method to comprehensively evaluate technological innovation;

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The second step is to build a VAR model of foreign trade and technological innovation, and use impulse response analysis and variance decomposition to analyze the dynamic relationship between them.

2 Measurement Model

2.1 Entropy Weight Method

Technological innovation is a complex dynamic process. In order to measure the technological innovation level of a country more scientifically, this paper uses the entropy weight method [1–2] to calculate the comprehensive score reflecting the technological innovation level. The calculation idea of entropy weight method is as follows:

The first step is to dimension Alize the original indicators and calculate the same metrics p_{ij}, see (1).

$$p_{ij} = x_{ij} \Big/ \sum_{j=1}^{m} x_{ij} \tag{1}$$

Step 2: calculate the entropy e of each three-level index e_i, m is the number of samples, see (2).

$$e_i = -k \sum_{j=1}^{n} \left(\mathrm{p_{ij}} \cdot \mathrm{lnp_{ij}}\right), k = -1/lnm \tag{2}$$

Step 3: calculate the difference coefficient g of each three-level indicator g_i, see (3).

$$g_i = 1 - e_i \tag{3}$$

Step 4: calculate the weight w of each three-level indicator w_{ij}, , and calculate the score, see (4).

$$w_{ij} = g_i \Big/ \sum_{j=1}^{m} g_i, \quad F_i = \sum_{j=1}^{m} (w_{ij} \cdot p_{ij}) \tag{4}$$

2.2 VAR Model

In order to more scientifically evaluate the dynamic relationship between foreign trade and technological innovation, this paper assumes that the lag order of the two variables of foreign trade and technological innovation is p, then we can build a $p-$order standard vector autoregression model, as shown in (5).

$$\boldsymbol{X}_t = \boldsymbol{A}_0 + \boldsymbol{A}_1\boldsymbol{X}_{t-1} + \boldsymbol{A}_2\boldsymbol{X}_{t-2} + \cdots + \boldsymbol{A}_p\boldsymbol{X}_{t-p} + \boldsymbol{e}_t \tag{5}$$

where, $\boldsymbol{A}_i$ is the coefficient matrix of the predetermined endogenous variable vector $\boldsymbol{X}_{t-i}$ $(i = 1, 2, \cdots, p)$, $\boldsymbol{e}_t$ is the random interference term.

After constructing the VAR model, it is still necessary to calculate the impulse response function, and the response of endogenous variables to their own or other endogenous variables. Therefore, using the special solution of the $p-$order VAR model when it is stable, we can get (6):

$$\boldsymbol{X}_t = \boldsymbol{\mu} + \sum\nolimits_{i=0}^{\infty} \boldsymbol{\varphi}_i \boldsymbol{\mu}_{t-i} \tag{6}$$

Among them $\boldsymbol{\mu}_{t-i}$ is the cumulative effect of the unit pulse, $\boldsymbol{\varphi}_i$ is the impulse response function.

Using (6) for prediction, the error of n steps can be obtained as (7).

$$\boldsymbol{X}_{t+n} - \boldsymbol{E}_t\boldsymbol{X}_{t+n} = \sum\nolimits_{i=0}^{n-1} \boldsymbol{\varphi}_i \boldsymbol{\mu}_{t+n-i} \tag{7}$$

3 Variables and Data

3.1 Variable Selection

According to the above analysis, the variables determined for analysis are foreign trade and technological innovation level, which are measured by the comprehensive score of technological innovation (V1) and the total amount of foreign trade exports (V2). Because there are significant differences between the relativity of products with different technology levels and technological innovation, in order to further analyze the dynamic relationship between foreign trade and technological innovation in the robustness analysis, foreign trade is further divided into low technology products foreign trade and high-tech products foreign trade, and measured by other exports (V3) and high-tech products exports (V4). Among them, the other export volume is the difference between the total export volume and the export volume of high-tech products.

3.2 Data Description

The time span selected in this paper is from 1995 to 2019. Based on the experience of econometric model research, natural logarithms are taken for such time series as economic data to eliminate the influence of heteroscedasticity of original data as much as possible. In addition, the scientific research input and scientific research output in the technical innovation indicators are selected from the relevant data of industrial enterprises above the designated size, because the data of new product development is selected from the relevant data of large and medium-sized industrial enterprises. The data in this paper are from the China Statistical Yearbook and the official website of the National Bureau of Statistics.

4 Technical Innovation Index

4.1 Construction of Technical Innovation Index System

Technological innovation is a complex process of comprehensive reform. Different scholars have measured the innovation ability of regional Hu from different angles. For example, Wang Peng et al. [3] measured the efficiency of scientific and technological innovation activities R&D and economic output in the Pearl River Delta region from the aspects of scientific and technological innovation input, scientific and technological innovation achievements, expected output of scientific and technological innovation economy, and unexpected output of scientific and technological innovation economy. Dai Wei et al. [4] constructed a comprehensive evaluation index system for the support of science and technology finance for the development of science and technology innovation from three aspects: science and technology finance, science and technology innovation and social development. Combined with the scholars' research, this paper sets up three second-level indexes and six third-level indexes based on the three aspects of scientific research input, scientific research output and new product development, in order to comprehensively evaluate the technological innovation ability of our country.

4.2 Weight Analysis of Technology Innovation Index System

According to economic experience, the three indexes have a positive impact on technological innovation, so they are all positive indicators. According to the calculation steps of the entropy weight method mentioned above, (4) can be used to calculate the weight of each three-level index of technological innovation, and the results are shown in Table 1. At the same time, the calculated comprehensive evaluation score is recorded as V1 for subsequent research.

5 Empirical Results of VAR Model

5.1 Unit Root Test

Since the empirical test of VAR model requires stationarity of time data to avoid the problem of "spurious regression", the ADF unit root test is adopted in this paper. Stata software is used to conduct ADF unit root test. Generally speaking, there are three types of test, which are no constant term and no time trend, with time trend and constant term and only with drift term. In this paper, the ADF unit root test with drift term and lag period of phase 0 was selected. At the confidence level of 1%, 5% and 10%, the critical values of the ADF test were -2.528, -1.725 and -1.325, respectively. The test results of variables are shown in Table 2.

According to the test results, the ADF statistics of the four variables of technological innovation (LNV1), foreign trade (LNV2), low technology foreign trade (LNV3) and high technology foreign trade (LNV4) cannot pass the significance test. After first-order difference processing of the aforementioned variables, the ADF statistics of the above four variables are all less than the critical value corresponding to the significance level of 5%, and the null hypothesis of the existence of unit root is rejected. Therefore, the first-order difference (d.) of the data of the four variables is a stationary time series, which can be analyzed in the next step.

Table 1. Index and weight of technology innovation evaluation system

level I indicator	level II indicator	level III indicator	weight
Comprehensive score of technological innovation	Scientific research investment	Full time equivalent of research and test development personnel	0.0649
		Research and experimental development expenditure	0.1796
	Scientific research output	Number of patent applications accepted	0.1898
		Number of invention patent applications accepted	0.2043
	new product development	Funds for new product development	0.1879
		Sales revenue of new products	0.1735

Table 2. ADF test results of model variables

variable type	ADF test value	conclusion
LNV1	−0.064	unstable
d.LNV1	−4.198**	stable
LNV2	−2.296	unstable
d.LNV2	−3.873**	stable
LNV3	−2.317	unstable
d.LNV3	−3.939**	stable
LNV4	−2.264	unstable
d.LNV4	−3.933**	stable

Note: 1) "* ", "* *" and "* * * " mean significant at the confidence level of 1%, 5% and 10% respectively; 2) LNV represents the logarithm of the original data of the variable, and d. represents the first order difference

5.2 VAR Model Estimation

VAR model is used to construct a set of time series systems (LNV1, LNV2), which can analyse the dynamic impact between technological progress and foreign trade growth. Before the empirical analysis of VAR model, the optimal lag period of variable group should be determined first. In this paper, the five statistics of LR, FPE, AIC, SC and HQ are used to judge the optimal lag period, and the optimal lag period is determined according to the principle of the minimum value of the criteria of most test indicators. The results are shown in Table 3 (Table 4).

The test results show that the optimal lag period of the variable group (LNV1, LNV2) is one period, so VAR (1) model can be constructed, and the standard form of (8) can be obtained.

$$\begin{bmatrix} LNV1 \\ LNV2 \end{bmatrix} = \begin{bmatrix} -0.956586 \\ 0.030600 \end{bmatrix} + \begin{bmatrix} 0.841294 & -0.052481 \\ 0.179919 & 1.028103 \end{bmatrix} \begin{bmatrix} LNV1_{t-1} \\ LNV2_{t-1} \end{bmatrix} + \begin{bmatrix} \delta 1t \\ \delta 2t \end{bmatrix} \quad (8)$$

The output results of the software show that the R-SQUARE and modified R-SQUARE of the VAR (1) model are both above 98.5%, which fully indicates that the fitting effect of the model is very good and the explanatory ability is strong. According to the estimation results of (8), when the lag period is one stage, the change of LNV1 is mainly influenced by its own factors in the previous period, and its influence factor reaches 0.84. However, LNV2 has little influence, and its influence is negative. Moreover, LNV2 will be affected by both LNV1 and itself. The factor affected by its last stage

Table 3. Test Results of VAR Model's Optimal Lag

Lag	LL	LR	df	FPE	AIC	HQIC	SBIC
0	−23.43				0.044	2.544	2.563
1	56.19	159.3*	4	0.000	0.000*	−5.02*	−4.96*
2	57.77	3.16	4	0.532	0.000	−4.777	−4.680
3	60.36	5.18	4	0.270	0.000	−4.636	−4.499
4	64.53	8.34	4	0.080	0.000	−4.653	−4.478

Note: "* " indicates the optimal lag period under this criterion

Table 4. Variance decomposition of prediction error.

periods	ANOVA of LNV1			ANOVA of LNV2		
	S.E.	LNV1	LNV2	S.E.	LNV1	LNV2
1	0.055449	100.0000	0.000000	0.127559	44.96368	55.03632
2	0.084931	95.98123	4.018770	0.181567	44.12339	55.87661
3	0.113054	89.80599	10.19401	0.223331	43.36523	56.63477
4	0.141224	83.48799	16.51201	0.258482	42.68006	57.31994
5	0.169479	77.78415	22.21585	0.289149	42.05979	57.94021
6	0.197577	72.87328	27.12672	0.316410	41.49733	58.50267
7	0.225248	68.71661	31.28339	0.340902	40.98646	59.01354
8	0.252254	65.21126	34.78874	0.363048	40.52176	59.47824
9	0.278409	62.24805	37.75195	0.383150	40.09850	59.90150
10	0.303570	59.73027	40.26973	0.401437	39.71252	60.28748

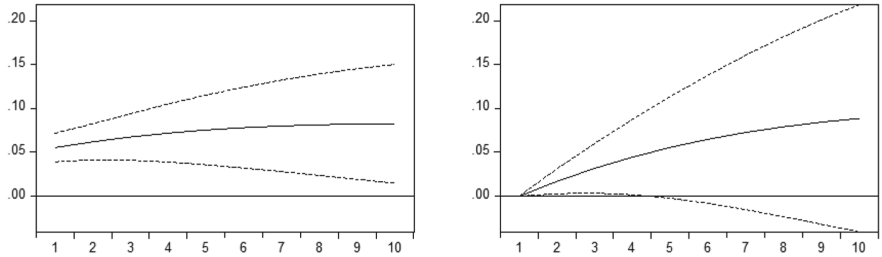

Fig. 1. Impact of technological innovation on technological innovation(left); Impact of technological innovation on foreign trade(right). Note: The solid line represents the time path of the impulse response function of one-unit impulse impact, and the dotted lines on both sides represent the confidence interval of two standard deviations.

is 1.03, and the factor affected by the last stage of LNV1 is 0.18. In other words, technological innovation has a great impact on itself, indicating that technological innovation has the characteristics of self-endogenous evolution, and is less affected by the level of foreign trade. In turn, the level of foreign trade will be greatly affected by the evolution of technological innovation.

5.3 Impulse Response Function

The impulse response function reflects how the endogenous variable responds to changes in itself and all other endogenous variables. On the basis of the estimation of the VAR model mentioned above, the influence relationship between variables after mutual impact is continued to be analyzed. The impulse response function of VAR (1) model is shown in Fig. 1.

Figure 1(left) shows the impulse response function of technological innovation and itself. After the impact of one standard deviation on the technological innovation itself, the impact effect shows a slow increasing phenomenon from the first period. This indicates that the effect of initial technological innovation on oneself becomes weaker as the period goes on. Figure 1(right) shows the impulse response function of technological innovation to foreign trade. From the first period to the 10th period, the impact of technological innovation on foreign trade showed an obvious trend of strengthening. This strong effect began to weaken from the sixth stage. Figure 2 show the impulse response functions of foreign trade to technological innovation and itself. Obviously, the effect of foreign trade is not obvious, showing a relatively stable effect.

5.4 Variance Decomposition Analysis

Impulse response function, which describes the influence trajectory of random disturbance term on endogenous variables, is very helpful to reveal the relationship between technological progress and foreign trade. Therefore, the analysis of variance decomposition on this basis can further study the important information of the random interference term. Table 3 shows the changes in the movement proportion between variables LNV1 and LNV2 caused by the impact of each other. From the results, the contribution of

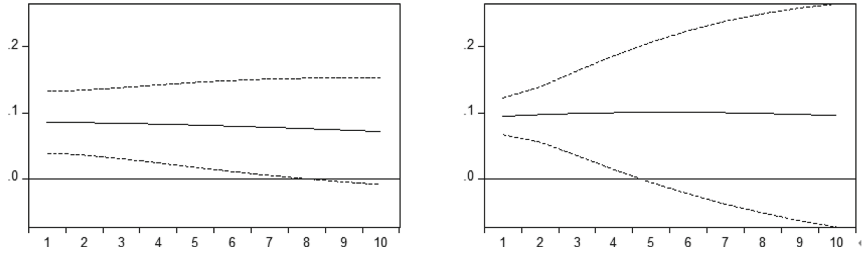

Fig. 2. Impact of foreign trade on technological innovation(left); Impact of foreign trade on foreign trade(right). Note: The solid line represents the time path of the impulse response function of one-unit impulse impact, and the dotted lines on both sides represent the confidence interval of two standard deviations.

LNV1 to its own growth showed obvious attenuation, but this attenuation gradually weakened with the change of time. The contribution of LNV1 to the growth of LNV2 did not respond at the beginning, but increased rapidly from the second period to the tenth period, with a contribution rate of 40.27%. The contribution of LNV2 to the growth of LNV1 did not change much, from 44.96% in the first stage to 39.71% in the 10th stage, indicating that this attenuation effect was not obvious. On the contrary, the contribution of LNV2 to its own growth showed a weak promoting effect.

According to the above analysis, we can draw conclusions: First, the superposition effect of technological innovation in different periods will play an increasingly important role in the growth of foreign trade, and the impact of technological innovation is profound; Second, the impact of foreign trade growth on technological innovation is short-term, weak and unsustainable.

6 Conclusions

This paper uses VAR model to analyze the relationship between foreign trade and our country's technological innovation using the data from 1995 to 2019. The above research results are of great significance for the choice of technological innovation strategies in China. First, the research results show that the exogenous evolution of technological innovation driven by the development of foreign trade using the principle of comparative advantage is not the only reason for the technological progress in the past 25 years. The endogenous evolution of technology plays a significant role in the independent breakthrough of some key technologies. Although in the process of global industrial transfer, according to comparative advantages is the best way for China to quickly integrate into the global value chain and participate in the international division of labor. It can also help our country in the long term to absorb advanced technology and knowledge by using the backward advantage of the developed country, and realize climbing to the high-end of the industrial chain. However, in the captured global value chain led by developed countries [5], focusing on the production and export of low-technology added value products is not conducive to our country breaking through the "technological blockade" of developed countries as soon as possible and realizing independent innovation of core technologies. Therefore, it is imperative to promote the endogenous evolution of technology. Second, it can be seen from the empirical results that the process of exogenous evolution of technological innovation is the process of qualitative change caused by quantitative change of technology, which can only play a role in the long run. In order to improve the possibility of qualitative change of technological innovation in the short term, it is still necessary to play the role of endogenous evolution of technological innovation.

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