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Study on the Influence of Digital Investment on the Upgrading of Global Value Chain of Chinese Manufacturing Industry

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Abstract:

Under the background of accelerated integration of digitalization and manufacturing, in this paper, the development status of China's manufacturing digitalization was analyzed firstly, and then the panel data of 18 departments of Chinese manufacturing industry from 2000 to 2014 were analyzed by using fixed-effect model, to explore the influence of digital investment on the GVC upgrade of Chinese manufacturing industry. The empirical results show that digital investment has a positive effect on China's manufacturing GVC upgrading, labor productivity and overseas demand also have a positive effect on China's manufacturing GVC upgrading, while capital stock and factor returns have a negative effect. Finally, suggestions are made based on the empirical results.

Keywords*: Digital investment, Chinese manufacturing industry, Global value chain, Upgrading.*

I. INTRODUCTION

Over the past few decades, Chinese manufacturing industry has boomed and successfully integrated into the global value chain. According to the United Nations Industrial Development Organization (UNIDO), global value chains are defined as global, cross-enterprise networks that link the production, sale, recycling and other processes for the realization of the value of goods or services, covering the entire process, from the procurement and transport of raw materials, the production and distribution of semi-finished and finished products, to final consumption and recycling. Different from the manufacturing industry in most developed countries, Chinese manufacturing industry mainly depends on its own better infrastructure construction and the cost advantage of production factors embedded in GVC, and mainly involves the labor-intensive and low-end technology-rich value-added links in GVC. In recent years, due to the gradual decline of the demographic dividend and the significant reduction of the cost advantage of factors of production, China cannot rely solely on the low value-added production of the manufacturing industry to maintain the continuous growth of trade. Chinese manufacturing industry needs to upgrade to the high-end GVC. Under the background of today's digital economy development, how to make full use of a series of digital means and technologies such as big data, artificial intelligence, Internet of Things, cloud technology, etc., to promote Chinese manufacturing industry to "overtake at corners", get rid of the dilemma of low-end lock-in, and transform from a manufacturing power to a manufacturing power to

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upgrade the global value chain has become a big problem to be solved urgently.

Currently, some scholars have done a lot of research on the influence of digital economy on global value chain. However, most of them study how to transform and upgrade China's industries from the perspective of global value chain, and there is little research on the topic of upgrading China's manufacturing global value chain from the perspective of digitalization. Therefore, on the basis of constructing the research model, an empirical study was made in this paper on whether digital investment can promote GVC upgrading of Chinese manufacturing industry by collecting the panel data of 18 departments of Chinese manufacturing industry from 2000 to 2014, so as to enrich the quantitative research of digital investment on GVC upgrading of Chinese manufacturing industry.

II. INFLUENCE MECHANISM

Don Tapscott (1995) put forward the concept of "digital economy" and described the road map of digital transformation of enterprises in various industries [1]. At the institutional level, digital organizational form, digital infrastructure and digital institutional cornerstone are new institutional arrangements that are crucial for digital innovation and transformation [2]. The manufacturing industry has entered a new era in which data links are everywhere, and the core production factors driving its transformation and upgrading are gradually being replaced by big data [3, 4]. At the same time, digital information is increasingly becoming a "necessity" in the industrial chain, and the manufacturing industry chain will be deconstructed and reconstructed to gradually realize the goal of comprehensive digital transformation [5]. Aiming at the influence mechanism of digitalization on the embedding of global value chain in manufacturing industry, some scholars have carried out exploratory empirical research and got some different results from different levels. Andrea Szalavetz (2020) studied manufacturing enterprises to analyze how digital transformation can help factory-economical digital enterprises integrate into the highly concentrated global value chain of automobiles [6]. Matarazzo Michela (2021) and others conducted research on the digital transformation of small and medium-sized manufacturing enterprises in Italy, and concluded that digital tools are helpful to the innovation of their business model, which confirmed the relevance of perception and learning ability as triggers of digital transformation [7]. Li Fuyi (2018) found that digital investments had different effects on the promotion of GVC status of different technology types of manufacturing industry, that is, the role of low-tech manufacturing sector is not as good as expected or even has a reverse effect, which has a positive effect on low-tech manufacturing sector and high-tech manufacturing sector [8]. The empirical study by He Wenbin (2020) from the perspective of knowledge density found that digital investment has a positive effect on the upgrading of GVC in low-and medium-high knowledge-intensive manufacturing sectors, among which the manufacturing sector with stronger research and development efforts has a better effect [9]. Ren Yida (2019) found that the development of digital economy has a significant role in promoting the division of labor status index of global value chains in developed countries, but the opposite is true in developing countries [10].

Generally speaking, increasing the digital investment of each manufacturing sector can affect the GVC participation, division of labor status and its ability to obtain value added through three aspects. First, labor

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levels have a significant impact on enhancing core competitiveness and promoting GVC upgrading, and increasing digital investments can increase labour productivity and thus promote GVC upgrading. Secondly, digital investment can create new factors of production and new added value. Under the background of the rapid development of digital economy, compared with other production factors with limited resources, the core production factor, which has the characteristics of unlimited replication and sharing, can provide new momentum for sustainable economic development. Third, digital investment can act directly on global value chains. Increasing digital investment can speed up the upgrading of products, promote the replacement of old and new products, promote the functional upgrading and optimize the upgrading production process.

III. METHODOLOGY

3.1 Modeling

In order to study the influence of digital investment on the global value chain upgrading of Chinese manufacturing industry, in this paper, the theoretical model was constructed by referring to the related research of Li Fuyi (2018) [8] taking into account the relevance and availability of sample data, as follows:

$$\ln GVCPt\_f_{dt} = \partial + \beta \ln \mathrm{Digin}_{dt} + \gamma \ln C_{dt} + \delta_d + \varepsilon_t + \theta_{dt}$$

Where,

d= the industry;

t=the year;

$GVCPt\_f_{dt}$ = China's manufacturing GVC participation;

$Digin_{dt}$ =the digital investment;

C_{dt}= the control variables, including the department's overseas demand (Abro), capital stock (Capi), factor return (KL), and labor productivity (Prod);

α=the intercept term;

β =the elastic coefficient of digital investment, which reflects the effect of digital investment on GVC of Chinese manufacturing industry;

γ=the elastic coefficient of control variable;

δ_d = the individual effect;

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ε_t = the time effect;

and$\theta_{d,t}$ = the residual term.

3.2 Measurement of Variables

Some scholars have gradually formed and improved the accounting methods of global value chains and trade added value from both micro and macro levels in the existing research on embedding of global value chains, which can be roughly divided into four types, namely, single enterprise case analysis, industry observation through sample enterprises, single country input-output analysis, and regional or global input-output overall analysis [11]. From the broad sense of global value chain, the mainstream direction of the international community is to calculate the trade added value with the input-output model. For example, Chen Xikang (1990) put forward the Input-Occupation-Output Model (DPN method) [12], and Koopman et al. (2014) put forward the accounting framework of trade added value, which can identify the repeated calculation part of trade flow (KWW method) [13]. The explained variable in this model is the participation in global value chain of China's manufacturing sector, which is measured by the forward linkage participation index. It specifically refers to the value of a sector in a country that uses domestic factors of production and meets the condition of at least one cross-border activity in the GVC (including the value of intermediate exports absorbed by the importing country and the value of intermediate exports re-exported to a third country). It can accurately measure the proportion of the added value of GVC production and trade activities in the total departmental added value, that is, GVC participation. The index data is calculated by the following formula:

$$GVCPt\_f^2 = \frac{V\_GVC^2}{\mathrm{V}^3\mathrm{X}^3} = \frac{V\_GVC\_R^2}{\mathrm{V}^3\mathrm{X}^3} + \frac{V\_GVC\_D^2}{\mathrm{V}^3\mathrm{X}^3} + \frac{V\_GVC\_F^2}{\mathrm{V}^3\mathrm{X}^3}$$

Where,

V_GVC=the added value of intermediate products;

VX=the total added value;

V_GVC_R=the added value of intermediate products used by importing countries;

V_GVC_D =the added value of consumer goods exported to a third country and sold back to China;

and V_GVC_F = the added value of foreign consumer goods exported to a third country.

Digin is the explanatory variable, which represents the digital investments from various manufacturing sectors in the PRC. In this paper, based on the narrow sense concept of input-output and the availability of

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data, the digital investment was measured by the added value input of communication industry and information service industry to various manufacturing sectors, which can be obtained from the world input-output database published by WIOD2016.

In addition, the control variables of this study were measured as follows: Abro represents overseas demand, measured by the value-added export of the department. Capi represents the capital stock, measured by the nominal capital stock of the department. KL represents the factor return, measured by the ratio of capital return of a department to labor return of that department. Factor return greater than 1 indicates that capital return is higher than labor return. Prod represents the labor productivity, measured by the ratio of the added value of a department to the number of employed laborers in that department.

3.3 Data Sources

The data samples for the empirical analysis in this paper are the panel data of 18 sectors of Chinese manufacturing industry from 2000 to 2014. These 18 sectors are the 19 manufacturing industries covered by the WIOTS excluding machinery repair and installation industries with large data gaps, including manufacture of food products, beverages and tobacco products, manufacture of textiles, wearing apparel and leather products, manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials, manufacture of paper and paper products, Printing and reproduction of recorded media, manufacture of coke and refined petroleum products, manufacture of chemicals and chemical products, manufacture of basic pharmaceutical products and pharmaceutical preparations, manufacture of rubber and plastic products, manufacture of other non-metallic mineral products, manufacture of basic metals, manufacture of fabricated metal products, except machinery and equipment, manufacture of computer, electronic and optical products, manufacture of electrical equipment, manufacture of machinery and equipment n.e.c., manufacture of motor vehicles, trailers and semi-trailers, manufacture of other transport equipment, manufacture of furniture; other manufacturing. In this paper, the forward contact participation comes from UIBE database data, the digital investment data comes from the world input-output database published by WIOD2016, and the control variables come from the social and economic accounts published by WIOD2016.

IV. EMPIRICAL ANALYSIS

4.1 Model Pretest

In this paper, Eviews10.0 software tool was used for empirical analysis. Firstly, the unit root test was carried out to determine the stability of variables. According to TABLE I, after the IPS, ADF and PP tests, the statistical value of each variable is less than 0.01, indicating that each variable sequence is stable.

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TABLE I. The results of unit root test

Variables	IPS	ADF	PP	Conclusions
$LnGVCPt\_f_d$	-6.73341*** (0.0000)	104.327*** (0.0000)	108.758*** (0.0000)	Stable
LnDigin	-2.49081*** (0.0064)	55.2389** (0.0211)	51.4690** (0.0456)	Stable
LnAbro	-11.6923*** (0.0000)	170.091*** (0.0000)	240.830*** (0.0000)	Stable
LnCapi	-7.41087*** (0.0000)	115.907*** (0.0000)	133.583*** (0.0000)	Stable
KL	-8.77929*** (0.0000)	132.954*** (0.0000)	256.307*** (0.0000)	Stable
LnProd	-5.43081*** (0.0000)	86.7720*** (0.0000)	112.188*** (0.0000)	Stable

(Note: *, * *, * * * indicate the significance at the levels of 10%, 5% and 1%, respectively, with the accompanying probability in brackets.)

Because all variables in the unit root test show horizontally stable results, the regression model can be directly estimated without co-integration test. In this paper, F test and Hausman test were used to judge the regression model. According to TABLE II, the statistical value of F test is significant at the level of 5%, so the fixed effect model is superior to the mixed effect model, and the statistical value of Hausman test is significant at the level of 1%, so the fixed effect model is superior to the random effect model. Thus, the fixed effect model was used for regression analysis according to the panel estimation test results.

TABLE II. Panel estimation results

Test methods	Test indicators	Statistical value	Results
F test	F statistics	25.129859** (0.0333)	Fixed effect is selected
Hausman test	Hausman statistics	22.233829*** (0.0005)	Fixed effect is selected

4.2 Regression Result

According to the results of regression analysis (TABLE III), Digin passed the significance test at the level of 5%, with a P value of 0.0163, indicating that Digin has a significant effect on the upgrading of China's manufacturing GVC; the regression coefficient is 0.029101, indicating that every 1% increase in

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Digin will push China's manufacturing GVC up to the high-end GVC by 0.029101%; and this variable has a positive effect on the upgrading of China's manufacturing GVC.

Overseas demand (Abro) passed the significance test at the level of 1%, with a P value of 0.0000 and a regression coefficient of 0.755946, indicating that every 1% increase in overseas demand will push China's manufacturing GVC up to the high-end GVC by 0.755946%, which has a significant positive effect on China's manufacturing GVC upgrade.

The capital stock (Capi) passed the significance test at the level of 1%, with a P value of 0.0000 and a regression coefficient of -0.120924, indicating that the capital stock has a significant reverse effect on the upgrading of China's manufacturing GVC; every 1% increase in capital stock will push China's manufacturing GVC down to the low-end GVC by 0.120924%, indicating that the effect of capital stock on China's manufacturing GVC is negative.

The factor return (KL) passed the significance test at the level of 5%, with a P value of 0.0199 and a regression coefficient of -0.085835, indicating that it has a reverse effect on the upgrading of GVC in Chinese manufacturing industry.

Labor productivity (Prod) passed the significance test at the level of 1%, with a P value of 0.0000 and a regression coefficient of 0.953467, indicating that it has a significant positive effect on upgrading the GVC in Chinese manufacturing industry, and its effect is the most significant among all variables.

TABLE III. Panel regression results

Explanatory variables	Regression coefficient	Standard error	T test value
C	-0.852884*** (0.0030)	0.284099	-3.002070
LnDigin	0.029101** (0.0163)	0.012036	2.417742
LnAbro	0.755946*** (0.0000)	0.044717	16.90517
LnCapi	-0.120924*** (0.0000)	0.024307	-4.974836
KL	-0.085835** (0.0199)	0.036624	-2.343692
LnProd	0.953467*** (0.0000)	0.142414	6.695022
R^2	0.626198		

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F	22.04231***
N	270

V. CONCLUSION AND ENLIGHTENMENT

The empirical results show that digital investment, labor productivity and overseas demand have a positive effect on China's manufacturing GVC upgrade, while capital stock and factor returns have a negative effect. The above results also provide inspiration for China to upgrade its manufacturing GVC.

First of all, it is necessary to further enhance digital investment in the development of the digital economy, and to speed up the promotion of digital innovation, digital facilities construction and digital governance while ensuring the sustained and healthy development of the digital industry. Secondly, overseas demand has a significant positive impact on the upgrading of China's manufacturing global value chain. Therefore, attention should be paid to the changes in overseas markets, and research and development, innovation and change in the manufacturing field should be carried out in a timely manner according to the needs of overseas customers, so as to achieve the new occupancy in GVC first. Labor productivity has a significant positive impact on the upgrading of GVC in Chinese manufacturing industry. Therefore, the research and application of digital transformation common technologies and key technologies should be accelerated. On the premise of ensuring data security and privacy protection, support should be given to exploring new generation of digital technology application and integration innovation in qualified manufacturing sectors, and the role of digital investment in improving labor productivity should be strengthened. At the same time, strong support should be given to the construction of digital transformation service institutions to improve the efficiency and quality of digital transformation in manufacturing enterprises.

VI. RESEARCH LIMITATIONS AND PROSPECTS

The core data of this study comes from WIOD2016 and ADB-MRIO2018, whose data were collected from 2000-2014 and 2000-2017, respectively, without data for recent years. At the same time, considering the availability of data, the research in this paper is based on the concept of digital investment in a narrow sense, but lack of research on a broad sense, which limits the research of this paper. In the future, the research can be further deepened in the following aspects: Other methods and indicators can be selected to measure GVC upgrading of Chinese manufacturing industry; the influencing factors of participation and location in the value chain upgrading can be further discussed; a more comprehensive method can be chosen in the measurement of digital investment according to the availability of data.

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