Carbon Emissions of China's Manufacturing Industry under the Background of "Double Carbon Target": An Empirical Study on the Impact of Global Value Chain Embedded

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Abstract: As a new model of world economic trade collaboration, global value chain (GVC) connects the economies of various countries, bringing a steady stream of opportunities to each economy in the value chain. While enjoying the development dividend, all countries are also dealing with common problems: global warming. As a high energy consumption industry, manufacturing industry produces a large amount of CO_2 in production activities. Therefore, analyzing the evolution law of GVC participation in China's manufacturing industry and exploring its impact on carbon emissions will help to explore the energy-saving and carbon reduction mode of manufacturing industry to achieve "carbon neutrality" and the countermeasures to improve the international competitiveness of China's manufacturing industry, in order to pave the way for the development of high-quality foreign trade with "high value and low emission". Theoretically, this paper analyzes the influence mechanism of GVC insertion on China's manufacturing CO_2 emissions from three aspects: scale, technology and structural effects. In the empirical aspect, the degree of GVC embeddedness and carbon emissions of China's manufacturing industry from 2000 to 2018 are calculated, and the impact of GVC embeddedness on China's manufacturing carbon emissions is studied by using OLS method. The results show that the value of GVC embeddedness in China's manufacturing industry shows an "M" trend from 2000 to 2018.The overall embeddedness of GVC in China's manufacturing industry is high, and the backward embeddedness is much higher than the forward embeddedness. GVC embeddedness has a positive impact on China's manufacturing carbon emissions. Finally, policy suggestions are put forward from the perspective of actively embedding GVC high-end links, accelerating industrial transformation and upgrading and optimizing energy structure.

1. Introduction

Although China's traditional development approach has brought about rapid economic development, it has also plunged China into a quagmire of high carbon emissions, and there is a long way to reduce carbon emissions. In order to effectively implement the concept of "community of human destiny", closely link China's development with global development, and assume the ecological responsibility of a great power, in September 2020, at the 75th United Nations Conference, President Xi Jinping solemnly announced that China would strive to reach the carbon peak by 2030 and achieve carbon neutrality by 2060. This demonstrated to the world China's determination and sincerity in implementing its carbon reduction plan. Among the factors that affect carbon emissions in each country, the new form of international division of labor, the global value chain, is noteworthy. While actively participating in the division of labor and competition in global

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value chains has promoted China's technological progress and economic growth, it has also significantly increased carbon emissions. In this paper, it is important to study the impact of GVC embedding on carbon emissions in manufacturing industry, in order to carry out effective carbon emission reduction in manufacturing industry under the goal of "double carbon".

In the literature involving GVC and carbon emissions, studies by foreign scholars have focused on the impact of GVC embedding on manufacturing productivity. Davide Del Prete et al. (2017) analyzed the global value chain participated by North African companies and its impact on productivity, and found that enterprises entering the global value chain performed better in advance and showed additional productivity gains afterwards[1]. Yanikkaya et al. (2021) showed that almost all forward and backward measures of GVC significantly contribute to output growth in manufacturing and services[2]. Studies on the impact of GVC embedding on carbon emissions in manufacturing are relatively rare in the domestic literature, focusing mainly on studies on carbon productivity and carbon efficiency. Xie Huiqiang et al. (2018) found that the level of GVC participation has a significant contribution to carbon productivity in China's manufacturing industry[3]. Li Yan et al. (2021) indicated that GVC embedding can improve the CO_2 emission efficiency of countries along the Belt and Road[4].

In summary, the existing literature rarely links GVCs with carbon emissions. In the studies on GVCs, scholars have adopted various methods to measure the degree of GVC embedding. The research on carbon emissions focuses on examining carbon emission efficiency, carbon productivity and other indicators. This is due to the different data, methods and measurement models selected by scholars, but the deeper reason is the complexity of the relationship between GVC embedding and carbon emissions. In this paper, we select the representative manufacturing time series data, use the method proposed by Koopman et al. to calculate the degree of GVC embedding, avoiding the possible errors caused by other methods, and establish a multiple regression model to investigate the correlation between GVC embedding and carbon emissions in manufacturing industry, so as to provide some policy suggestions for the realization of the "double carbon" development goal. This will provide some policy suggestions for achieving the goal of "double carbon" development.

2. Measurement Analysis of Global Value Chain Embedding and Carbon Emission of China's Manufacturing Industry

2.1. Measurement of Global Value Chain Embedding Degree

The GVC participation index overcomes many limitations of the HIY method and can accurately quantify a country's GVC participation, which is used by many scholars. Therefore, in this paper, we refer to the calculation method proposed by Koopman et al. (2010) with the following formula.

$$GVC_{\mathrm{par}} = \frac{IVA_{\mathrm{in}}}{E_{\mathrm{in}}} + \frac{FVA_{\mathrm{in}}}{E_{\mathrm{in}}} \tag{1}$$

In the above equation (1), the GVC participation index measures the degree of participation of a country's industry in the GVC division of labor as a whole, and the lar ger the index is, the deeper the participation of the country's industry in the GVC division of labor. It is defined as the sum of domestic indirect added value and foreign added value as a share of total export added value, and includes GVC forward participation and GVC backward participation. A larger forward participation indicates that industry n country i exports more intermediate goods to foreign countries with domestic factors, while a larger backward participation indicates that industry n country i is more dependent on imports from foreign countries.

2.2. Carbon Emission Measurement Method of Manufacturing Industry

This paper draws on the energy consumption measurement method proposed by Yang Xiang et al. (2015)[5], which first measures the carbon emission coefficient, various fossil CO_2 consumed by energy can be calculated by multiplying the energy consumption by the carbon emission factor, and the carbon emission of the manufacturing industry can be calculated by summing the CO_2

consumption of several fossil energy sources mainly consumed by the manufacturing industry, and the specific measurement formula is as follows.

$$CO_2 = \sum_{i=1}^{8} CO_{2,i} = \sum_{i=1}^{8} E_i * NCV_i * CEF_i * COF_i * \frac{44}{12} \tag{2}$$

In the formula, i represents the specific types of fossil energy, which are coal, crude oil, coke, fuel oil, gasoline, diesel, kerosene and natural gas, selected from the China energy statistical yearbook. E_i refers to the consumption of various fossil energies, with the unit of 104 tons. NCV_i refers to the average low calorific value of various fossil energies, with the unit of kJ/kg (natural gas unit of kJ/m^3). CEF_i refers to the carbon content of various fossil energies, with the unit of kgC/TJ. COF_i refers to the carbon oxidation factor of various fossil energies, and the value is 1 when the energy is completely oxidized. The carbon emission coefficient is calculated by multiplying NCV_i, CEF_i and COF_i, and the unit is tC/t (natural gas unit is kgC/m^3). 44 and 12 are the chemical relative molecular weights of CO_2 and C, respectively.

3. Empirical Analysis of the Impact of Global Value Chain Embeddedness on China's Manufacturing Carbon Emissions

3.3. Model Setting and Measurement Method Selection

3.3.1. Model Setting

The impact of GVC embeddedness on China's manufacturing carbon emissions has been described in theory. This chapter will take three core variables as the main line, add the corresponding control variables to build an econometric model, and study the impact of GVC embeddedness on manufacturing carbon emissions from a quantitative perspective.

In this paper, the measurement model (1) is set as follows:

$$\ln CO_2 = \beta_0 + \beta_1 \ln GVC_{\mathrm{par}} + \beta_2 \ln GDP + \beta_3 \ln IS + \beta_4 \ln ES + \beta_5 \ln RD + \beta_6 \ln FDI + \varepsilon_{\mathrm{t}} \tag{3}$$

Where t is the year, ε_t represents random disturbance term, $\beta_1 \ldots \beta_6$ are the parameters to be estimated. CO_2 refers to the carbon emission of China's manufacturing industry, which is used to measure the carbon emission level of China's manufacturing industry; GVC_{par} refers to the participation index of China's manufacturing industry in the global value chain, which is used to investigate the embedding of China's manufacturing industry in the global value chain. Other variables are control variables. See Table 1 for the description of variables. In order to avoid the possible influence of extreme values in the calculation process, all variables are logarithmicized in this paper.

Table 1 Meanings and data sources of model variables.

Symbol	Variable type	Variable name	Unit	Data source
CO_2	Explained variable	Carbon dioxide emissions	104 tons	By calculating
GVC_{par}	Explanatory variable	GVC participation	/	By calculating
GDP	Control variable	Economic scale	million yuan	China Statistical Yearbook
IS	Control variable	Industry structure	/	China Industrial Statistics Yearbook
ES	Control variable	Energy consumption structure	/	China Energy Statistics Yearbook
RD	Control variable	R&D investment intensity	/	China Science and Technology Statistics Yearbook
FDI	Control variable	Foreign direct investment	/	China Statistical Yearbook

3.3.2. Selection of Measurement Method

Because the time series data of China's manufacturing industry spanning 19 years are used in this paper, it is difficult to avoid the possible problems of autocorrelation and heteroscedasticity. Therefore, selecting multiple linear regression model and ordinary least squares (OLS) for regression analysis can better improve the effectiveness of parameter estimation.

3.4. Statistical Characteristics of Variables and Data Test

3.4.1. Descriptive Statistics

Table 2 Descriptive statistical results of variables.

Symbol	Variable name	Mean	Maximum	Minimum	Std
CO_2	Carbon dioxide emissions	472253.30	671599.30	198498.30	179469.00
GVC_{par}	GVC participation	0.70	0.72	0.67	0.02
GDP	Economic scale	151895.00	301089.30	40258.50	85928.45
IS	Industry structure	0.88	0.97	0.83	0.06
ES	Energy consumption structure	0.62	0.65	0.59	0.02
RD	R&D investment intensity	1.61	2.15	0.9	0.43
FDI	Foreign direct investment	4101748.00	5210054.00	2584417.00	689045.70

According to the descriptive statistical table, the order of magnitude of carbon dioxide emissions, economic scale and foreign investment is large, and the standard deviation is also large, indicating that these variables fluctuate greatly. The standard deviation of GVC participation, industry structure and energy consumption structure is less than 0.1, indicating that the fluctuation range of these variables is relatively small and the data is relatively stable.

3.4.2. Stability Test

In this paper, first of all, the original variables are tested for stationarity, and it is found that the variable data is unstable. In order to make the data stable, this paper takes the logarithm of the variable, which can not only make the variable have economic significance, but also make the data more stable to pass the stability test. The following table shows the stability test results after logarithm of variables:

Table 3 Stability test results.

Method	Statistical value	P-value	Conclusion
LLC	-4.0760	0.0000	Stable
IPS	-2.4619	0.0069	Stable
ADF-Fisher	27.4395	0.0169	Stable
PP-Fisher	43.2650	0.0001	Stable

In this paper, four test methods are used to test the stationarity of the data. Generally, if there is the original hypothesis of rejecting the existence of unit roots in both tests, the sequence can be said to be stable. According to the results in the above table, it is found that the P-value of LLC test, IPS test and PP test is less than 0.01, and the ADF test is less than 0.05, which all pass the stability test, indicating that the data can be further regressed.

3.5. Empirical Regression Results and Analysis

3.5.1. Empirical Regression Results

Based on the selection of the above regression model, we use Eviews software for OLS regression, and the regression results are shown in Table 4.

Table 4 OLS regression results.

Variable	OLS
$lnGVC_{par}$	1.0852*** (3.0668)
lnGDP	0.2081** (2.5593)
lnIS	-0.4982** (-2.5937)
lnES	2.2205*** (8.7976)
lnRD	1.1180*** (5.2812)
lnFDI	-0.1974** (-2.7978)
CONS	14.4211*** (8.9986)
R-squared	0.9976
Adjusted R-squared	0.9964
F value	840.5583***

Note: * * *, ** *, * respectively indicate that the coefficient is significant at the significance level of 1%, 5% and 10%

According to the regression results, the coefficient of GVC participation is positive and significant at the significance level of 1%, indicating that the increase of GVC participation will increase carbon emissions. For every 1% increase of GVC participation, carbon emissions will increase by 1.0852 percentage points. Among the control variables, except for the negative coefficients of industry structure and foreign investment, the coefficients of other control variables are positive.

3.5.2. Analysis of Regression Results

GVC participation has a positive impact on the growth of carbon emissions in China's manufacturing industry. China's manufacturing industry will be dominated by the backward participation in GVC, mainly involving the production of products with high energy consumption and low added value. Therefore, the higher its GVC participation, the greater the energy consumption of the manufacturing industry. In conclusion, the increase of GVC participation is detrimental to China's manufacturing carbon emission reduction.

Among the control variables, energy consumption structure (ES) has the most influence on GVC embeddedness, and there is a positive correlation between them, with the correlation coefficient as high as 2.2205. Economic scale (GDP) passed the significance level test of 5%, indicating that there is a positive relationship between economic scale and China's manufacturing carbon emissions. There is a significant positive correlation between R&D investment intensity(RD) and manufacturing carbon emissions at the level of 1%.

The other two control variables, industry structure (IS) and foreign direct investment (FDI), have opposite effects on China's manufacturing carbon emissions. The regression results show that the upgrading of industry structure can reduce the CO_2 emissions of China's manufacturing industry. FDI has an inhibitory effect on China's manufacturing carbon emissions. Specifically, the inflow of FDI has changed the industrial structure of China's manufacturing industry. By reasonably guiding the entry of foreign capital and increasing the investment attraction of environment-friendly enterprises, carbon emissions can be effectively reduced. In addition, some environmental protection technologies that are conducive to carbon reduction and emission reduction may flow into China with FDI. This type of technological progress will help to achieve the carbon reduction goal.

4. Conclusions and Suggestions

This paper takes the GVC Embeddedness and carbon emissions of China's manufacturing industry as the research object, and draws the following three conclusions by empirically testing the time series data of China's manufacturing industry from 2000 to 2018. First, the overall GVC embeddedness shows an "m" trend, which is not only related to the annual development of China's manufacturing industry, but also affected by national policies and economic environment. Second, the GVC in China's manufacturing industry is highly embedded as a whole, but the backward embeddedness is much higher than the forward embeddedness, indicating that the manufacturing industry is currently dominated by the downstream manufacturing links of the " Smiling Curve" in the international division of labor, with low added value. Third, GVC embeddedness has a significant positive impact on China's manufacturing carbon emissions. The deeper the embeddedness, the greater the carbon emissions of manufacturing.

Combined with the above conclusions, this paper puts forward the following policy recommendations. Firstly, enterprises can actively participate in the high-end links of the global manufacturing value chain, enhancing China's value chain extension space in the high-end manufacturing field. Secondly, China's manufacturing industry can accelerate the pace of transformation and upgrading, and strengthen low-carbon technological innovation. Thirdly, enterprises should optimize their energy structure, increase the use of zero carbon fuels, and promote clean energy.

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