1. GLOBAL VALUE CHAIN PARTICIPATION AND SUSTAINABLE GROWTH: EVIDENCE FROM CHINA

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Abstract

Utilizing panel data of China's industrial sectors from 2000 to 2014, this study explores the causal relationship between GVC participation and sustainable growth measured by green total factor productivity (GTFP). The results show that both forward and backward participation have a positive impact on GTFP, and the former is more significant. Specifically, both simple and complex activities of forward GVC participation show a positive effect on GTFP, while only complex activities of backward participation show a positive effect. Mediation analyses suggest that GVC participation affects sustainable growth through two channels: environmental regulation and technology spillover. Moreover, GTFP responses to GVC participation vary by technology orientation, pollution intensity, and FDI intensity.

***Keywords**: sustainable growth; green total factor productivity; global value chain; mechanism analysis.*

***JEL Classification**: F14, F43, F64, O44, O53*

1. Introduction

Over the past decades, sustainable growth has become a significant topic for economies in the middle or low end of global value chains (GVC), making trade-offs necessary between economic growth and environmental amenities (Hu et al.,2021). As an essential hub of GVC with the largest trade volume, China has been suffering severe environmental problems such as growing greenhouse gas emissions (Baldwin and Yan, 2014 ; Hua et al., 2022). With increasing global

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production fragmentation, it is essential to understand the role of GVC participation in sustainable growth.

GVC participation has two key features, namely forward and backward participation. Forward participation in GVC represents the domestic value added of a country-sector's GVC activities that are exported to other countries. This includes the value added domestically in intermediate exports, which is then utilized by the importing country to produce goods for domestic consumption. Specifically, an industry with high forward participation usually engages in activities such as research and product design. Backward participation in GVC refers to the foreign value added by intermediate imports to the home country, which is the value added by foreign suppliers in intermediate imports that are used in domestic production. Specifically, an industry with high backward participation usually involves low value-added activities like processing and assembly (Hummels et al., 2001). Both forward and backward GVC participation can be decomposed into simple and complex activities. Complex value-added activities across the border at least twice, thus involving more production links and a higher GVC position than simple activities (Wang et al., 2017). Thus, different categories of GVC participation may have different impacts on the green economy. Here come our research questions: Does forward or backward participation have more impact on sustainable growth? Do simple or complex activities show greater impact?

Existing studies have not tackled these research questions. This study tries to fill these gaps and examines the impact of GVC participation on green total factor productivity (GTFP) in China. By using a combined dataset between 2000 and 2014 , we measure GTFP based on the SBM-DEA method (Färe et al., 1994) and calculate GVC participation channels through which GVC participation affects the green economy by applying the causal step regression method (Baron and Kenny, 1986). Our results show that GTFP improvement is more sensitive to forward participation than backward participation. In particular, both simple and complex activities of forward GVC participation show a positive effect on GTFP and the latter is more significant, while only complex activities of backward participation present a positive effect. Besides, industries' response is heterogeneous, depending on their technology orientation, pollution intensity, and foreign direct investment (FDI) intensity.

In summary, we make three contributions to the literature. First, this study contributes to the literature on the impact of GVC on sustainable development. Existing studies usually treated GVC participation without distinguishing between forward and backward GVC participation (Hua et al., 2022; Zhang et al., 2021). This study goes one step further to examine the causal effect of different types of GVC participation on GTFP and aims to explore the relationship between GVC and sustainable development. Besides, existing studies have not discovered the effects of simple and complex GVC activities. This paper extends the existing research and finds that both complex activities of forward and backward GVC participation promote GTFP more than simple activities. In this sense, our study contributes to the debates on the "Pollution Paradise Hypothesis".

Second, this study also contributes to verifying the mechanisms through which GVC activities could affect sustainable growth, which has not been discovered in most of the existing literature. This study empirically estimates the channels through which GVC participation may influence GTFP. Investigating the possible mechanism helps clarifying how GVC participation affects GTFP and assists policymakers in imposing targeted policy approaches depending on the channels.

Third, our paper contributes to the literature examining the heterogeneous effect of sectors' GVC participation. Our results confirm that the GVC activities of industries with high-tech orientation, low-pollution, and low-FDI intensity may have significant positive effects on GTFP. This study provides a brand-new understanding of China's current GVC participation and sheds light on effective economic policies to promote sustainable development according to industry heterogeneity.

The remaining sections proceed as follows. Section 2 and Section 3 present the literature review and method, respectively. Section 4 provides data analysis and empirical results. Section 5 illustrates further analysis, including mechanism analysis and industry heterogeneity. In the last section, we discuss the major findings, policy implications and some limitations.

2. Literature Review

2.1. GVC Participation

The measurement of GVC participation is initially proposed by Hummels et al. (2001) who adopts the Input-Output (IO) table to calculate the vertical specialization index (VSI) of each OECD country. Following this study, researchers proposed using measurements from multiple aspects to describe the global production network (Wang et al., 2017; Koopman et al., 2012, 2014). For example, Koopman et al. (2012) provided a mathematical framework to decompose value-added trade that avoids the double-counting of traditional trade statistics. Subsequently, Wang et al. (2017) decomposed GVC activities from a more detailed perspective, including value-added for domestic demand, traditional trade, simple GVC activities, and complex GVC activities.

Many scholars pointed out that developed countries have more forward participation than developing countries (Li et al., 2019). Daudin et al. (2011) examined cross-country input-output data from GTAP and found that China's forward participation is lower than its backward participation.

This study adopts the production decomposition model proposed by Wang et al. (2017). Both forward and backward GVC participation include simple and complex activities. Simple activities mean that the intermediates are traded only once, and they are used to produce final goods in the importing country directly. Complex activities denote that the intermediate goods are traded more than once, and they are used by the importing country to produce intermediate goods for export to the home country or a third country (Wang et al., 2017). Li et al. (2019) pointed out that complex activities are positively correlated with the technology (knowledge) intensity of a sector. They noted that the USA and Germany are the most important hubs in complex GVC activities, while China is playing an important role in simple networks.

2.2 Sustainable Growth

Sustainable growth is a comprehensive index that includes economic development, resource utilization, technological progress, and environmental protection (Zhu et al., 2020). GTFP is widely regarded as a measure of sustainable growth since it captures both technology development and environmental protection.

There are two different ways of measuring GTFP: parametric and non-parametric methods. The parametric method is represented by the production function and arithmetic index method (Abramvitz, 1956). The parametric model construction process is relatively simple, but it needs to predefine the specific function form and accurately collect the price of input and output variables. Moreover, it must follow the law of returns to scale. The non-parametric method does not need a specific function form, and Data Envelopment Analysis (DEA) is the dominant method here, including the Shephard Distance (Shephard, 1970), the Slack-Based Measure (SBM) (Morita et al., 2005), the Epsilon-Based Measure (EBM) (Tone, 2001) and the Malmquist-Luenberger index (ML) (Färe et al., 1994). It compared the decision-making unit with the constructed optimal random frontier, and then combined this with the index method for calculation. The DEA method can incorporate undesired output into the analysis framework and does not require data from a non-dimensional process, which makes it very popular among researchers (Ding et al., 2017). Currently, many articles adopted SBM combined with ML to measure total factor productivity (TFP) at the industry level.

2.3 GVC Participation and Sustainable Growth

Relevant literature can be classified into three sets. The first set supports a positive linkage between GVC and sustainable growth. In terms of the TFP or technological progress, existing studies revealed that GVC participation improved productivity through technology spillover and competitive effects (Loecker, 2007; Song and Wang, 2017). Lööf and Andersson (2010) pointed out that high proportions of imports from developed countries increased labor productivity. In terms of the environment, some researchers pointed out that GVC participation would encourage developing countries to achieve higher environmental standards through the import of developed-country green technology (Reppelin-Hill, 1999; Eskeland and Harrison, 2003). Therefore, GVC participation will have more positive impacts than negative ones for the host country.

The second set of literature supports a negative correlation between GVC participation and sustainable growth. Cole (2004) supported the "Pollution Haven Hypothesis", and emphasized that developing countries were forced to take on high-polluting production processes. Purcel (2020) also pointed out that economic growth may lead to environmental pollution for developing countries. Relying on first-mover advantages, developed countries at the high end of GVC transfer the processing and assembly sectors to developing countries. Restrictions from intellectual property rights hinder technological upgrading in developing countries, making it more difficult to improve production technology for them.

The third set of the literature suggests that GVC participation is a double-edged sword, and the effects depend on the types of production activities. For example, Qian et al. (2022) examined the GVC participation and CO2 in RCEP countries and found that only forward participation reduced emissions and led to environmental improvement, while backward participation may not. Wang and Zheng (2019) confirmed that the complex activities of backward GVC participation were positively related to export technical sophistication, while simple activities were not significantly correlated with it. To our best knowledge, although these studies focused on different types of GVC activities, their research only emphasized one aspect, such as environmental or technological progress. Few studies try to examine the direct link between GVC and sustainable development.

Therefore, to fill the research gap, we measure the GVC participation and GTFP following the latest methods, and explore whether different types of GVC participation have different impacts on sustainable growth. We will further explore the mechanisms behind the effects.

3. Data and Method

3.1. Data

The research object of this study is China's industrial sectors, and all indicators are at the industry level. The initial source for calculating GVC-related indicators is the World Input-Output Database (WIOD), which contains 56 sectors and covers 43 countries (28 EU countries and 15 other major countries) for the period 2000-2014. The processed data is obtained from the Research Institute for GVC of the University of International Business and Economics . As for other indicators, three data sources are used: the China Statistical Yearbook, the China Industrial Statistical Yearbook, and the China Energy Statistical Yearbook. We merge these databases according to industry names. Finally, we acquire 300 samples involving 20 industries from 2000 to 2014.

3.2 Key Variables and Measurement

3.2.1 Green Total Factor Productivity

The calculation of GTFP is based on the DEA method. This study considers energy input and undesired output (i.e., CO2) that pollutes the environment. Then the non-radial and non-angle

SBM model is combined with the dynamic Malmquist-Luenberger (ML) index to measure GTFP and its growth rate. This can make up for the defects of the radial model, such as not considering undesired output. Specifically, this study treats each industry as a decision-making unit (DMU). Input factors include labor, capital, and energy. Total output and CO2 emissions are output and undesired output variables, respectively. Considering China's consumption of eight kinds of fossil energy, including coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas, we can calculate the CO2 emissions of each industry:

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

where E_i represents the consumption of fossil fuels, NVC_i indicates the low calorific value, and CEF_i and COF_i are carbon content and carbon oxidation factor, respectively. This paper calculates the carbon emission coefficient based on the "China Industrial Statistical Yearbook" and the carbon content provided by the Intergovernmental Panel on Climate Change (IPCC).

Next, we incorporate energy and CO2 emission constraints into the TFP accounting framework, constructing a dynamic ML index:

$$ML_{t,t+1} = \left[\frac{D_t(x_t, y_t^g, y_t^b)}{D_t(x_{t+1}, y_{t+1}^g, y_{t+1}^b)} \times \frac{D_{t+1}(x_t, y_t^g, y_t^b)}{D_{t+1}(x_{t+1}, y_{t+1}^g, y_{t+1}^b)} \right]^{1/2} \tag{2}$$

D refers to the SBM directional distance considering resource and environmental factors. The ML index can be further decomposed into efficiency change index (EC) and technological progress index (TC), namely ML=EC*TC.

$$EC_{t,t+1} = \frac{D_t(x_t, y_t^g, y_t^b)}{D_{t+1}(x_{t+1}, y_{t+1}^g, y_{t+1}^b)} \tag{3}$$

$$TC_{t,t+1} = \left[\frac{D_{t+1}(x_{t+1}, y_{t+1}^g, y_{t+1}^b)}{D_t(x_{t+1}, y_{t+1}^g, y_{t+1}^b)} \times \frac{D_{t+1}(x_t, y_t^g, y_t^b)}{D_t(x_t, y_t^g, y_t^b)} \right]^{1/2} \tag{4}$$

where EC reflects the changes in the efficiency of inter-period green technology. If EC is greater than 1, it indicates that the efficiency is improved. TC measures the changes in inter-period green technological progress. If TC exceeds 1, it means the best frontier is shifting upwards and technology progresses.

3.2.2 Global Value Chain Participation indices

In this study, following the production activity decomposition framework proposed by Wang *et. al* (2017), we measure several pairs of indices for participation in GVC. The participation indices of GVC are as follows:

$$GVC\_fp = \frac{V\_GVC}{Va'} = \frac{V\_GVC\_S}{Va'} + \frac{V\_GVC\_C}{Va'} = \frac{\hat{V}LA^F L\hat{D}}{Va'} + \frac{\hat{V}LA^F (B\hat{Y} - L\hat{Y}^D)}{Va'} \tag{5}$$

$$GVC\_bp = \frac{V\_GVC}{Y'} = \frac{V\_GVC\_S}{Y'} + \frac{V\_GVC\_C}{Y'} = \frac{VLA^F L\hat{D}}{Y'} + \frac{VLA^F (B\hat{Y} - L\hat{Y}^D)}{Y'} \quad (6)$$

Equation (5) denotes the forward participation in GVC, it represents the domestic value-added of a country-sector's GVC activities through downstream sectors as a share of total value-added. The first term on the right-hand side of equation (5) represents the simple forward-linkage GVC participation index, and the second term represents the complex one. Equation (6) denotes the backward participation of GVC, and it measures the percentage of a country-sector's total final products and services that donates the value-added created by upstream sectors participating in GVC. Similarly, the first term on the right-hand side of equation (6) is the simple backward-linkage GVC participation index, and the second term represents the complex one.

3.3 Methodology

Based on the above analysis, we build the following baseline multivariate regression model to assess how participation in GVC affects green TFP:

$$MI_{it} = \alpha + \beta GVC_{it} + \gamma X_{it} + \mu_{ind} + \mu_{year} + \varepsilon_{it} \quad (7)$$

where MI_{it} is the chain base index of green TFP for industry *i* at year *t*. GVC_{it} represent forward or backward participation, both of which involve simple and complex activities. X_{it} are control variables. We also control industry and year fixed effects using a series of dummy variables. ε_{it} represents a random perturbation term.

Following the relevant empirical literature (Wang *et al.*, 2019; Zhu *et al.*, 2020), we control for a vector of industry characteristics. For example, Qu *et al*. (2020) pointed out that FDI is conducive to green growth through knowledge spillovers. Therefore, we control for FDI intensity (*FDI*), measured by the proportion of total assets of foreign-invested enterprises to that of all industrial enterprises above designated size. According to the Rebzinski theorem, changes in per-capita capital stock (*KL*) will affect the output structure of industrial sectors, thereby impacting resource consumption and environmental TFP. To calculate this variable, we use the ratio of the industry's net fixed assets to the number of employees. We also control for energy structure (*ES*, coal consumption as a percentage of total energy consumption) and energy efficiency (*EE*, output per unit of energy) that are known to influence green growth. As R&D reflects the technological progress and innovation, we control for R&D intensity (*RD*), measured by the ratio of the industry's research expenditure to value-added. Additionally, industry structure (*IS*) is also considered, which is proxied by the percentage of value-added to total value added of all industries.

4. Results

4.1 Results of GTFP and GVC Indices

Table 1 shows the results of the GTFP index[4] and its decomposition. As it can be seen, China's GTFP index shows a slight increase from 2001 to 2014. In particular, the average value in 2001 was 1.019, and it increased to 1.037 in 2014. The technical efficiency index of 2001 and 2014 are 1.000 and 0.977, respectively, which represents a modest fall. Meanwhile, the technological progress during this period increases from 1.023 to 1.066. The last three columns present the

[4] *In this study, we treat the chain base index of GTFP as its index. The base year is set at 2000 and its GTFP index is 1. Table 1 presents this index from 2001 to 2014, and the index of 2000 is included in the following empirical research.*

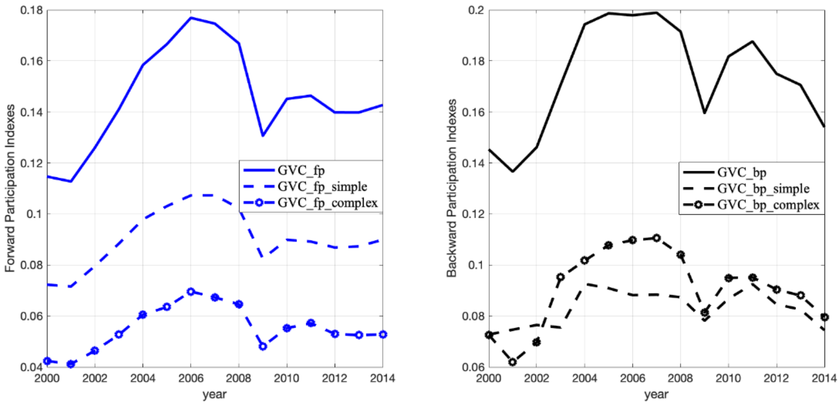
mean of GTFP and its decomposition for each industry. The indices of each industry are consistent with the basic characteristics of the whole. For most sectors, the technological progress index is higher than the technical efficiency index. In contrast, the technological progress index (1.119) for manufacturing of machinery and equipment (C17) is slightly lower than the technical efficiency index (1.120). The results corroborate the findings of Ding *et al*. (2017), which also found that technological progress contributed more to GTFP than the efficiency index. Therefore, we can conclude that the improvement of China's GTFP during this period mainly relies on technological progress instead of efficiency.

Table 1. Green TFP index and decomposition, 2001 to 2014

Industry Code	*2001*			*2014*			*Mean*		
	MI	*EC*	*TP*	*MI*	*EC*	*TP*	*MI*	*EC*	*TP*
C1	1.078	1.122	0.961	1.050	1.032	1.018	1.073	1.025	1.051
C2	1.064	1.081	0.984	0.945	0.801	1.181	1.092	1.097	1.131
C3	1.017	1.041	0.977	0.996	0.944	1.055	1.051	1.018	1.050
C4	1.099	1.000	1.099	1.000	1.000	1.000	1.136	1.000	1.136
C5	1.060	1.097	0.967	1.089	1.079	1.010	1.046	1.000	1.053
C6	1.004	1.040	0.965	1.143	1.135	1.007	1.046	1.011	1.049
C7	1.246	1.000	1.246	1.114	1.000	1.114	1.179	1.000	1.179
C8	0.987	0.767	1.291	1.013	0.812	1.247	1.078	0.986	1.105
C9	0.896	0.919	0.974	1.038	0.990	1.049	1.062	1.094	1.186
C10	1.036	1.086	0.954	0.901	0.769	1.171	1.035	1.000	1.059
C11	0.854	0.865	0.987	0.991	0.991	1.000	1.061	1.016	1.049
C12	1.026	1.000	1.026	1.064	1.000	1.064	1.155	1.000	1.155
C13	0.943	0.901	1.048	0.922	0.922	1.000	1.018	0.982	1.055
C14	0.986	1.000	0.986	1.000	1.000	1.000	1.093	1.000	1.093
C15	0.890	0.868	1.026	1.065	0.940	1.133	1.057	0.999	1.088
C16	1.085	1.125	0.965	0.986	0.986	1.000	1.037	.0.9951	1.051
C17	1.083	1.098	0.987	1.000	1.000	1.000	1.157	1.120	1.119
C18	0.718	1.000	0.718	0.921	0.947	0.973	0.929	0.928	1.046
C19	1.142	1.000	1.142	1.214	1.198	1.014	1.095	0.958	1.157
C20	1.162	1.000	1.162	1.294	1.000	1.294	1.396	1.000	1.396
Mean	1.019	1.000	1.023	1.037	0.977	1.066	1.090	1.012	1.110

Figure 1 indicates the GVC participation of China from 2000 to 2014. Since China joined WTO in 2001, the forward participation and backward participation have shown an upward trend until 2006. Shocked by the financial crisis in 2008, the GVC participation declined rapidly and rebounded from 2010 to 2014, and went through some fluctuations. As discussed in Section 3, GVC activities can be decomposed into simple and complex activities. In Figure 1, GVC forward participation of China is dominated by simple activities, while complex activities are the leading factors of backward participation. In addition, China has more backward participation than forward participation due to its abundant labor resources in most downstream sectors (Hua *et al*., 2022; Kee and tang, 2016). These patterns are consistent with the findings of previous literature (Wang *et al.*, 2017).

Figure 1. GVC Participation indices,2000 to 2014



4.2. Benchmark Regression Results

Table 2 reports the estimation results, which show that activities in GVC are significantly and positively correlated with GTFP. Hua *et al.* (2022) argue that GVC participation may turn China into a “pollution refuge”, which is not beneficial to the low-carbon economy. In our study, GVC activities proved their roles in promoting environmental and technological progress. The coefficient of forward participation (1.625) is greater than that of backward participation (0.765), and the influence of complex activities is greater. This proves that engaging in high value-added links such as research and design is more beneficial to promote sustainable development. As for backward participation, the impact of simple activities is not significant, while the coefficient of complex activities is positive at the 5% level. The explanations for the above findings may be that complex activities can better realize the benefits of a specialized division of labor. Many low-end manufacturing activities may not only increase resource input and environmental pollution but also hinder the acquisition of core technologies. Hence, our findings support the idea that firms should engage in more complex and high value-added activities, especially participating in GVC via forward-linkage, which is crucial to sustainable development (Wang *et al.*, 2017; Zhang *et al.*, 2021; Hua *et al.*, 2022).

In addition, the increase in energy efficiency and per-capita capital will give industries a higher GTFP. The energy structure reveals a significantly negative correlation with GTFP, indicating that the greater proportion of coal in energy consumption generates much more pressure on the environment. R&D intensity does not promote GTFP, which may be due to the improper structure and low efficiency of R&D capital. The coefficient of FDI intensity is also negative, implying that foreign enterprises may cause damage to China’s environment by transferring high-polluting production processes.

Table 2. Benchmark regression results

Variables	Forward participation			Backward participation		
	(1)	(2)	(3)	(4)	(5)	(6)
	MI	*MI*	*MI*	*MI*	*MI*	*MI*
GVC	1.625***			0.765***		
	(0.560)			(0.250)		
SIMPLE		2.627**			0.170	
		(0.956)			(0.645)	
COMPLEX			3.684***			1.191**
			(1.132)			(0.481)
RD	-2.994**	-2.846*	-2.983**	-1.979**	-1.362	-1.932*
	(1.401)	(1.362)	(1.397)	(0.911)	(0.944)	(1.025)
KL	0.100***	0.098***	0.103***	0.095**	0.112**	0.101**
	(0.033)	(0.033)	(0.032)	(0.042)	(0.041)	(0.040)
ES	-0.128**	-0.121**	-0.138**	-0.156**	-0.130*	-0.121**
	(0.048)	(0.047)	(0.051)	(0.061)	(0.065)	(0.054)
FDI	-0.127**	-0.124*	-0.134**	-0.110	-0.152*	-0.131*
	(0.060)	(0.061)	(0.060)	(0.079)	(0.078)	(0.075)
IS	0.592	0.898	0.144	0.013	0.431	0.490
	(1.307)	(1.320)	(1.275)	(1.119)	(1.143)	(1.115)
EE	0.136**	0.133**	0.141**	0.144**	0.141**	0.143**
	(0.054)	(0.054)	(0.055)	(0.059)	(0.060)	(0.058)
Industry/year effect	Yes	Yes	Yes	Yes	Yes	Yes
N	300	300	300	300	300	300

*Note: () is standard error; ***, ** and * indicate 1%, 5% and 10% significance, respectively. The note applies to the following tables.*

4.3 Robustness Checks

We adopt different model specifications to examine the robustness of our results. For brevity, we do not report the coefficients of control variables. First, we recalculate the dependent variable, re-estimating the model with MI based on variable returns-to-scale assumptions. The estimated results are shown in Panel A of Table 3. Second, the endogeneity problem occurs when the GVC activities may be influenced by green growth or both may be jointly impacted by other unmeasured factors (Hu *et al.*, 2021). To address the endogeneity issue, we take the one-period lag of the core explanatory variable as the instrumental variable and run the two-stage least squares method in Panel B of Table 3. As shown in Panel B, except for SIMPLE of backward participation, coefficients of other key independent variables remain positive and significant at least at the 10% level, which is qualitatively consistent with those in Table 2.

Table 3. Robustness analysis

Panel A: vrs						
Variables	Forward participation			Backward participation		
	(1)	(2)	(3)	(1)	(2)	(3)
	MI	*MI*	*MI*	*MI*	*MI*	*MI*
GVC	0.810**			0.467**		
	(0.292)			(0.204)		
SIMPLE		1.317**			0.170	
		(0.498)			(0.645)	
COMPLEX			1.822***			0.860**
			(0.570)			(0.380)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	300	300	300	300	300	300
Panel B: IV						
Variables	Forward participation			Backward participation		
	(1)	(2)	(3)	(1)	(2)	(3)
	MI	*MI*	*MI*	*MI*	*MI*	*MI*
GVC	2.357**			1.850*		
	(1.060)			(0.956)		
SIMPLE		3.944**			-0.052	
		(1.649)			(1.475)	
COMPLEX			5.055**			2.335**
			(2.561)			(1.076)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	300	300	300	300	300	300

5. Further Analysis

5.1 Mechanism analysis

We now extend our discussion to investigate a possible mechanism by which GVC could affect green growth. Referring to Baron and Kenny (1986), this study adopts the mediation models to verify the mechanism:

$$MI_{it} = a_0 + a_1 GVC_{it} + a_2 X_{it} + \mu_{ind} + \mu_{year} + \varepsilon_{it} \quad (8)$$

$$channel_{it} = b_0 + b_1 GVC_{it} + b_2 X_{it} + \mu_{ind} + \mu_{year} + \varepsilon_{it} \quad (9)$$

$$MI_{it} = c_0 + c_1 GVC_{it} + c_2 channel_{it} + c_3 X_{it} + \mu_{ind} + \mu_{year} + \varepsilon_{it} \quad (10)$$

where the channel is a mediation indicator, which in this study accordingly represents environmental regulation or technology spillover. The estimation of Equation (8) is consistent with the benchmark model, so we focus on the empirical analysis of Equation (9) and Equation (10) in this section.

There is a consensus among all countries that environmental regulation should be more stringent. In the process of forward participation, upstream sectors tend to set stricter environmental protection standards to force downstream enterprises to meet their standards. Environmental standards in developed countries are usually more stringent. To meet their standards, downstream enterprises should develop green technology in their production process to achieve energy savings and emission reductions. Moreover, GVC participation is important for achieving technological progress through technology spillover (Qian *et al.*,2022). Upstream enterprises tend to diffuse knowledge and technology to the downstream enterprises in GVC dominated by multinational companies. It is through technological externalities that downstream enterprises may obtain advanced technologies to promote green economy.

Following the existing literature (Wang and Li, 2020; Zhang *et al.*,2020; Qian *et al*.,2022), we utilize industrial environmental pollution investment (*ERI*) to measure environmental regulation intensity, and industrial production efficiency (*efficiency*) to measure technology spillover effect. Then causal step regression is used to test the mediating role of ERI and efficiency[5]. Table 4 reports the mediation effects of environmental regulation and production efficiency. The results show that the influences of forward and backward participation on ERI and efficiency are both significantly positive. The coefficients of ERI and efficiency on MI are also positive at the 5%. Hence, GVC participation increases GTFP through environmental regulations and technology spillover effects (Zhang *et al.*,2020; Qian *et al*.,2022). More importantly, the mediating effect of forward participation is greater. The explanations are that the increase in GVC forward participation means increases in domestic value-added and high-end GVC activities, which is more beneficial in promoting technology diffusion (Qian *et al.*,2022).

Table 4. Mediation regression results

	Environmental Regulation Effect				*Technology Spillover Effect*			
Variables	*Forward*		*Backward*		*Forward*		*Backward*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	ERI	*MI*	*ERI*	*MI*	*efficiency*	*MI*	*efficiency*	*MI*
GVC_fp	0.878*	1.509**			2.404***	1.552***		
	(0.468)	(0.591)			(0.507)	(0.542)		
ERI		0.052**		0.018**				
		(0.023)		(0.008)				
efficiency						0.039***		0.024*
						(0.004)		(0.013)
GVC_bp			0.752*	0.665***			1.456**	0.269***
			(0.363)	(0.228)			(0.584)	(0.086)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	300	300	300	300	300	300	300	300

[5] *Efficiency is calculated by DEA method: total output is the output variable and input variables include labour and capital.*

5.2 Accounting for Industry Heterogeneity

5.2.1 Industry Heterogeneity by Technology Orientation

Technology orientation may affect the absorptive capacity of an industry, which in turn influences the impact of GVC participation on technology efficiency and pollution emissions. Using the classification standards from OECD, we divide the samples into three groups: high-technology industries, medium-technology industries, and low-technology industries. In Table 5, the participation of the low-tech industry has no obvious correlation with GTFP, where only the coefficient of SIMPLE (2.577) in forward participation is positive at 1%. The low-technology industries of China mainly involve the processing of imported intermediate goods and are mostly labor-intensive. These industries are intrinsically characterized by highly polluting and energy-intensive, which may lead to participating in GVC may not increase green productivity. The impacts of GVC, SIMPLE, and COMPLEX in forward participation of high-technology industries are all significantly positive. Compared with backward participation, complex activities of forward participation have a greater impact on GTFP. This may be due to the fact that engaging in high-value-added, high-tech activities not only helps reduce carbon emissions, but also brings technological progress. On the other side, simple GVC has high carbon intensity per unit of value added (Li *et al.*, 2022). Additionally, simple GVC activities involve relatively few production links, which may constrain the potential for technological spillover effects. Consequently, the impact of simple GVC on the environment and productivity may be relatively insignificant.

Table 5. Industry heterogeneity by technology orientation

Variables	*High-tech*		*Middle-tech*		*Low-tech*	
	Forward	*Backward*	*Forward*	*Backward*	*Forward*	*Backward*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	MI	*MI*	*MI*	*MI*	*MI*	*MI*
GVC	2.318**	1.149*	1.739**	1.177*	3.214	0.348
	(0.757)	(0.511)	(0.656)	(0.561)	(2.182)	(0.603)
SIMPLE	4.433**	0.216	1.131	-0.245	4.837	-1.478
	(1.679)	(1.437)	(1.201)	(0.843)	(3.556)	(0.967)
COMPLEX	3.667**	1.032*	2.945**	1.099*	2.577***	2.104
	(0.949)	(0.416)	(0.854)	(0.519)	(0.621)	(1.657)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	90	90	90	90	120	120

5.2.2 Industry Heterogeneity by Pollution Intensity

Because of limited environmental regulations, developing countries are usually forced to take on the high-polluting industries from developed countries, producing more carbon emissions (Cole, 2004; Hu *et al.*, 2021). Hence, for pollution-intensive industries, participating in GVC may hurt the environment. We divide the samples into high-pollution and low-pollution industries. Columns (1)-(4) of Table 6 show the results. For forward participation, coefficients of both SIMPLE (2.196) and COMPLEX (2.805) in low-pollution industries are significantly positive, and the latter has higher effects. In contrast, the coefficients in high-pollution industries are all insignificant. For backward participation, the effect of COMPLEX in low-pollution industries on GTFP is positive at 1% while that of SIMPLE is insignificantly negative. High-pollution industries are also insignificantly positive.

In general, for pollution-intensive industries, participation in GVC may not lead to improvements in environmental performance.

5.2.3 Industry Heterogeneity by FDI Intensity

Some studies argue that developed countries may transfer part of highly polluting industries to developing countries through FDI, thereby leading to environmental degradation in developing countries (Copeland and Taylor, 1994). However, an opposing view suggests that there is no inevitable relationship between FDI and environmental pollution (Hille *et al.*, 2019; López *et al.*, 2018).To investigate the consequences of industry heterogeneity by FDI Intensity, we divide the sample into two groups: high-FDI industries and low-FDI industries. The findings can be seen in columns (5)-(8) of Table 6. Forward participation has a significant positive spillover effect on both groups, but the low-FDI industries are more affected. Moreover, the coefficient of COMPLEX is significantly higher than that of SIMPLE, indicating a more specific division of labor can better improve GTFP. Backward participation shows different results. The spillover effect of COMPLEX on GTFP in high-FDI industries (1.407) is only significant at the 10% level, which is much smaller than that in low-FDI industries (3.449).

Table 6. Industry heterogeneity by pollution and FDI intensity

Variables	*High-pol*		*Low-pol*		*High-FDI*		*Low-FDI*	
	Forward	*Backward*	*Forward*	*Backward*	*Forward*	*Backward*	*Forward*	*Backward*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	MI	*MI*	*MI*	*MI*	*MI*	*MI*	*MI*	*MI*
GVC	2.384	0.908*	1.339**	1.082***	1.065**	1.509	2.327*	0.664**
	(1.441)	(0.455)	(0.532)	(0.317)	(0.399)	(1.379)	(1.063)	(0.242)
SIMPLE	3.805	0.403	2.196**	-0.845	1.628*	-4.987	4.051**	-0.852
	(2.457)	(0.373)	(0.956)	(0.939)	(0.718)	(2.741)	(1.821)	(1.301)
COMPLEX	5.882	0.127	2.805***	1.230***	2.438***	2.823*	5.045***	3.449***
	(.225)	(0.630)	(0.816)	(0.340)	(0.615)	(1.407)	(0.379)	(0.708)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	150	150	150	150	120	120	180	180

6. Conclusion and Discussion

This study investigates whether GTFP shows different responses to forward and backward GVC participation by taking China's industrial sectors as an example. The results suggest that GTFP is more sensitive to forward participation than to backward participation. For forward participation, both simple and complex activities show a positive effect on GTFP, while the latter is more significant. For backward participation, however, only complex activities present a positive effect. Furthermore, we investigate the possible channels through which GVC participation could affect GTFP, and explore the heterogeneity of industries with different technology orientations, pollution intensity, and FDI intensity. The results suggest that there is a positive mediating effect of spillover and environmental regulation on the relationship between GVC participation and sustainable growth. Moreover, the GVC activities of industries with high-tech orientation, low pollution, and low FDI intensity have more significant positive effects on GTFP.

China's economic growth and sustainable development have been significantly influenced by its participation in GVC (Lyu et al., 2023). By integrating into the global production network, China has emerged as the world's leading exporter and the "world's factory". This has provided China with opportunities to acquire cutting-edge technologies from more advanced economies (Ndubuisi et al., 2021), which has enhanced the competitiveness and productivity of local industries. Furthermore, Chinese firms have also gained advanced management experience through GVC participation, leading to the promotion of sustainable growth by optimization of production processes. Existing research also confirmed that GVC participation could serve as a crucial strategy for developing countries to promote sustainable development.

Our findings have important implications, especially for countries that are rapidly increasing their GVC participation. China should participate in the GVC division of labor activity and pay more attention to technological progress and environmental protection, which are two important components of sustainable development. Furthermore, other countries should notice the positive effect of forward participation on sustainable growth. Firms should enhance their R&D capabilities, strengthen the innovation and application of green technologies, and create more domestic value-added, which is beneficial for industrial upgrading and environmental technology. In backward GVC activities, firms should absorb and improve the technology from key technical equipment and intermediate products, thereby promoting energy efficiency and production technology.

Although this paper adds valuable insights to the existing literature, some limitations should be addressed in future research. First, our sample is focused on China, which is one of the largest developing countries. It is possible that our findings may not be generalized well to other developing countries given the differences in economic, institutional and cultural conditions. Thus, future research may benefit from comparing different developing countries in terms of GVC participation. Second, our analysis unit is on the industry level due to data availability. It would be more meaningful if future research could complement our study by investigating this topic with more comprehensive firm-level data.

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