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The Impact of Global Value Chains Participation on Carbon Emissions: New Evidence from Manufacturing Industries in Belt and Road Initiative Countries

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The emergence of global value chains (GVCs) has fundamentally reshaped the manufacturing landscape in these countries, which also exerts a profound impact on carbon emissions. This paper takes 35 BRI countries as a representative example of developed and developing nations, and selects panel data of their manufacturing industries from 2007 to 2019 to empirically investigate the impact of the participation of manufacturing in GVCs on carbon emissions. The results show that an increase in the forward participation of manufacturing industries in GVCs can significantly reduce carbon emissions, while the enhancement of backward participation does not have the same effect. The spatial spillover effects analysis reveals that there is a significant positive spatial spillover effect of carbon emissions within the manufacturing industries of BRI countries. In addition, an increase in the forward participation of neighboring countries also leads to a slightly reduction in their own carbon emissions. The findings in this paper can serve a valuable reference for policymakers seeking to enhance regional economic exchange and cooperation by leveraging the reconfiguration of global value chain so as to achieve the common goal of reducing carbon emissions.

Key words: Carbon emissions, Global value chains, Belt and Road Initiative, Manufacturing, Spatial spillovers effects

INTRODUCTION

Over recent years, global climate change has been notable with frequent episodes of extreme hot and cold weather. The occurrence of the extreme weather events is having significant impacts on human health, ecosystems, economy, agriculture, energy, and water supply, and it is widely recognized as closely related to the considerable rise in human greenhouse gas emissions. As a result of this, governments around the world have made concerted efforts to address climate change. The Kyoto Protocol and the Paris Agreement are the examples. These agreements already signed by countries also suggest that the framework for reducing emissions has transitioned from the top–down approach of the former to the bottom–up model of the latter. Furthermore, the gathering support of the international community not only demonstrates the importance of acting on climate change but also attests that international cooperation must be in place to address climate change.

Manufacturing, as a fundamental, strategic, and pioneering industry in national economy development, remains one of the most energy–intensive sectors and is now recognized as the primary contributor to carbon emissions. According to the data from the International Energy Agency (IEA) in 2022, the global manufacturing accounted for approximately 22.2% of global energy consumption, and it was responsible for around 20% of global carbon emissions. Among these, manufacturing industries in many developing countries exhibit higher levels of carbon emissions, especially the countries participating in the Belt and Road Initiative. For example, valid data from the China Carbon Accounting Databases (CEADs) shows that in 2022, China's carbon emissions were total 11 billion tons, accounting for about 28.87% of global carbon emissions. Among them, 4.2 billion tons was emitted by the manufacturing industry, accounting for 38.18% of national carbon emissions. Currently, there is a widely shared consensus within the manufacturing industry that the pace of transitioning towards green and low–carbon practices must be accelerated. In this context, it is imperative to intensify carbon reduction efforts in these countries.

A global value chain (GVC) is a combination of all the activities that create value throughout the life cycle of a product, spanning from its initial design phase to the culmination of its utility. Nowadays, GVCs have emerged as the prevailing paradigm for the international organization of production, and the production of most goods and services is vertically fragmented across different countries. The position in GVC generally reflects the levels of participation of a country or its industries in different segments in global trade (Qian *et al.*, 2022). Currently, due to a lack of core technologies, developing countries often find themselves at lower positions in GVC. This inherent disadvantage ultimately restricts their ability to create and capture higher levels of added value. If developing countries aim to shift their positions to the high–value–added segment in GVC, it is essential

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for them to upgrade their manufacturing industries in terms of processes, products, and functions. This can also be seen as an opportunity to promote carbon emissions reduction through the adoption of clean and green technologies, thus achieving sustainable development goals.

In the literature, the examination of the relationship between international trade and the environment has consistently remained as a hot topic. Numerous of studies, both theoretical and empirical, has delved into this subject. Grossman and Krueger (1991) developed a general equilibrium model to explore the trade–environment relationship, focusing on the scale, structural, and technology effects, and found that the North American Free Trade Agreement could potentially influence the environment through these three effects. Antweiler *et al.* (2001) subsequently tested these three effects using data on sulfur dioxide concentrations, and also found the similar results. However, some other studies also presented an opposite conclusion (Chen *et al.*, 2023; Khan and Safdar, 2023; Martínez–Zarzoso *et al.*, 2020), and thus there is still no consensus on the trade–environment nexus. This is primarily because carbon emission itself is a controversial topic.

In addition, as the emergence of GVCs has transformed integrated production processes into international intra–product specializations, with nations specializing in specific stages of production according to their comparative advantages (Yan *et al.*, 2023), a series of studies have been conducted to explore different indicators for measuring the GVCs participation features (Li and Peng, 2011; Hu, 2016; Wang *et al.*, 2017a, 2017b; Yang *et al.*, 2017). Researchers have also examined the relationship between GVCs and the environment at both macro– and micro– levels, exploring aspects like the respective influence of participating in GVCs, and upgrading GVCs positions on carbon emissions (Liu *et al.*, 2020; Lv *et al.*, 2019; Meng *et al.*, 2018, 2019; Shi *et al.*, 2022). In comparison, there are few spatial econometric empirical studies focusing on carbon emissions. For instance, Peng *et al.* (2013) spatially analyzed the causality and five major decomposition effects between China's manufacturing GVCs and its carbon emissions. Han *et al.* (2017) explored the impact of the agglomeration of productive service industries on carbon emissions and its spatial effects.

Overall, current studies (including the ones mentioned above) have discussed the effect of GVCs on carbon emissions from various perspectives like different model design, parameters selection, or different research objectives towards carbon issues. However, most studies typically focus on a single GVC indicator such as GVCs participation or position index, and primarily examine the impact of GVCs participation on carbon emissions at the national level. In other words, few ones consider this matter from the point view of specific industries across different countries. Indeed, different industries participating in specific segments of GVCs generate varying levels of carbon emissions, and this is particularly evident in the developing countries. In this regard, it becomes necessary to conduct industry–specific studies in a categorized manner.

Based on the above discussion, this paper employs panel data of 35 BRI countries' manufacturing industries over the period of 2007–2019 to empirically explore the relationship between GVCs participation and carbon emissions. In contrast to prior studies that concentrate on overall national carbon emissions, this paper specifically concentrates on the manufacturing industries and investigates the impacts of their forward and backward participation in GVCs on carbon emissions in BRI countries at the industry–level. To achieve this goal, we select several manufacturing indicators to measure both the forward and backward participation in GVCs, and examine their different impacts on carbon emissions. The analysis also considers national heterogeneity. Building upon this, we then analyze the mechanisms through which the GVCs participation affects carbon emissions: the scale, the structural and the technology effects. In addition, given the fact that the objective factors like wind flow can influence the carbon emissions of nearby regions, this paper also incorporates an empirical analysis of spatial measurement and examines both the direct and indirect effects of moving up the value chain of the manufacturing on carbon emissions of neighboring countries. The findings in this paper could serve as valuable inspiration for BRI countries on how to elevate their manufacturing industries to higher positions within the global value chains, thereby more effectively promoting low–carbon transitions in these countries.

METHODOLOGY AND DATA

Model design of the impact of GVCs participation on carbon emissions

Suppose an economy produces only two products, X and Y. X is capital–intensive and associated environment pollution issues. Y is labor–intensive and represents a cleaning product. Both X and Y can be produced using two factors: capital and labor, with each of them assumed to have perfectly inelastic supply. The price of Y is assumed to be $P_Y = 1$, while the relative price of X is denoted as P_X. It is also assumed that markets have no tariff barriers and are perfectly competitive, thereby ensuring that economies of scale remain constant. Finally, with regard to pollution, we focus solely on carbon emissions and disregard other factors.

The aggregate production function for the contaminated product X is given as follows $X_g = Q(L_x, K_x)$, where L_x and K_x represent labor and capital inputs, respectively. $Q(L_x, K_x)$ represents the potential output of product X. In the context of being embedded in GVCs, the economy will import intermediate goods, and as a result, the production function for product X can be rewritten as $X_g = Q(L_x, K_x)Gvc$, where Gvc denotes the level of a country's participation within GVCs and takes a value between 0 and 1. Then, in compliance with the agreements such as the Paris Agreement and the Kyoto Protocol, governments have to implemented regulatory policies aimed at reducing carbon emissions. Under these policies, the emissions will be reduced by decreasing a fraction $\theta(0 < \theta < 1)$ of potential output. Thus, the efficient production function for polluting product X is $X_g = Q(L_x, K_x)Gvc$.

Accordingly, carbon emissions are calculated as $C = \varphi(\theta)Q(L_x, K_x)Gvc$, where $\varphi(\theta)$ represents carbon emissions per unit of output and is a function of technology T. Higher levels of technology are assumed to correspond to lower carbon emissions, and this relationship is $\varphi(\theta) = \frac{1}{T}(1-\theta)^{\frac{1}{\alpha}}$, $0 < \alpha < 1$. By incorporating the corresponding position in the global value chain, we can obtain a new effective output function for product X, that is, $x = (T \cdot C)^{\alpha} \cdot (Q \cdot Gvc)^{(1-\alpha)}$, where $(T \cdot C)$ represents the carbon emissions under technological treatments, and $(Q \cdot Gvc)$ denotes the output after embedding in the global value chain.

From the firms' perspective, they aim to produce product X at the lowest possible total cost, which includes the expenses of labor and capital, and government environmental pollution taxes due to carbon emissions. In the context of the international division of labor, the cost per unit of output is assumed as $c^f(w,r)$. Thus, for a given a tax level and prices of capital and labor, firms need to determine the optimal level of carbon emissions and output embedded in GVCs to minimize the total cost of producing X, that is, $\min\{c^f(w,r)Q(L_x, K_x)Gvc + \tau T \cdot C\}$, with subject to $(T \cdot C)^{\alpha} \cdot (Q \cdot Gvc)^{(1-\alpha)} = 1$, where τ is the Lagrange multiplier. By employing the Lagrangian approach and differentiating the partial derivatives with respect to carbon emissions with technological treatments and output embedded in GVCs, we can obtain $\frac{c^f}{\tau} = \frac{(1-\alpha)T \cdot C}{\alpha Q \cdot Gvc}$. If the market is perfectly competitive, the firm's net profit will be zero, that is, $\pi = P_x \cdot x - c^f Q \cdot Gvc - \tau T \cdot C = 0$. Combined with the above equations, we have $x = \frac{c^f Q \cdot Gvc + \tau T \cdot C}{P_x} = \frac{\tau T \cdot C}{\alpha P_x}$. The carbon emissions $\varphi(\theta)$ per product embedded into GVCs are $\varphi(\theta) = \frac{C}{X} = \frac{\alpha P_x}{\tau T}$. Substituting it into the above equations and rewriting it, we have the following result

$$C = \frac{\alpha}{\tau T} \cdot Q(L_x, K_x) \cdot Gvc = (P_X X_g + P_Y Y_g) \cdot \frac{P_X X_g}{(P_X X_g + P_Y Y_g)} \cdot \frac{\alpha}{\tau T} \cdot Gvc = Sca \cdot Str \cdot \frac{\alpha}{\tau T} \cdot Gvc \quad (1)$$

where $Sca = (P_X X_g + P_Y Y_g)$ denotes the scale of the economy, and $Str = \frac{P_X X_g}{(P_X X_g + P_Y Y_g)}$ reflects the proportion of the value generated by producing product X within the total production value, often termed the product structure. Taking the logarithm of both sides of Equation (1), we have

$$\ln C = \ln Sca + \ln Str - \ln T + \ln Gvc + \ln\varepsilon \quad (2)$$

where $\varepsilon = \frac{\alpha}{\tau}$ is a constant. It is evident that the levels of carbon emissions can be influenced by several factors, including the scale of trade economy, the economic structure of a country, technology development, and the position in GVCs. These factors are commonly referred as the scale effect, the composition effect, the technology effect and the GVCs effect.

In order to investigate the impacts of different participation patterns within the value chains on carbon emissions, we further divides the value chain location indexes into forward and backward participation. Correspondingly, the benchmark model can be constructed as follows

$$\begin{aligned}\ln Carbon_{it} = \beta_0 + \beta_1 Gvc_{it} + \beta_2 Sca_{it} + \beta_3 Str_{it} \\ + \beta_4 Tec_{it} + \beta_5 Upop_{it} + \beta_6 Ivad_{it} \\ + \beta_7 Fdi_{it} + \delta_i + \mu_t + \varepsilon_{it}\end{aligned} \quad (3)$$

where i represents the cross–sectional data of 35 countries, t indicates the year, and $\beta_0 \ldots \beta_7$ are the parameters to be estimated. Furthermore, δ_i and μ_t represent the fixed effects associated with the country and the time, respectively, with ε_{it} representing the error term.

In this paper, GVCs serve as the core explanatory variable and the regressions for the level of the forward and backward participation are conducted separately. The scale effect, the composition effect, and the technological effect are selected to be the control variables. Furthermore, according to the analysis of Qian *et al.* (2022), we also choose another three control variables, that is, the proportion of urban population, the industrial value–added, and the international direct investment, to more accurately assess the impact of core explanatory variables on the explained variable. A comprehensive description of each variable is presented below.

The scale effect (*Sca*): the trade size, that is, the total goods exports of a country for the year, is chosen to measure the scale effect.

The composition effect (*Str*): the medium and high–tech industries' value–added share in the total value–added of manufacturing are selected to measure the composition effect.

The technology Effect (*Tec*): the percentage of education expenditure in relation to Gross National Income is selected to measure the technology effect.

The industrial value–added (*Ivad*): the industries contributing to value–added include mining, manufacturing, construction, electricity, water, and natural gas. The value–added indicator is specifically calculated by the net output of a sector, obtained by summing all outputs and then subtracting intermediate inputs.

The ratio of net inflows of foreign direct investment (FDI) to GDP (*Fdi*): this indicator is calculated by dividing the net inflows of investment from foreign investors into the economy (which accounts for new investment inflows minus divestment) by GDP.

The share of urban population (*Upop*): the urban population refers to the population residing in urban areas as defined by the national statistical office of each nation. It is calculated by the population which estimates from the World Bank and urban ratios from the United Nations World Urbanization Prospects.

The calculations of GVCs participation

To examine the effect of different modes of value chain participation on carbon emissions, we further divide the participation of a country in GVCs into the forward and backward participation indexes. Following Wang and Li (2015), the level of the forward participation in GVCs is given as

$$gvc_f = \frac{V_{GVC}}{Va'} = \frac{V_{GVCs}}{Va'} + \frac{V_{GVCc}}{Va'} \tag{4}$$

where gvc_f denotes the level of the forward participation in GVCs, Va' is the total value–added generated by a country or an industry. V_{GVC} represents the cumulative domestic total value added embodied in the intermediate goods exported by an industry to the global market, including the exports are directly absorbed by importers and the complex global value chain activity of re–exporting/re–importing, denoted by V_{GVCs} and V_{GVCc} , respectively.

Similarly, the level of the backward participation in GVCs is given as

$$gvc_b = \frac{Y_{GVC}}{Y'} = \frac{Y_{GVCs}}{Y'} + \frac{Y_{GVCc}}{Y'} \tag{5}$$

where gvc_b represents the level of the backward participation in GVCs. Y' is the final products and services produced by a country or an industry where it is located. Y_{GVC} denotes the value added of both the domestic and foreign industries in imported intermediate goods, including both the domestic use industry value–added from products imported from other countries, Y_{GVCs} , and the industry value added from products imported from other countries that are reexported after the domestic production and processing, Y_{GVCc} .

Data sources and processing

This paper selects panel data of 35 BRI countries' manufacturing industries over the period of 2007–2019. In order to facilitate a more comprehensive analysis of heterogeneity among target counties in GVCs, we classify these countries into developed and developing economies with the detailed information for each country. All the carbon emission data for the 35 BRI countries' manufacturing industries are sourced from the Climate Watch database. The raw data for the indicators related to GVCs are obtained from the Asian Development Bank database (ADB), while other control variable data is retrieved from the World Bank database (WDI). The latitude and longitude data for the spatial weighting matrix are obtained from the CEPII database.

EMPIRICAL ANALYSIS

The evolution of GVCs participation of BRI countries' manufacturing industries

Figure 1 depicts the forward and backward participation of the 35 BRI countries' manufacturing industries in 2007 and 2019, respectively. Overall, the forward participation levels of the surveyed BRI countries exhibit a consistent upward trend, with all values remaining below 1. Additionally, the evolution trends of the GVCs participation are different between the developed and developing countries. Specifically, the average level of forward participation of developed countries' industries was 0.197 in 2007, and it significantly increased to 0.288 in 2019. In the contrary, developing countries experienced a slower increase in the average level of forward participation, which raised from 0.138 to 0.149 during the same period. However, the manufacturing transformation and upgrade process in the developing countries during this period was relatively slow.

In addition, the backward participation levels of developed countries exhibit a stable trend, with the exceptions being Belgium and Portugal. These two countries have experienced significant growth in the levels of their backward participation between 2007 and 2019, respectively. Furthermore, among these developing countries, Brunei processes the highest level of backward participation, and has also experienced significant growth in the level of backward participation between 2007 and 2019. On the contrary, the level of the backward participation in China has decreased between these two years, potentially as a result of the comprehensive low–carbon transformation policies that were implemented in the manufacturing sector from the 11th Five–Year Plan to the 13th Five–Year Plan period. Since China has redirected its focus towards more sustainable and eco–friendly manufacturing processes, it exhibits a low backward participation level in GVCs.

The evolution of carbon emissions of BRI countries' manufacturing industries

Figure 2 shows the proportion of carbon emissions of the BRI countries' manufacturing industries in the same type countries in 2007 and 2019, respectively. The share of carbon emissions from the manufacturing industry in the developed countries as a proportion of total global carbon emissions decreased from 14.82% to 11.56% over the period 2007 to 2019. On the other hand, carbon emissions from the manufacturing industry in the developing countries increased from 128.46 million tons to 155.96 million tons between 2007 and 2019, reflecting a 21.40% increase. Apparently, carbon emissions are significantly higher in the developing countries than in the developed countries. Within the developing countries, China and Indonesia exhibit substantial carbon emissions stemming from their manufacturing sectors. Conversely, among the developed countries, South Korea and Italy contribute significantly to carbon emissions through their manufacturing industries. These findings illustrate that in the short term, the developing countries have not yet achieved full decoupling of economic growth from carbon emissions.

The benchmark estimation results

Before conducting panel data regression, we first

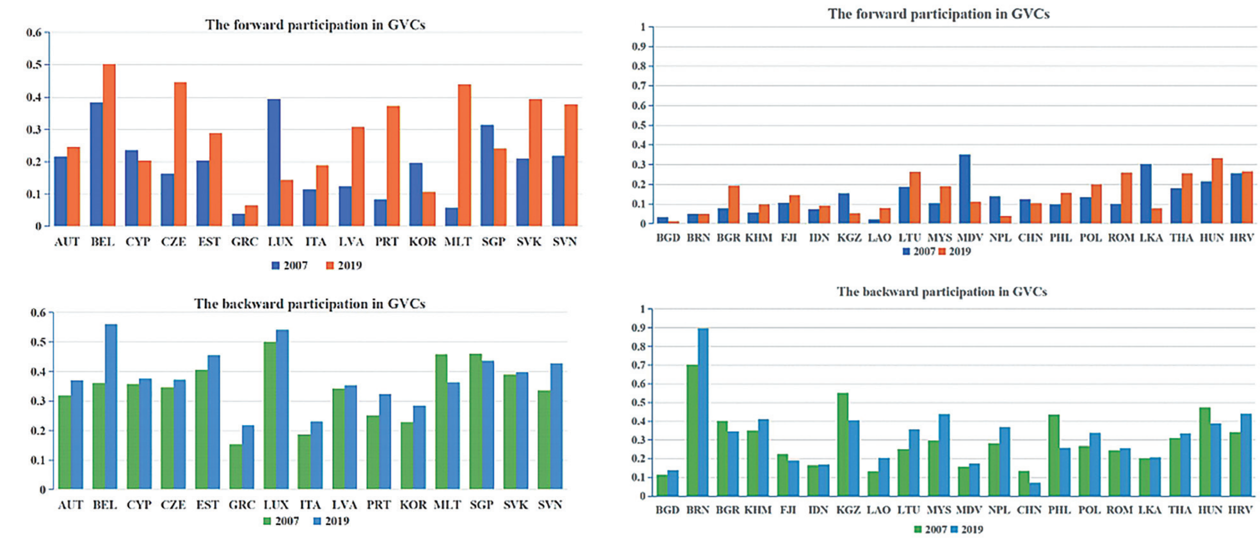

Fig. 1. The forward and backward participation of the developed (left) and developing (right) BRI countries' manufacturing industries in 2007 and 2019.

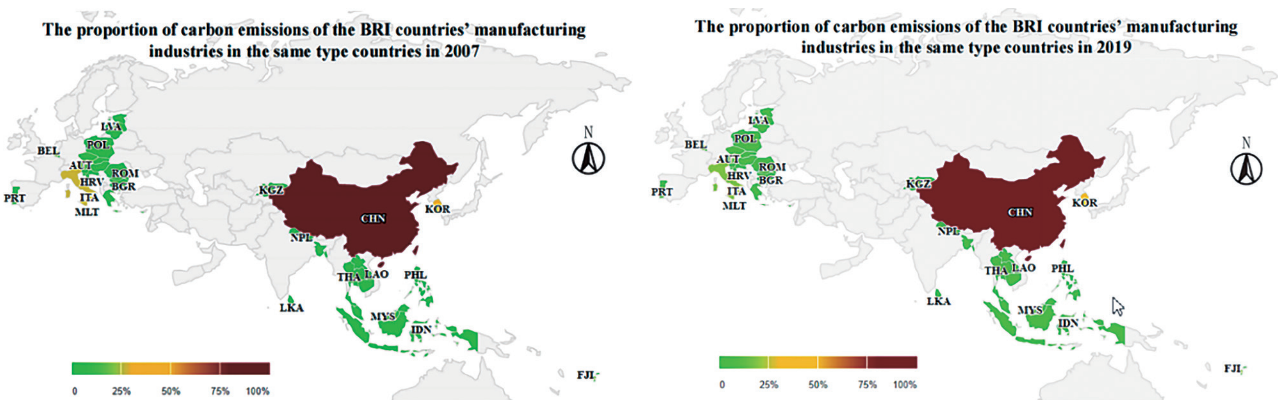

Fig. 2. The proportion of carbon emissions of the BRI countries' manufacturing industries in the same type countries in 2007 and 2019, respectively.

use the Hausman Test to determine the appropriate model between fixed effects or random effects, and the results show that the fixed effects is preferred. Therefore, the next step is to employ the fixed effects model to calculate the benchmark estimation results for Equation (3), and the detailed results are presented in Table 1. Specifically, Columns (1) and (2) separately report the results of employing the two–way fixed effects and the random effects models, with using forward participation in GVCs as the primary explanatory variable, and the scale, the composition, and the technological effects as the control variables. Column (3) reports the results of employing the two–way fixed effects model by incorporating the other three control variables mentioned in the previous section. Columns (4) and (5) separately report the results obtained by replicating the calculations in Columns (1) and (2) when using the backward participation in GVCs as the primary explanatory variable. Correspondingly, the results by incorporating the other three control variables mentioned in the previous section are shown in Column (6).

The benchmark estimation results reveal that there is a significant and negative relation between the forward participation in GVCs of BRI countries and carbon emissions from their manufacturing industries. Specifically, the basic estimation results in Columns (1) and (3) show that the correlation coefficients are –1.033 and –0.920 for the forward participation in GVCs with and without the consideration of control variables, respectively. This suggests that an increase in the position in GVCs can significantly reduce carbon emissions in the manufacturing industries, and the forward participation has a substantial emission reduction effect, including the upstream activities such as design, R&D, and marketing, as depicted in the smile curve. Currently, most BRI countries have relatively low forward participation in GVCs. With the increase in the forward participation in GVCs, they could be engaged in

Table 1. The benchmark estimation results

	(1) CARBON	(2) CARBON	(3) CARBON	(4) CARBON	(5) CARBON	(6) CARBON
Fm	–1.033***	–1.243***	–0.920***			
	(–4.236)	(–4.922)	(–3.828)			
Bm				–0.118	–0.650**	–0.009
				(–0.360)	(–2.008)	(–0.028)
Sca	0.399***	0.523***	0.179*	0.386***	0.536***	0.145
	(4.978)	(10.486)	(1.911)	(4.710)	(10.717)	(1.519)
Tec	–0.124***	–0.138***	–0.104***	–0.121***	–0.136***	–0.101***
	(–4.098)	(–4.534)	(–3.458)	(–3.901)	(–4.334)	(–3.288)
Str	–0.005	–0.002	–0.001	–0.006*	–0.002	–0.002
	(–1.551)	(–0.591)	(–0.273)	(–1.768)	(–0.587)	(–0.474)
Upop			0.032***			0.035***
			(2.829)			(3.013)
Ivad			0.031***			0.034***
			(4.167)			(4.486)
Fdi			–0.000			–0.000
			(–0.738)			(–0.510)
_cons	–6.644***	–10.367***	–3.986*	–6.494***	–10.704***	–3.536
	(–3.229)	(–8.634)	(–1.792)	(–3.080)	(–8.922)	(–1.559)
N	455.000	455.000	455.000	455.000	455.000	455.000
R^2	0.159		0.169	0.122		0.139
year	Yes	No	Yes	Yes	No	Yes
country	Yes	No	Yes	Yes	No	Yes

Notes: 1. The values in brackets under the coefficient are their t–values. 2. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

higher–end and cleaner production processes, thereby reducing carbon emissions. There is also a result that the backward participation in GVCs does not have a significant effect on carbon emissions reduction. Nonetheless, this will be further examined in our subsequent heterogeneity analysis.

Additionally, from the basic estimation results in Columns (3) and (6), we can also obtain that the scale of trade and industry value added are significantly positively correlated with carbon emissions. The expansion of trade and industrial scale accelerate energy consumption, consequently leading to environmental pollution. A significant negative correlation is found between technological effect and carbon emissions, indicating that technological advancements contribute to the reduction of carbon emissions. However, it should be noted that the coefficients for the international direct investment and composition effects are relatively small and insignificant. This implies that after investing in the manufacturing industry, it is essential to view carbon emissions in a dialectic manner.

Robustness Test

To ensure the robustness of the results, this paper conducts the robustness test from four aspects: (*i*) we replace the proportion of urban population (*Upop*) to the total population to the urban population growth rate (*UpopG*); (*ii*) we replace the net inflow of international direct investment as a share of GDP (*Fdi*) to the value of the net inflow of international direct investment (*Idi*); (*iii*) without contravening the theoretical framework, we incorporate a new control variable, energy intensity (*Ei*), which refers to the amount of energy used to produce one unit of economic output. A lower ratio indicates less energy used to produce one unit of economic output.

According to the results of the robustness test and the spatial empirical regression in Table 2, we can see that the coefficient of the core explanatory variable and the forward participation in GVCs is negative at the 1% significance level in all robustness tests, and the size of the coefficient has not significantly changed compared to the benchmark estimation results in Table 1. These results confirm the robustness of the model and demonstrate the existence of a consistent positive correlation between the forward participation of the manufacturing industries in GVCs and carbon emissions reduction. However, the other explanatory variable, the backward participation of the manufacturing industries in GVCs, has a negative correlation twice and a positive correlation once with carbon emissions reduction. The coefficients in these three cases are very small, which require further exploration in our heterogeneity regression.

Table 2. The robustness test results

	(1) CARBON	(2) CARBON	(3) CARBON	(4) CARBON	(5) CARBON	(6) CARBON
Fm	–0.964***		–0.911***		–0.900***	
	(–3.922)		(–3.781)		(–3.744)	
Bm		–0.078		–0.012		0.007
		(–0.242)		(–0.038)		(0.021)
Sca	0.250***	0.218**	0.178*	0.143	0.160*	0.125
	(2.735)	(2.352)	(1.892)	(1.500)	(1.696)	(1.311)
Tec	–0.107***	–0.107***	–0.108***	–0.106***	–0.107***	–0.102***
	(–3.465)	(–3.396)	(–3.512)	(–3.384)	(–3.553)	(–3.358)
Str	–0.003	–0.004	–0.001	–0.001	–0.001	–0.002
	(–0.938)	(–1.085)	(–0.241)	(–0.428)	(–0.384)	(–0.509)
UpopG	0.001	–0.018				
	(0.023)	(–0.639)				
Ivad	0.027***	0.030***	0.030***	0.033***	0.032***	0.035***
	(3.584)	(3.969)	(3.970)	(4.234)	(4.207)	(4.542)
Fdi	–0.000	–0.000	–0.000	–0.000	0.000	0.000
	(–0.504)	(–0.369)	(–0.777)	(–0.565)	(0.675)	(0.883)
Upop			0.033***	0.036***	0.031***	0.034***
			(2.873)	(3.074)	(2.750)	(2.947)
Ei			0.024	0.033		
			(0.631)	(0.840)		
_cons	–3.753*	–3.203	–4.029*	–3.599	–3.427	–3.004
	(–1.671)	(–1.398)	(–1.809)	(–1.585)	(–1.549)	(–1.334)
N	455.000	455.000	455.000	455.000	455.000	455.000
R^2	0.153	0.120	0.170	0.140	0.169	0.140
year	Yes	Yes	Yes	Yes	Yes	Yes
country	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1. The values in square brackets under the coefficient are their *t*–values. 2. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Heterogeneity test

In this section, we conduct additional heterogeneity analysis to examine the different effects of GVCs participation on carbon emissions between the developed and developing countries.

In Table 3, the results of Columns (1), (3), (5) and (7) show that both in the developed and developing nations, an increase in the forward participation of both light or heavy industries in GVCs can significantly reduce carbon emissions. This is in line with the reality, and the reason might be that most producers in the upstream are from high value–added and low carbon emission industries. The results of Columns (4) and (8) reveal that the impact of the backward participation of heavy industry in GVCs on carbon emissions differs between developed and developing countries. For the developed countries, an increase in the backward participation in GVCs can significantly decrease carbon emissions at 1% level, with the correlation coefficient of –0.678. However, for the developing countries, the impact of increasing the backward participation in GVCs on carbon emissions is insignificant, with the correlation coefficient of –0.593. Furthermore, as shown by the values in Columns (1) and (5), (4) and (8), it is evident that the reduction in carbon emissions is more significant in the developed countries compared to the developing countries at each fixed position in GVCs. This observation confirms a fact that at the same position in GVCs, it is comparatively easier for the developed countries to achieve carbon emission reductions than the developing countries.

It is worth noting that the impacts of net FDI inflows on carbon emissions are heterogeneous for developed and developing countries. According to the results of Columns (2) and (4), the inflow of FDI leads to a significant increase in carbon emissions of the developing countries, while it indicates a significant reduction in carbon emissions of the developed countries, as shown by the results of Columns (6) and (7). In contrast, the international investment that flows into the developing countries is relatively limited, and it largely concentrates on the heavy industries and the manufacturing of primary products, which may cause many environmental pollution issues. Hence, even with the support of international direct investment, these developing countries still lack the ability to achieve decoupling from carbon emissions.

Table 3. The results of heterogeneity test between the developed and developing countries

	(1) CARBON	(2) CARBON	(3) CARBON	(4) CARBON	(5) CARBON	(6) CARBON	(7) CARBON	(8) CARBON
Lfm	–1.039** (–2.098)				–1.640*** (0.366)			
Lbm		–1.450** (–2.295)				–0.891** (–2.030)		
Hfm			–1.193*** (–3.412)				–1.229*** (–3.981)	
Hbm				–0.593 (–1.270)				–0.678** (–2.074)
Fdi	0.005 (1.550)	0.006* (1.959)	0.005 (1.608)	0.005* (1.813)	–0.001* (–1.805)	–0.001* (–1.854)	–0.001* (–1.723)	–0.001 (–1.571)
_cons	2.875*** (16.976)	2.947*** (16.342)	2.848*** (18.028)	2.838*** (16.227)	3.205*** (11.697)	2.746*** (10.464)	3.164*** (11.255)	2.829*** (10.096)
N	260.000	260.000	260.000	260.000	195.000	195.000	195.000	195.000
R^2	0.078	0.081	0.106	0.066	0.195	0.118	0.176	0.119
year	yes	yes	yes	yes	yes	yes	yes	yes
country	yes	yes	yes	yes	yes	yes	yes	yes
type	The developing countries				The developed countries			

Notes: 1. The values in brackets under the coefficient are their *t*–values. 2. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

FURTHER DISCUSSIONS

Spatial spillover effects

Before conducting the spatial econometric analysis, we perform the Lagrange Multiplier (LM) and the Likelihood Ratio (LR) tests, and the results indicate the preference for a spatial lag model (SAR) with double fixed effects. Based on the basic form of the spatial lag model, the empirical model of the GVCs participation and carbon emissions is given as follows.

$$\begin{aligned} Carbon_{it} = {} & \alpha + \beta\sum_{i=1}^{35} w_{ij}\, Carbon_{jt} + \beta_1\, Gvc_{it} \\ & + \beta_2\, Sca_{it} + \beta_3\, Str_{it} + \beta_4 Tec_{it} + \beta_5\, Upop_{it} \\ & + \beta_6\, Ivad_{it} + \beta_7\, Fdi_{it} + \theta_1\sum_{j=1}^{35} w_{ij}\cdot Gvc_{jt} \\ & + \theta_2\sum_{j=1}^{35} w_{ij}\cdot Sca_{jt} + \theta_3\sum_{j=1}^{35} w_{ij}\cdot Str_{jt} \\ & + \theta_4\sum_{j=1}^{35} w_{ij}\cdot Tec_{jt} + \theta_5\sum_{j=1}^{35} w_{ij}\cdot Upop_{jt} \\ & + \theta_6\sum_{j=1}^{35} w_{ij}\cdot Ivad_{jt} + \theta_7\sum_{j=1}^{35} w_{ij}\cdot Fdi_{jt} + \varepsilon_{it} \end{aligned} \tag{6}$$

where w_{ij} represents the element in the i–th row and j–th column of a standardized spatial weight matrix W which is calculated according the actual latitude and the longitude. This spatial weight matrix W is actually an adjacency matrix with the bandwidth of 0–12. The control variables in this auxiliary regressions model are in line with those in the main regression model. Due to space constraints, the results of the auxiliary regression for the control variables are not presented here. Given the possible bias of using point estimation to test the spillover effects, this paper continues to use the partial differential method to estimate the direct, indirect, and total effects of different levels of GVCs participation on carbon emissions.

Table 4 shows the direct and indirect spatial spillover effects of varying levels of GVCs participation on carbon emissions. The spatial auto–correlation coefficients, *spatial rho*, range from 0.109 to 0.120, indicating that

Table 4. The empirical results of spatial spillover effects

	(1) Direct	(2) Indirect	(3) Total
Spatial rho	0.120** (0.048)	0.109** (0.047)	0.114** (0.048)
Variance sigma2_e	0.060*** (0.004)	0.057*** (0.004)	0.061*** (0.004)
*W*Lfm*	–1.689*** (0.297)	–0.155** (0.076)	–1.844*** (0.323)
*W*Lbm*	–1.547*** (0.370)	–0.178** (0.081)	–1.726*** (0.416)
*W*Hfm*	–1.476*** (0.222)	–0.152** (0.067)	–1.628*** (0.247)
*W*Hbm*	–0.727*** (0.274)	–0.078* (0.043)	–0.805*** (0.303)
N	455.000	455.000	455.000
R^2	0.574	0.512	0.429
year	Yes	Yes	Yes
country	Yes	Yes	Yes

Notes: 1. The values in brackets under the coefficient are their standard errors. 2. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

the carbon emissions from the manufacturing industries of BRI countries exhibit significant positive spatial spillover effects. That is, if a country reduces its carbon emissions due to an increase in its participation in GVCs, its neighboring countries will also experience a corresponding reduction in carbon emissions due to spatial spillover effects. In addition, the coefficient of the direct effect in Column (1) is approximately equal to the regression coefficient of industry heterogeneity. The numerical difference indicates the presence of feedback effects in the spatial econometric model, implying that the influence of one region on other regions can, in turn, affect the original region. Furthermore, the coefficient of the indirect effect in Column (2) represents the reverse spatial spillover effect, with the value ranging from 0.078 to 0.178. It indicates that an increase in the participation of neighboring countries in GVCs can slightly reduce carbon emissions of the host country. The total effect in Column (3) is the sum of the direct and indirect effects, the level of which is greater than that of the regression model that does not consider the spatial spillover effects. It suggests that BRI countries should cooperate and actively integrate into the GVCs and meanwhile, promote inter–regional cooperation to achieve the effect of "1 + 1 > 2."

The mechanism of how the GVCs participation affects carbon emissions

To further clarify the mechanism of the participation of the BRI countries' manufacturing industries in GVCs on carbon emissions, we formulate the following model to explore whether the scale, structural, and technological effects play the same role in the impacts of the forward participation in GVCs on carbon emissions.

$$\begin{cases} Media_{it} = b_0 + b_1\, Gvc_{it} + \beta \cdot Y_{it} + \delta_i + \mu_t + \varepsilon_{it} \\ lnC_{it} = c_0 + c_1\, Gvc_{it} + c_2 \cdot Media_{it} + \beta \cdot Y_{it} \\ \qquad\qquad + \delta_i + \mu_t + \varepsilon_{it} \end{cases} \tag{7}$$

From the analysis of heterogeneity, it is evident that the larger number of developing countries in the sample results in the effect of the backward participation in GVCs on carbon emissions reduction not being significant. Therefore, we only consider the forward participation of manufacturing industries in GVCs to examine the scale, structural, and technological effects on carbon emissions. The control variables and constant term regression coefficients are not shown in Table 5 for easier comparison.

Specifically, when the scale effect is taken as a potential mediating variable, it constrains the impact of the forward participation in GVCs on carbon emissions reduction. This might be due to an increase in production demand as the trade volume grows, consequently leading to an increase in carbon emissions. When the technology effect is taken as a potential mediating variable, it contributes significantly to the positive impact of the forward participation in GVCs on carbon emissions reduction, suggesting that technological progress is one pathway through which the GVCs participation can influence carbon emissions reduction in manufacturing. When the structural effect is taken as a potential mediating variable, the coefficient for the structural effect is not significant. The possible reason is that products produced in the manufacturing industries of BRI countries are more energy–intensive.

CONCLUSIONS AND POLICY IMPLICATIONS

Conclusions

This paper takes 35 BRI countries as an example of developed and developing nations, and selects panel data of their manufacturing industries over from 2007 to 2019 to empirically investigate the impact of the GVCs participation of manufacturing industries on carbon emissions. The empirical results show that, an increase in the forward participation of a BRI country's manufacturing industry in GVCs can significantly lead to carbon emissions reduction, and this reduction effect is greater than that of the backward participation in GVCs. Furthermore, the examination of heterogeneity show that, the scale effect and carbon emissions are significantly positively correlated. This relationship suggests that the expansion of trade and industrial scale will accelerate energy consumption, consequently leading to environmental pollution; the technological effect and carbon emissions exhibit a significantly negatively corre-

Table 5. The analysis of impact pathways

	(1) *Sca*	(2) CARBON	(3) *Tec*	(4) CARBON	(5) *Str*	(6) CARBON
Fm	1.539***	–0.920***	4.211***	–0.920***	21.428***	–0.920***
	(4.751)	(–3.828)	(8.271)	(–3.828)	(3.533)	(–3.828)
Media		0.179*		–0.104***		–0.001
		(1.911)		(–3.458)		(–0.273)
_cons	20.803***	–3.986*	5.536***	–3.986*	–160.526***	–3.986*
	(148.261)	(–1.792)	(3.427)	(–1.792)	(–9.573)	(–1.792)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	455.000	455.000	455.000	455.000	455.000	455.000
R^2	0.913	0.169	0.451	0.169	0.689	0.169

Notes: 1. The values in brackets under the coefficient are their *t*–values. 2. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

lation, and vigorously promoting the development of education and training of talents is a foundation for further technological advancements; however, the impact of structural changes on reducing carbon emissions is insignificant.

In addition, the reduction in carbon emissions is more significant in the developed countries compared to the developing countries at each fixed position in GVCs. The effects of international direct investment flowing into the developed and developing countries on carbon emissions are quite different. The international direct investment significantly increases the carbon emissions in the developing countries, while it significantly reduces the emissions in the developed countries. At last, there is a significant positive spatial spillover effect of carbon emissions within the manufacturing industries of BRI countries, and an increase in the participation of neighboring countries in GVCs will also slightly reduce carbon emissions of the host countries.

Policy implications

Based on the empirical results, some policy implications are given as follows. Firstly, both developed and developing member countries of the Belt and Road Initiative should actively engage into the global development, and participate in the division of labor and collaboration within the value chain according to their own capabilities. Secondly, the developing countries could also attract more international foreign direct investment from the developed nations into cleaner production sectors. It is also essential to pay more attention technological spillover effects of the international foreign direct investment. Thirdly, the positive spatial spillover effect of carbon emissions from the manufacturing industries of BRI countries can be used to strengthen inter–regional economic exchanges. These countries could jointly explore and implement more environmentally conscious solutions, and cooperate with each other to achieve the common goal of reducing carbon emissions. At last, at the micro–level, it is also crucial to strength the green consciousness for both businesses and consumers.

AUTHOR CONTRIBUTIONS

L. Yang designed the study. Z. Sun analyzed the data and wrote the paper. L. Tong, B. Qin, G. Lin, Y. Takahashi, and M. Yabe participated in the design of the study and supervised the work. Y. Takahashi assisted in editing of the manuscript and approved the final version.

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APPENDIX

A 1. The selected 35 Belt and Road Initiative countries and their corresponding country codes

Country Name	Country Code	Country Name	Country Code	Country Name	Country Code
Austria	AUT	Singapore	SGP	Malaysia	MYS
Belgium	BEL	Slovak Republic	SVK	Maldives	MDV
Cyprus	CYP	Slovenia	SVN	Nepal	NPL
Czech Republic	CZE	Bangladesh	BGD	People's Republic of China	CHN
Estonia	EST	Brunei Darussalam	BRN	Philippines	PHL
Greece	GRC	Bulgaria	BGR	Poland	POL
Luxembourg	LUX	Cambodia	KHM	Romania	ROM
Italy	ITA	Fiji	FJI	Sri Lanka	LKA
Latvia	LVA	Indonesia	IDN	Thailand	THA
Portugal	PRT	Kyrgyz Republic	KGZ	Hungary	HUN
Republic of Korea	KOR	Lao People's Democratic Republic	LAO	Croatia	HRV
Malta	MLT	Lithuania	LTU		