International Journal of Environmental Science and Technology (2023) 20:13347–13358
https://doi.org/10.1007/s13762-023-04885-x

ORIGINAL PAPER

Impact of global value chain and technological innovation on China's industrial greenhouse gas emissions and trend prediction

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Received: 17 October 2022 / Revised: 18 December 2022 / Accepted: 28 February 2023 / Published online: 29 April 2023

Abstract
The global value chain has introduced profound changes in international trade, economic development, and technology progress as well as greenhouse gas emissions worldwide. This paper investigated the impact of the global value chain and technological innovation on greenhouse gas emissions by introducing a partially linear functional-coefficient model based on panel data of 15 industrial sectors in China from 2000 to 2020. Moreover, the greenhouse gas emission trends of China's industrial sectors from 2024 to 2035 were predicted using the autoregressive integrated moving average model. The results showed that (1) Greenhouse gas emissions were affected negatively by global value chain position and independent innovation. Nevertheless, foreign innovation had the opposite effect. (2) The results of the partially linear functional-coefficient model implied that the inhibitory effect of independent innovation on GHG emissions decreased with an improvement in the global value chain position. (3) The positive effect of foreign innovation on greenhouse gas emissions increased and then, decreased as the global value chain position improved. (4) The prediction results indicated that greenhouse gas emissions will continue on an upward trend from 2024 to 2035, while industrial carbon dioxide emissions should peak at 10.21 Gt in 2028. This carbon-peaking goal would be achieved in China's industrial sector by actively improving the global value chain position. Addressing these issues will enable China to take full advantage of the development opportunities of participating in the global value chain.

Keywords Autoregressive integrated moving average · Climate change · Foreign innovation · Global value chain position · Independent innovation · Partial linear functional-coefficient model

Introduction

Over the past two decades, the expansion of the global value chain (GVC) has profoundly promoted international trade, which was accompanied by a large amount of greenhouse gas (GHG) emissions. In the GVC, production procedures were dispersed in different countries or regions through intermediate goods trading. GVC enabled developing countries to integrate into the global division rapidly. For example, after accession to the World Trade Organization (WTO) in 2001, China integrated into the GVC with its labor and resource endowments. From 2000 to 2019, China's GVC participation rate grew from 37.9 to 44.6%, which made it a key participant in the GVC (Asian Infrastructure Investment Bank 2021). However, many low-value-added and polluting production stages were transferred to China's industrial sector through GVC. China's GHG emissions experienced a rapid increase from 5.39 Gt CO_2 equivalent (CO_2 eq) in 2000 to 14.3 Gt CO_2 eq in 2020 (Olivier 2022). An estimated 27% of China's GHG emissions were induced by foreign demand through international trade (Yamano and Guilhoto 2020). China has set a goal of actively and steadily achieving carbon peaking by 2030 and carbon neutrality by 2060, which required China to make adjustments in the mid and long run. Therefore, a critical concern was how China could manage GHG emissions in GVC.

Previous studies have focused on the impact of GVC on carbon dioxide (CO_2) emissions which contribute the most to global warming. One group of scholars supports that GVC helps to reduce CO_2 emissions. Trade-induced CO_2

Editorial responsibility: Rui Zhao.

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emissions in the global production fragmentation system were investigated by Dietzenbacher et al. (2012). They discovered that CO_2 emissions embodied in processing exports were 34% lower than those in standard exports, which indicated that the GVC pattern caused less CO_2 emissions. Other scholars, however, have offered contradictory findings. Wang et al. (2020) found that China's export reduced pollution in developed countries but increased it in developing countries. With the introduction of the GVC accounting system in the recent decade, Meng et al. (2018) found that CO_2 emission intensity through GVC was 1.9 times higher than that through domestic production networks. Following the establishment of a GVC measurement, econometric models have been constructed to explore the impact of the GVC on CO_2 emissions (Assamoi et al. 2020; Liu and Zhao 2021). An inverted U-shaped relationship between GVC participation and per capita CO_2 emissions was first identified by Wang et al. (2019) based on an econometric model. To date, empirical studies mainly employ CO_2 as an indicator of GHG. However, non-CO_2 GHG emissions, such as methane (CH_4) and nitrous oxide (N_2O), have global warming potentials (GWPs) that are tens to hundreds of times than that of CO_2. Notably, the non-CO_2 GHG emissions also have greater reduction potentials. The growth rate of CO_2 emissions dropped to 0.8% in 2020, while non-CO_2 emissions increased by 4% in China (Olivier 2022). To this end, it is important for China to clarify the effects of the GVC on multiple GHG emissions.

Technology was a vital factor in mitigating GHG emissions (Jaffe et al. 2003; Lantz and Feng 2006; Chen and Lee 2020), and global trade was one of the most critical channels for transmitting new technologies. Knowledge, skills, investment, and human capital were transferred from upstream to downstream in GVC, which made GVC an essential way for downstream countries to realize technological progress (Gereffi et al. 2005; Morrison et al. 2007). However, industries that have long been downstream of the GVC might not achieve core technological innovation. The global division might solidify the technology gap between China and developed countries and hinder technological progress. Understanding how the GVC has shaped the relationship between technological innovation and GHG emissions can balance the trade benefits and the adverse effects of inequality in trade status (Wang et al. 2022a, b). Therefore, China should consider the technical and environmental impacts of GVC in an integrated manner.

Previous studies have demonstrated that international trade had a technological effect on GHG emissions (Managi and Kumar 2009; Ahmad et al. 2022). Two issues need to be clarified when discussing the problem. First, the related literature has mainly incorporated interaction terms in the model to reflect a moderating effect (Copeland and Taylor 2005; Ang 2009). However, the interaction terms assumed a rigorous linear relationship between variables (Du et al. 2020). In this paper, the impact of GVC on technological innovation might not be linear due to the complexity of economic systems. Thus, the construction of interaction terms might suffer model misspecification and lead to estimation bias. Under these circumstances, a partially linear functional-coefficient (PLFC) model was employed to reveal the impact of the GVC position and technological innovation on GHG emissions. The PLFC model introduced a functional-coefficient into the model, which addressed the risk of model misspecification.

Second, the effect of technological innovation on GHG emissions might have different outcomes in the context of internationalization (Wang et al. 2021). Technological innovation was implemented through two channels: (1) independent innovation and (2) foreign innovation efforts (Coe and Helpman 1995; Fu and Gong 2011; Meng and Zhao 2022). Independent innovation was critical to technological progress and significantly affected GHG emissions (Baldwin and Hanel 2003; Fisher-Vanden and Sue Wing 2008). With the deepening of globalization, foreign innovation efforts became vital to obtain new technologies and thus, imposed an uncertain impact on GHG emissions. As the world's largest developing country, China has had to consider the effects of both technological innovation channels on GHG emissions. Yang et al. (2014) employed a spatial panel data model and found that indigenous innovation effectively reduced CO_2 intensity in China, while foreign innovation efforts had the opposite effect. In contrast, Yu and Du (2019) proposed that independent innovation positively affected CO_2 emissions. Introducing innovation was found to reduce CO_2 emissions by improving China's technology level and increasing productivity. As a result, the effects of technological innovation on GHG emissions should be considered from independent and foreign innovation efforts separately.

Currently, GVC has shown a trend of complexity and variability due to new challenges, such as trade frictions and the novel coronavirus disease (COVID-19) outbreaks. It is foreseeable that the impact of GVC and technological innovation on GHG emission trends will change dramatically. Besides, China proposed the Long-Range Objectives Through the Year 2035, which set the targets of a "steady decline in carbon emissions after peaking." Therefore, this paper attempted to identify the impact of GVC and technological innovation on GHG emissions from the perspective of future GHG emission trends. This paper predicted the GHG emission trends of China's industrial sector from 2024 to 2035 based on the autoregressive integrated moving average (ARIMA) model. Most existing studies predict GHG emission trends at the national or provincial level (Zhu et al. 2015; Zuo et al. 2020). In contrast, this paper predicted GHG emissions trends at the sectoral level, which provided a new perspective for China to develop GHG reduction policies. Due to the industrial sector's significant contribution to China's GHG emissions, sector-level predictions are required.

This paper aims to bridge these gaps in the literature and advance our understanding of how GVC and technological innovation affect GHG emissions in China. Firstly, this paper investigated the impact of the GVC and technological innovation on three GHG emissions based on the panel data of China's industrial sectors from 2000 to 2020. Most recent research on GHG emissions has used only CO_2 emissions as an indicator, which might be deceptive. Other non-GHG emissions have significantly reduced the warming effect in the short term and should be explored more thoroughly. Thus, three major greenhouse gases (i.e., CO_2, CH_4, and N_2O) that account for 94% of all GHG emissions were incorporated in the analysis framework. Secondly, using the PLFC model, the moderating effect of the GVC on the link between technological innovation and GHG emissions was investigated. The PLFC model that considers nonlinear moderating effects obtained novel insights. Finally, the GHG emission trends of China's industrial sector from 2024 to 2035 were predicted based on the ARIMA model. The Long-Range Objectives Through the Year 2035 state China will continue reducing GHG emissions and raising its international trade standing through 2035. Investigating the future trend of GHG emissions has helped achieve the goal of carbon peaking and mitigating climate change.

The rest of this paper is organized as follows: Sect. "Materials and methods" introduces the methodology and data sources; Sect. "Results and discussion" presents the results and discussion of the empirical study; and Sect. "Conclusion" presents the conclusions and policy implications.

Materials and methods

Measuring GVC position index

To reflect the actual situation of the GVC, scholars have constructed several accounting systems and measures (Koopman et al. 2014; Wang et al. 2017). Previously, GVC position was calculated mainly by the upstream and downstream indexes proposed by Antràs and Chor (2013). However, inconsistent results emerged when measuring the GVC position of the same country-sector by upstream and downstream. Given the contradictions between the above two indexes, this paper adopted the latest method proposed by Wang et al. (2017) to construct the GVC position index. This index was calculated as the ratio of the forward to backward production lengths in the GVC:

$$\mathrm{PL}_{\mathrm{forward}} = \frac{Xv_{\mathrm{GVC}}}{V_{\mathrm{GVC}}}, \tag{1}$$

$$\mathrm{PL\_backward} = \frac{Xy\_\mathrm{GVC}}{Y\_\mathrm{GVC}}, \tag{2}$$

$$\mathrm{GVC}_{\mathrm{Position}} = \frac{\mathrm{PL}_{\mathrm{forward}}}{(\mathrm{PL}_{\mathrm{backward}})'}, \tag{3}$$

where PL_forward is the forward production length, indicating the distance to the end of the GVC; Xv_GVC and V_GVC denote the GVC-related domestic value added and its induced gross output, respectively; PL_backward is the backward production length of the GVC, which represents the distance to the starting point of the chain; Xy_GVC and Y_GVC are the foreign value added in intermediate imports and its induced gross output, respectively; and GVC_Position represents the GVC position index. A greater value means that the sector is relatively far from final consumption and is located relatively upstream.

Econometric model

To examine the impacts of the GVC position and technological innovation on GHG emissions, an econometric model was constructed based on the decomposition framework of scale, technique, and composition effect. This framework was first proposed by Grossman and Krueger (1991). It then became the classic analytical approach for the study of the trade-emission nexus (Antweiler et al. 2001; Cole and Elliott 2003). As the GVC was an important form of international trade, this paper followed the scale, technique, and composition effect framework to investigate the impact of GVC and technological innovation on GHG emissions, which ensured reliability. The general form can be expressed as follows:

$$\mathrm{GHG} = f(S, T, C), \tag{4}$$

where GHG represents GHG emissions; and S, T, and C denote the scale effect, the technique effect, and the composition effect, respectively. Both sides of Eq. (4) were taken as natural logarithm to reduce the heteroskedasticity problem. Considering the characteristics of industrial panel data, this paper controlled the individual fixed effects. Thus, the baseline econometric model can be expressed as follows:

$$\begin{aligned}\ln \mathrm{GHG}_{\mathrm{it}} = {} & \alpha_0 + \alpha_1 \ln \mathrm{GVC}_{\mathrm{it}} + \alpha_2 \ln \mathrm{RD}_{\mathrm{it}} + \alpha_3 \ln \mathrm{FINN}_{\mathrm{it}} \\ & + \beta' X_{\mathrm{it}} + \mu_i + \gamma_t + \in_{\mathrm{it}},\end{aligned} \tag{5}$$

where GVC is the GVC position, and RD and FINN indicate independent innovation and foreign innovation efforts, respectively. The control variable X includes industry size (VA), capital-labor ratio (CD), energy consumption (EC), environmental regulations (ER) and export intensity (EXP); i and t represent sector and year, respectively; α_i and β' are correlation coefficients; μ_i is the industry individual effect; γ_t captures time effect; and ϵ_{it} is an error term.

The variables were selected following the decomposition framework of scale, technique, and composition effects. In terms of scale effect, industrial value added was used as the indicator following Ansari and Khan (2021). In general, the larger the industry scale is, the more GHG emissions result from production activities (Wenlong et al. 2022).

The technique effect included the core variable technological innovation and was decomposed into independent innovation and foreign innovation efforts. First, a country could improve production efficiency and develop clean technologies through independent innovation, thereby reducing GHG emissions. Research and development (R&D) investment was crucial in determining the level of independent innovation of a specific industry (Baldwin and Hanel 2003). Therefore, we employed the proportion of the industry's internal expenditure on R&D to the gross output to represent independent innovation. Second, in the context of economic globalization, foreign innovation served as a crucial channel for technological innovation in the GVC participating nations. Less developed countries could import advanced technology and equipment from upstream countries. Thus, the percentage of imported technology funds was employed as a proxy for foreign innovation.

According to Cole and Elliott (2003), the composition effects incorporated direct and trade-induced composition effects. In this paper, the capital-labor ratio of the industry is a proxy for the direct composition effect (Antweiler et al. 2001). The trade-induced composition effect was represented by the GVC position, which reflected the comparative advantage. The GVC position captured a sector's ability to increase value based on its endowments. Embedding in relatively clean production links might reduce local GHG emissions. GVC position index is constructed in Sect. "Measuring GVC position index".

In addition, other control variables were chosen for the following reasons. First, energy consumption was one of the main drivers of GHG emissions in the industrial sector, which was included in the model as a control variable. Second, environmental regulation led the industrial sector to dispose the production pollution and control GHG emissions. This paper measured the environmental regulations by the ratio of total disposal costs of wastewater and emission to the gross output. Third, China was a "world factory" in GVC and produced many emission-intensive products for export. Thus, the export intensity was added in the model, represented by exports to the total output.

Participation in GVC was one of the most critical ways to rapidly integrate into the global production system and acquire production technologies, especially for developing countries. In addition to the direct impact of GVC on GHG emissions, there was also an indirect moderating impact on GHG emissions through technological innovation, which should not be ignored. To explore the moderating effect of GVC on technological innovation, PLFC models were established. Most empirical studies have introduced interaction terms to investigate moderating effects between variables. However, the interaction term had strict linear limits. The relationship between variables was not necessarily linear in practice. The PLFC model established a more generalized relationship by constructing functional coefficients, which reduced the risks of model misspecification and reflected the real moderating effect of GVC on technological innovation. PLFC model was employed to build Eqs. (6) and (7):

$$\begin{aligned}\ln \mathrm{GHG}_{\mathrm{it}} = \alpha_0 + g_1(\ln \mathrm{GVC}_{\mathrm{it}}) \ln \mathrm{RD}_{\mathrm{it}} + \alpha \ln \mathrm{FINN}_{\mathrm{it}} \\ + \beta' X_{\mathrm{it}} + \mu_i + \gamma_t + \in_{\mathrm{it}},\end{aligned} \tag{6}$$

$$\begin{aligned}\ln \mathrm{GHG}_{\mathrm{it}} = \alpha_0 + g_2(\ln \mathrm{GVC}_{\mathrm{it}}) \ln \mathrm{FINN}_{\mathrm{it}} + \alpha \ln \mathrm{RD}_{\mathrm{it}} \\ + \beta' X_{\mathrm{it}} + \mu_i + \gamma_t + \in_{\mathrm{it}} \cdot\end{aligned} \tag{7}$$

In this model, $g_1(\mathrm{lnGVC}_{\mathrm{it}})$ and $g_2\left(\mathrm{lnGVC}_{\mathrm{it}}\right)$ are the functions to measure the marginal impact of independent innovation and foreign innovation efforts on GHG emissions, respectively. For the specific estimation steps of the PLFC, refer to the methods in Du et al. (2020).

ARIMA and ARIMAX model

In this section, the ARIMA model and ARIMA with explanatory variables (ARIMAX) were used to predict the GHG emission trends of China's industrial sector from 2024 to 2035. The ARIMA model is a time series estimation method proposed by Box and Jenkins in 1976. For simple time series with small sample size, ARIMA models have more robust and efficient forecasting results and are widely used for time series forecasting in economic and environmental fields. This univariate prediction method, however, ignores the influence of external factors on the predicted series. Pankratz (1993) proposed the ARIMAX model to fit the information from external influencing factors in the series of interests (Zhu et al. 2015; Liu et al. 2018). The combination of the two models can help us better study the impact of changes in the position of GVC and technological innovation on future GHG emissions.

ARIMA model

The ARIMA (p, d, q) model consists of three components: the autoregressive model (AR), the moving average model (MA), and a preliminary step of differencing to remove trends (Integrated). The first step was to check for the stationarity of the original series. If the series was nonstationary, a differencing step was employed to make it stationary. The order of differencing is denoted by parameter d.

Table 1 Sector classification. *Source* ISIC Rev.3 and GB/T 4754—2017

No	Industries	ISIC Rev.3	GB/T 4754—2017
S1	Mining and quarrying	C	B
S2	Food products, beverages, and tobacco	D15–D16	C13–C16
S3	Textiles, textile products, leather, and footwear	D17–D19	C17–C19
S4	Wood and products of wood and cork	D20	C20–C21
S5	Pulp, paper, paper products, printing, and publishing	D21–D22	C22–C24
S6	Coke, refined petroleum, and nuclear fuel	D23	C25
S7	Chemicals and chemical products	D24	C26–C28
S8	Rubber and plastics	D25	C29
S9	Other nonmetallic minerals	D26	C30
S10	Basic metals and fabricated metal	D27–D28	C31–C33
S11	Machinery	D29	C34–C35
S12	Electrical and optical equipment	D30–D33	C38–C40
S13	Transport equipment	D34–D35	C36–C37
S14	Other manufacturing sectors	D36–D37	C41
S15	Electricity, gas, and water supply	E	D

The second step was to identify the autoregressive order p and moving average order q for AR and MA models, respectively. The optimal value of p and q was determined by examining the Akaike information criterion and Bayesian information criterion. The AR model is expressed as follows:

$$y_t = a + \sum_{i=1}^{p} \varphi_i y_{t-i} + e_t, \tag{8}$$

where y_t denotes the value of the predicted series at time t, φ_i is the autocorrelation coefficient, a is the constant term, and e_t is the error term.

The MA model is expressed as follows:

$$y_t = \mu + e_t + \sum_{i=1}^{q} \theta_i e_{t-i}, \tag{9}$$

where θ_i is the correlation coefficient of the error term, μ is the constant term, and e_{t-i} represents the error term at $t-i$.

In the third step, the best fit ARIMA (p, d, q) is determined and then, applied this model for the prediction. The ARIMA (p, d, q) model expressed by the lag operator B is as follows:

$$\varphi_q(B)(1-B)^d Y_t = \theta_p(B)e_t, \tag{10}$$

where $\varphi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p$, $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$.

ARIMAX model

ARIMAX introduces external variables affecting the original series based on the ARIMA model. Suppose two stationary time series exist: the response series Y_t and the input series X_t. Then, the ARIMAX model could be expressed by the lag operator B:

$$\varphi_q(B)(1-B)^d Y_t = \sum_{i=1}^{m} \frac{\omega_h(B)B^{b_i}}{\delta_r(B)} X_{\mathrm{it}} + \theta_q(B)e_t, \tag{11}$$

where $\omega_h(B)$ is the random perturbation term, $\delta_r(B)$ is the X_t, m denotes the number of input sequences, k_i represents the number of differences k of input sequence i, and $\frac{\omega_h(B)}{\delta_r(B)}$ is the transfer function of the input sequence.

Data sources

This paper employed the balanced panel data for 15 industrial sectors in China from 2000 to 2020. Data on internal expenditure of R&D investment, disposal costs of wastewater and emission, imported technology funds, number of workers, and energy consumption of each industrial sector were collected from the China Statistical Yearbook. The gross output, value added, gross exports, and raw data for the GVC position were collected from the World Input–Output Database (WIOD, 2013 version) from 2000 to 2006 (Timmer et al. 2015), and the Asian Development Bank Multi-Regional Input–Output Database (MRIO) from 2007 to 2020 following the work of Wang et al. (2022a, b). Data for the GVC position index were integrated according to the UIBE GVC indicators.[1] Because data from different sources followed two classification standards—that is, the International Standard Industrial Classification of All Economic Activities (ISIC) and China's National Economic Classification of Industries (GB/T 4754—2017)—we consolidated all industries into 15 major industries (Table 1). All data related to price were converted to 2010 constant.

Currently, GHG emission data published by the economic sector are lacking. So, emissions data were estimated based

[1] RIGVC UIBE, 2016, UIBE GVC Indicators, http://rigvc.uibe.edu.cn/english/D_E/database_database/index.htm

Table 2 Data sources for emission inventories

Gas	Year	Data sources
CO_2	2017–2020	Community Emissions Data System (CEDS)
CH_4 and N_2O	2010–2019	Community Emissions Data System (CEDS)
	2020	China Statistical Yearbook 2021

The emission inventory for CH_4 and N_2O in 2020 is currently unavailable. We constructed and augmented the emission inventory based on available data from China Statistical Yearbook 2021 and IPCC 2006 guidelines. The emission inventory of CO_2 was obtained from Community Emissions Data System (CEDS) (O'Rourke et al. 2021)

Table 3 Descriptive statistics of variables. *Source* Authors' elaboration

Variables	Unit	Mean	Sd.	Min	Max
lnGHG	Kilotons of CO_2 eq	11.24	1.879	7.443	16.04
lnGVC	%	0.0233	0.279	−0.492	0.713
lnVA	Million RMB	13.94	0.813	11.40	16.03
lnRD	%	−5.334	0.866	−7.990	−3.844
lnFINN	%	−8.114	1.853	−16.84	−4.881
lnCD	Millions of RMB per 10,000 people	2.620	0.799	1.023	5.147
lnEXP	%	−2.649	1.218	−6.112	−0.558
lnER	%	−6.533	1.200	−9.106	−4.111
lnEC	Million tons of standard coal equivalent	4.353	1.208	1.324	6.895

on the inventory data published by Emissions Database for Global Atmospheric Research (EDGAR) (Genty et al. 2012; Corsatea et al. 2019). The WIOD environmental accounts offered emission data for multiple pollutants according to economic sectors. Data on CH_4 emissions and N_2O emissions from 1995 to 2009 and data on CO_2 emissions from 2000 to 2016 were collected from the WIOD environmental accounts. To maintain consistency of estimation methods, we estimated the CH_4 emissions and N_2O emissions from 2010 to 2020 and CO_2 emissions from 2017 to 2020 based on inventory emission data (Genty et al. 2012). The data sources for inventory data are listed in Table 2. N_2O and CH_4 emissions were converted to CO_2 eq according to GWP, where the GWP of N_2O and CH_4 is 298 and 25, respectively. Descriptive statistics for all variables are shown in Table 3.

Results and discussion

Results of the baseline model

This section examined the direct impact of the GVC and technological innovation on industrial GHG emissions in China. Before estimation, an appropriate estimation strategy was selected. The Driscoll–Kraay standard error for fixed effects model was employed as the estimation method, following Hoechle (2007). The regression results of the baseline model are shown in Table 4. As shown in column (1), only the key variables (lnGVC, lnRD, and lnFINN) are included in the model. In columns (2)–(6), lnEC, lnVA, lnCD, lnER, and lnEXP are gradually added to the baseline model.

In column (6) of Table 4, the estimated coefficient of the GVC position (lnGVC) is − 0.560, and it is significant at the 1% level. This result indicated that the GHG emissions decreased by 0.560%, with a 1% increase in the GVC position. The improvement of the GVC position decreased GHG emissions in China's industrial sector. This result can be explained by the GVC upgrading theory proposed by Humphrey and Schmitz (2002). First, China improved its GVC position through functional upgrading. Functional upgrading meant that the countries acquired new functions or upgraded their existing functions to specialize in a higher position of the GVC. New functions consumed less energy to meet higher environmental standards of the countries. Second, the industrial sector also achieved intersectoral upgrading. Intersectoral upgrading refers to a sector entering new industries, which involves more productive and cleaner activities of the GVC.

Notably, the two technological innovation channels had opposite effects on GHG emissions. The coefficient of ln*RD* is − 0.157, and it is significant at the 1% level, that is, when independent innovation increased by 1%, the GHG emissions decreased by 0.157%. China's industrial sector has improved its production technology through indigenous efforts, which requires less energy. The estimation coefficient for lnFINN is 0.247, which meant that GHG emissions increased by 0.247% for every 1% increase in foreign innovation efforts. International technology transfer through foreign investment has brought about scale expansion and advanced technology to polluting industries, which causes more GHG emissions.

The estimation results of control variables are as follows: the coefficient of lnVA and lnEC are 0.462 and 1.172, respectively. The results showed that industrial

Table 4 Estimation results of the baseline model

Variables	(1)	(2)	(3)	(4)	(5)	(6)
lnGVC	−1.419***	−1.295***	−0.960***	−0.523***	−0.566***	−0.560**
	(−7.41)	(−6.20)	(−4.01)	(−3.17)	(−3.60)	(−2.62)
lnRD	−0.298***	−0.263***	−0.288***	−0.147***	−0.155***	−0.157***
	(−6.17)	(−6.57)	(−6.33)	(−4.70)	(−5.49)	(−3.01)
lnFINN	0.262**	0.304**	0.310**	0.270***	0.247***	0.247***
	(2.51)	(2.59)	(2.75)	(4.11)	(3.95)	(4.01)
lnVA		0.386	0.457*	0.488**	0.462**	0.462**
		(1.56)	(1.89)	(2.18)	(2.30)	(2.24)
lnCD			−0.169**	0.030	0.037	0.038
			(−2.23)	(0.61)	(0.75)	(0.76)
lnEC				1.210***	1.171***	1.172***
				(6.83)	(8.08)	(7.51)
lnER					−0.063	−0.063
					(−0.93)	(−0.90)
lnEXP						0.005
						(0.05)
Constant	8.283***	7.847***	10.113***	4.587***	4.088***	4.074**
	(31.61)	(21.69)	(11.07)	(5.79)	(3.18)	(2.74)
Observations	315	315	315	315	315	315
R-squared	0.971	0.972	0.973	0.984	0.984	0.984
Sectors	15	15	15	15	15	15

t-statistics in parentheses, $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

scale and energy consumption had positive effects on GHG emissions, which was consistent with the development of China's industrial sector. After China joined the WTO, intensive production activities were introduced to China's industrial sector. It caused rapid growth in economic scale and energy consumption, which led to GHG emissions. The coefficient of lnCD is 0.038, which demonstrated that a positive relationship existed between the capital/labor ratio and GHG emissions. Capital-intensive industries were more polluting than labor-intensive industries. The coefficient of ln*ER* is −0.063 but insignificant. Insufficient control of non-CO_2 GHG emissions in industrial sector might be the reason for the insignificant coefficient. There was an insignificant positive effect of export intensity. The export products were made for foreign demands and caused pollution in China. The positive but insignificant coefficient might be due to the presence of the 'learning-by-doing' effect, which increased productivity and was beneficial to reduce GHG emissions.

Results of the partial linear functional-coefficient model

After examining the direct impact of GVC and technological innovation on GHG emissions, this paper incorporated the moderating effect of GVC on technological innovation in the framework, which identified the indirect impact of GVC on GHG emissions. It took a more comprehensive view of the environmental impacts of GVC. To relax the linear assumption and model misspecification, the PLFC model was employed. Table 5 shows the regression results of the linear part of the PLFC model.

Figure 1 illustrates the marginal effect of independent innovation on GHG emissions under the impact of the GVC. As shown in Fig. 1, the impact of independent innovation on GHG emissions could be divided into three parts depending on the GVC position. When lnGVC$\leq$ 0.05, the marginal effect of independent innovation was significantly negative. The marginal effect diminished as the GVC position improved, which was ascribed to the industrial sectors' failure to take the lead in developing emission-reduction technologies. When lnGVC> 0.05, the 95% confidence interval of the estimated results of the response function $g_1\left(\text{lnGVC}_{it}\right)$ included 0, which implied that the result was statistically insignificant. China's industrial sector might suffer a "low-end lock-in" in the GVC, which indicated that core technology development was lacking when China's industrial sector tried to climb up the value chain. The industrial sector did not develop a comparative advantage in the cleaner production chain.

Further, the results of Fig. 1 helped to identify specific industries to analyze the heterogeneous impact of independent innovation on GHG emissions at different GVC positions. First, Fig. 1 indicated that the marginal effect of independent innovation was largest at around lnGVC= −0.5 (*GVC*= 0.61). In 2020, the GVC position

Table 5 Estimation results of the linear parts of the PLFC model

Variables	(1)	(2)
lnVA	−0.135*	−0.137**
	(−1.83)	(−2.12)
lnFINN	0.022	
	(0.67)	
lnRD		−0.004
		(−0.16)
lnEC	0.515***	0.505***
	(6.95)	(7.30)
lnCD	0.124***	0.120**
	(2.65)	(2.38)
lnER	−0.032**	−0.031**
	(−2.19)	(−2.26)
lnEXP	0.004	0.008
	(0.10)	(0.19)
Observations	300	300
R-squared	0.187	0.199

t-statistics in parentheses, ***$p<0.01$, **$p<0.05$, *$p<0.1$

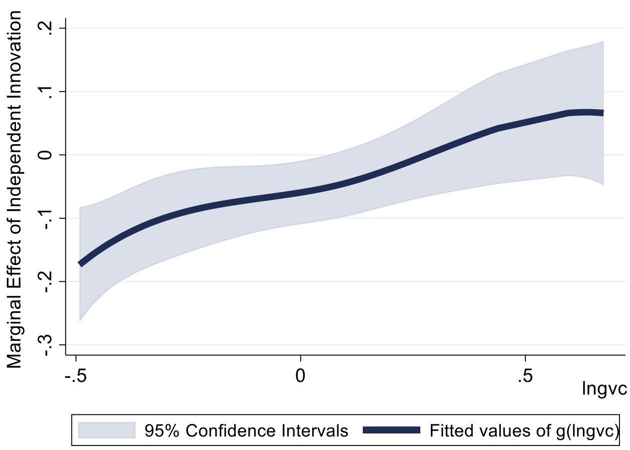

Fig. 1 Marginal effect of independent innovation

index of transport equipment manufacturing was 0.646, which was close to that point. The independent innovation of the transport equipment sector was attributed to the transformation of production technology which significantly improved productivity and controlled GHG emissions. However, China's transport equipment manufacturing industry did not have the strength to occupy the high end of the GVC. Second, the abatement effect of independent innovation turned from negative to positive around lnGVC = 0.05 (GVC= 1.05), which represented the wood and products of wood sector. The extraction and processing of wood products reduced the absorption of GHG emissions from the forest, resulting in an inflection point. The marginal effect of independent innovation was the smallest in the mining and quarrying sector, which closed

Fig. 2 Marginal effect of foreign innovation efforts

to final consumption in GVC. The mining and quarrying sector was pollution-intensive, and electricity consumption and emission escape from coal and mineral mining activities resulted in GHG emissions. Therefore, independent innovation did effectively reduce GHG emissions.

Figure 2 shows the marginal impact of foreign innovation on GHG emissions ($g_2(\ln GVC_{it})$). At $-0.45 < \ln GVC \le -0.25$, foreign innovation significantly contributed to GHG emissions, gradually increasing with the GVC position. Fundamentally, the type of technology that China introduced through the GVC was determined by its comparative advantage (Coe and Helpman 1995; Fracasso and Vittucci Marzetti 2015). Initially, China had comparative advantages in labor and resources. So, China directly imported foreign production technology and engaged in low-end production with high pollution intensity. When $-0.25 < \ln GVC \le 0.55$, the positive marginal effect of foreign innovation persisted, but this effect gradually diminished with an increase in the GVC position. As China's position improved, the technology spillover through GVC was no longer concentrated in highly polluting industries at this stage. So the marginal effect of foreign innovation efforts gradually diminished. When $\ln GVC > 0.55$, the results were statistically insignificant because the 95% confidence interval of $g_2(\ln GVC_{it})$ estimation results included 0.

Based on the results in Fig. 2, this section identified the industrial sector with the largest marginal effect of foreign innovation efforts. The most significant positive effect of foreign innovation efforts emerged at $\ln GVC = -0.25$ (GVC= 0.77). In 2020, the GVC position of electrical and optical equipment manufacturing was 0.787, close to the turning point. Electrical and optical equipment manufacturing was a technology-intensive sector, while China engaged in assembly-based high-pollution production. The imported technology mainly concentrated on assembly technology rather than manufacturing technology of core components. Besides, in China, there were many small and medium-sized enterprises in the electrical and optical equipment industry, and their awareness of emission reduction was weak. These points reflected the heterogeneity of the impact of technological innovation on GHG emissions at different GVC positions.

Prediction results of the industrial GHG emission trend in China

Following the examination of the impact of GVC and technological innovation on GHG emissions in the past, it is necessary to investigate the impact of GVC and technological innovation on future GHG emission trends. This is more conducive to providing a policy basis for China's mid-term decisions on climate change. This section applied ARIMA and ARIMAX to predict the GHG emission trends of China's industrial sectors from 2024 to 2035. Results were obtained by the following steps.

First, the stationarity and the difference order of the variables should be determined based on the unit root test. Each series was taken, and the augmented Dickey–Fuller (ADF) unit root test was used to check the stationarity of each series. Second, the parameters of the AR(p) and MA(q) models were determined. To assess the prediction accuracy of the model, root mean square (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were calculated as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(m_i - f_i)^2}{N}}, \tag{12}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|m_i - f_i\right|, \tag{13}$$

$$\text{MAPE} = \sum_{i=1}^{N}\left|\frac{m-f}{m}\right| \times \frac{100}{n}, \tag{14}$$

where N denotes the total number of samples, and m and f are the actual and predicted values of the sequences, respectively. The results of model selection and prediction accuracy of each series are presented in Table 6.

Prediction results of CO_2, CH_4, and N_2O emissions

To provide more detailed evidence, the emission trends for CO_2, CH_4, and N_2O were estimated separately. The results are illustrated in Fig. 3. CO_2 emissions from the industrial sector generally should follow an upward trend from 2024 to 2028 and are expected to reach a peak of 10.21 Gt CO_2 eq in 2028. Then, CO_2 emissions should follow a downward trend from 2029 to 2035. China's industrial sector should meet the carbon peak target by 2030. This would be made possible by a series of policies proposed by China to constrain CO_2 emissions from industrial sectors. CH_4 and N_2O, as the primary GHGs, showed increasing emission trends from 2024 to 2035. Establishing a complete emission reduction system and improving end-of-pipe treatment technologies for CH_4 and N_2O may not receive much attention from the industrial sector.

Table 6 Results of model selection and forecast accuracy. *Source* Authors' elaboration

Variables	Model	Fitted Model	Forecast Accuracy		
			RMSE	MAE	MAPE
CO_2	ARIMA	ARIMA (3,2,2)	0.030	0.025	0.036
CH_4	ARIMA	ARIMA (1,2,0)	0.017	0.014	0.032
N_2O	ARIMA	ARIMA (1,2,0)	0.011	0.007	0.031
GHG	ARIMA	ARIMA (3,2,2)	0.026	0.021	0.030
	ARIMAX	ARIMAX (1,0,0)	0.038	0.027	0.040

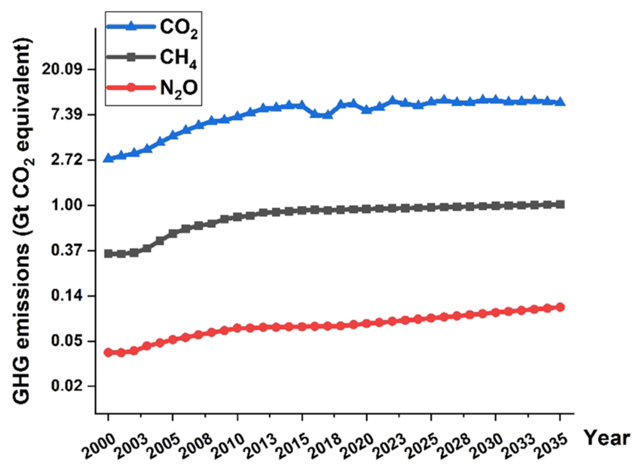

Fig. 3 Prediction results of CO_2, CH_4, and N_2O emissions trends

Prediction results of total GHG emissions

In order to identify the impact of GVC and technological innovation on future GHG emission trends, two scenarios were set to predict GHG emission trends from 2024 to 2035. First, an ARIMA model was established to simulate the emission trend in a business-as-usual (BAU) scenario. The BAU scenario identified the GHG emission trends of the current emission situation. Second, an ARIMAX model was used to predict GHG emission trends under the effect of the GVC position and technological innovation as a GVC-transition scenario. The trends of explanatory variables were obtained by the ARIMA model.

The emission trends of the two scenarios are shown in Fig. 4. In the BAU scenario, the predicted values of China's industrial GHG emissions from 2024 to 2035 followed an upward trend, which was 17.5 Gt CO_2 eq in 2030 and 23.55

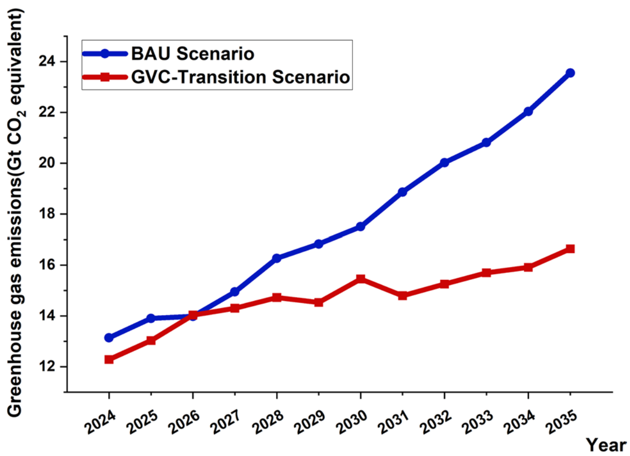

Fig. 4 Prediction results of GHG emissions based on ARIMA model

Table 7 Prediction results of the trend of GHG emissions under two scenarios. *Source* Authors' elaboration

Year	BAU scenario	GVC-transition scenario
2024	13.14	12.28
2025	13.90	13.03
2026	13.98	14.03
2027	14.95	14.30
2028	16.26	14.72
2029	16.83	14.53
2030	17.50	15.45
2031	18.86	14.80
2032	20.02	15.25
2033	20.81	15.70
2034	22.03	15.91
2035	23.55	16.64

Gt CO_2 eq in 2035. Conversely, the total industrial GHG emissions in the GVC-transition scenario still followed an upward trend from 2024 to 2035, but growth was moderate (Table 7).

Comparing the two scenarios of GHG emissions, the GHG emissions under the BAU scenario were 23.55 Gt of CO_2 eq in 2035, while emissions were only 16.64Gt in the GVC-transition scenario. That was attributed to the effect of the GVC position and technological innovation. Notably, it could be concluded that 2026 was a critical year from Fig. 4. From 2026 to 2035, the growth rate of the GVC-transition scenario was lower than in the BAU scenario. In the early stages, China concentrated on winning in the global market competition and embedded its position in the high-end GVC. Improving this GVC position and technological innovation have had a profound effect on GHG emissions for the industrial sector. The prediction results also showed that China was able to realize high-quality development in GVC as well as mitigate GHG emissions.

Conclusion

Based on the panel data of China's industrial sector from 2000 to 2020, this paper explored the impacts of the GVC position and technological innovation on GHG emissions. Then, a PLFC model was constructed to provide an in-depth analysis of how an improved GVC position influenced the role of technological innovation on GHG emissions. In addition, the emission trends of GHG in China's industrial sector from 2024 to 2035 were predicted according to the ARIMA model. The main conclusions of this paper were as followed: first, the GVC position significantly reduced GHG emissions in China's industrial sector. China's industrial sector has improved its GVC position through functional and chain upgrading and has reduced GHG emissions. Second, independent innovation generally inhibited GHG emissions, but this emission reduction effect changed with the GVC position. At the backward position of the GVC, the abatement effect decreased as the GVC position moved up. At the forward position of the GVC, the effect of independent innovation was statistically insignificant. This proved that China's industrial sector was not sufficiently powerful in its independent innovation, and thus, it faced the "low-end lock-in" dilemma. Third, the effect of foreign innovation increased and then, decreased as the GVC position improved, but it remained positive. Finally, GHG emissions in China's industrial sector maintained an increasing trend from 2024 to 2035. The industrial sector's CO_2 emissions should peak in 2028, with emissions of 10.21 Gt CO_2 eq. China has been able to meet this carbon peak target. Compared with the BAU scenario, the GVC-transition scenario resulted in lower GHG emissions. This result reflected the curbing effect of the GVC position and technological innovation on GHG emissions.

Based on these conclusions, we propose several policy implications. First, according to the findings in Fig. 1, the GHG emissions reduction effect of independent innovation was more significant in industries with lower GVC positions. Thus, industries at downstream of GVC should accelerate independent innovation to complete the transformation of production technology and improve core technology. For example, China should encourage digital technological innovation to improve productivity in the transport equipment manufacturing industry. In addition, for sectors upstream of GVC, such as the mining and quarrying industry, governments should raise carbon taxes and increase subsidies for green technology innovation to guide pollution-intensive industries to control GHG emissions.

Second, the results of Fig. 2 indicated that the positive marginal effect of foreign innovation efforts increased and then, diminished with the GVC position improving. Although the impact of introducing innovation remains positive, there is a clear downward trend. Therefore, China's industrial sectors should use introduced innovations for technological transformation while raising the technology access threshold and actively introducing low-carbon technologies. Notably, the GVC position of the electrical and optical equipment industry is nearing the turning point. The positive impact of technology introduction on GHG emissions is high. The electrical and optical equipment industry's reliance on technology introduction should be weakened, and its awareness of independent innovation should be strengthened.

Third, the GHG emission growth rate of the BAU scenario first exceeded that of the GVC-transition scenario in 2026, as shown in Fig. 4. This demonstrated the importance of the increased position of GVC for future GHG reductions. Consequently, China should take the initiative to foster the turning point in 2026. Domestically, China could accelerate industrial upgrading in knowledge-intensive sectors to form international competitive advantages and realize chain upgrading, thus controlling GHG emissions. Internationally, China should follow the trend of GVC restructuring, strengthen trade cooperation with emerging economies, and release domestic production potential.

In addition, this paper had the following limitations. Due to the availability of input–output tables, the impact of GVC and technological innovation on GHG emissions in China was only investigated at the sectoral level. The perspective from provincial or firm levels was ignored in this study. Moreover, GVC is undergoing reconstruction, and China should make full use of its strong domestic market. To address this transition, China has suggested the "dual-circulation" strategy. Combining the domestic and global value chains in the analysis framework is more conducive to exploring the actual impact of GVC on China's GHG emissions. Future studies can distinguish the environmental effects of domestic and global value chains and provide policy recommendations from both domestic and foreign perspectives.

Acknowledgements The authors wish to thank all who assisted in conducting this work.

Author contributions All authors contributed to the study conception and design. Funding acquisition, project administration and supervision were conducted by YY. Material preparation, model construction and results analysis were performed by JS and YD. The first draft of manuscript was written by JS, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding This study was supported by "the Funds for First-class Discipline Construction of Beijing University of Chemical Technology (XK1802-5)."

Data availability All the data and materials were freely available from China's National Bureau of Statistics, World Input–Output Database, and databases listed in the references.

Declarations

Conflict of interest The authors declare that they have no competing interests.

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