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Dynamics between global value chain participation, CO_2 emissions, and economic growth: Evidence from a panel vector autoregression model

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ABSTRACT

Resolving the conflict between economic growth and CO_2 reduction is critical for sustainable growth. Increasing integration into global value chains (GVCs) is an inevitable trend for countries to develop their international markets. However, the dynamic relationships between GVC participation, CO_2emissions, and economic growth have not been fully clarified. This study analyzes these relationships and the underlying mechanisms using a panel vector autoregressive model approach with data for 63 countries and regions from 2005 to 2015. The major findings are: (1) GVC participation promotes environmentally-friendly growth in the long run by increasing per capita gross domestic product (GDP) and reducing per capita CO_2 emissions. (2) GVC participation increases as per capita CO_2 emissions increase; it decreases as per capita GDP grows. (3) These relationships vary by industry and income. The variation of GVC participation in high-CO_2 emission industries explains a large proportion of the variation in per capita CO_2emissions, and in high value-added industries, GVC variation explains a large proportion of the variation in per capita GDP. Further, high-income countries benefit more from GVC participation compared to low-income countries. An important policy recommendation is that countries should actively participate in GVCs to promote sustainable growth.

1. Introduction

The disappearance of Okjökull, the first Icelandic glacier lost to climate change, in 2014, once again reminded the world that global warming cannot be ignored. "In the next 200 years all our glaciers are expected to follow the same path," reads the plaque commemorating the loss of Okjökull. Greenhouse gas is the well-known culprit of global warming. CO_2 emissions account for about two-thirds of global greenhouse gas emissions (Oliver et al., 2016). In recent decades, global CO_2 emissions have continued to increase. From 1990 to 2018, the overall CO_2 emissions and CO_2 per capita grew by 61% and 12%, respectively (Fig. 1). Consequently, CO_2 emissions have become a crucial worldwide topic in studies on climate change and environmentally-friendly growth (Tol, 2005; Raupach et al., 2007; Chen et al., 2019). During this period, the world economy and international trade have also developed significantly. Clarifying the relationships between CO_2 emissions, economic growth, and international trade is of great importance to sustainable growth. The emergence of global value chains (GVCs), resulting from vertical specialization and worldwide intra-industry trade, complicates these relationships.

Per capita income is the primary driver of CO_2 emissions (Parker and Bhatti, 2020), largely because of energy consumption during the production process (Wang et al., 2005; Su and Ang, 2012; Wang et al., 2014; Xu et al., 2014; Zhang and Da, 2015). Energy consumption varies significantly across industries, which implies that industry composition is one of the determinants of CO_2 emissions. Fig. 2 shows that the electricity and heat production sector produced the largest share of global CO_2 emissions during the period 1990 to 2014, followed by transport, manufacturing and construction, residential buildings and commercial and public services, and other sectors. Therefore, besides improving energy efficiency, a way for a country to reduce its CO_2 emissions would be to curb domestic production in CO_2-generating industries, transfer them overseas, and import the products of these environmentally unfriendly industries to meet the domestic demand. This process is popularly known as emission transfer via international trade (Kleemann and Abdulai, 2013; Aklin, 2016).[1] In other words,

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[1] It is worth noting that emission transfer may not reduce global CO_2 emissions if it simply transfers emissions from one country to another.

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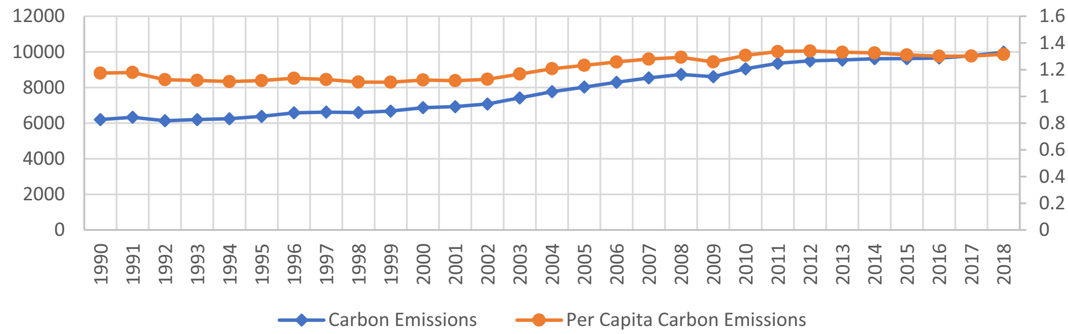


Fig. 1. Carbon emissions (million tons, left axis) and per capita carbon emissions (tons/person, right axis) from fossil fuel combustion and cement production, 1990–2018.
Data Sources: Carbon emissions data come from The Global Carbon Budget 2019; population size data used to compute per capita carbon emissions come from the World Bank Database.
Note: 1 million tons carbon = 3.664 million tons of CO_2.

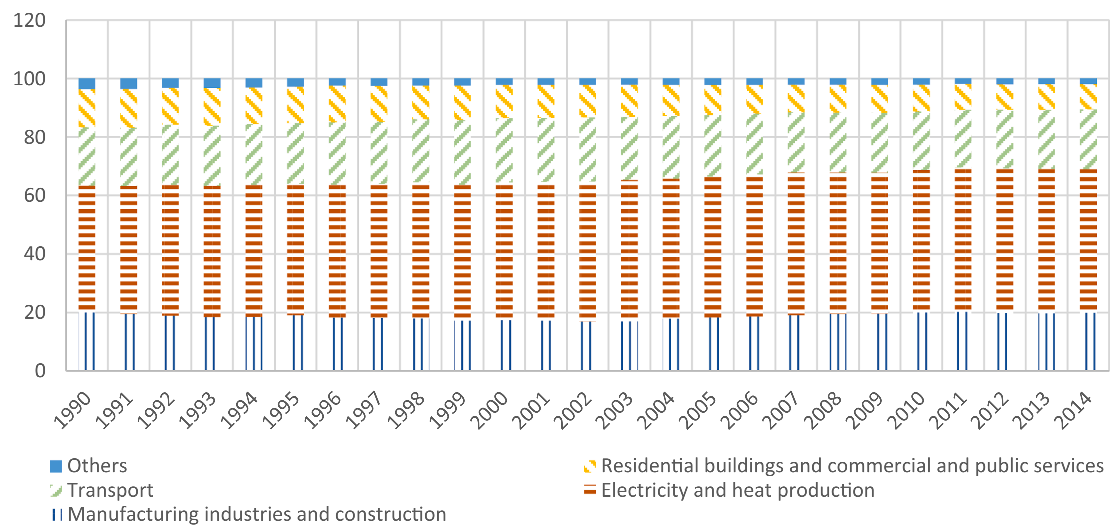


Fig. 2. Industry composition of global CO_2 emissions, 1990–2014 (%).
Data Source: The World Bank Database.

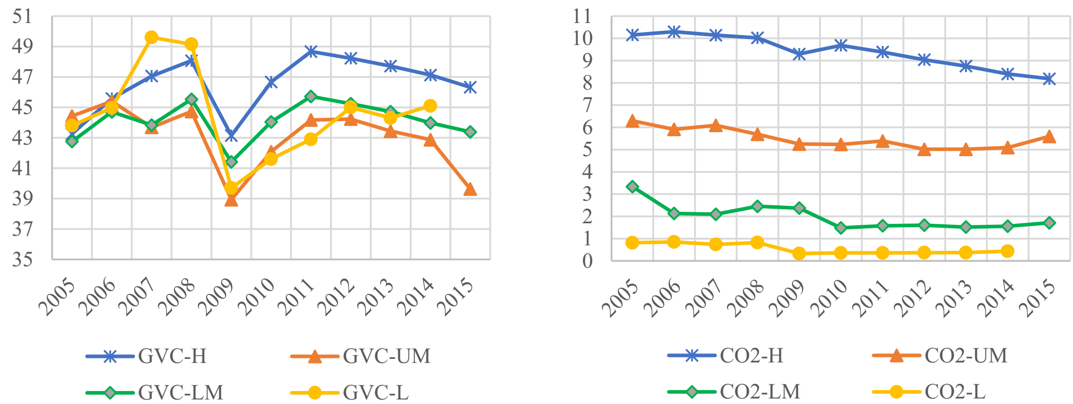
international trade plays a critical role in CO_2 emissions and CO_2 redistributions across countries and regions.

As intra-industry trade plays an increasingly key role in international trade, the world economy has entered the GVC era (Wang et al., 2019). Within the framework of GVCs, the production processes are distributed globally (Zhang et al., 2017), and countries are responsible for one or more sections of GVCs instead of completing the whole production process independently. The emergence of GVCs makes the relationships between trade, CO_2 emissions, and economic growth more complicated. Fig. 3 shows the GVC participation degrees and per capita CO_2 emissions of 63 countries and regions from 2005 to 2015.[2] Based on the World Bank Analytical Classifications 2005–2015, we divided these countries into four groups: high-income (H), upper-middle-income (UM), lower-middle-income (LM), and low-income (L). An observation of Fig 3(a) and 3(b) revealed that: (1) The average GVC participation degree of high-income countries was generally higher than others, as were average per capita CO_2 emissions. Moreover, per capita CO_2 emissions increased as income levels increased, while there was neither a continuous positive nor negative correlation between GVC participation and income. (2) After experiencing a slump during the 2008–2009 financial crisis and a subsequent recovery period in 2010–2011, except for the low-income group, GVC participation showed a downward trend after 2011. (3) The per capita CO_2 emissions of the high-income group decreased over time, while those of other groups showed a slight upward trend after 2010.

Four effects—scale effect, technique spillover effect, composition effect, and competition effect—simultaneously act on the GVC–CO_2 nexus (Wang et al., 2019). Thus, GVC participation has differentiated impacts on CO_2 emissions across countries and sectors. Similarly, the impact of integration into GVCs on economic growth differs across countries and sectors (Jouanjean et al., 2017). Additionally, the reverse effects of CO_2 emissions and economic growth on GVC participation cannot be ignored. On the one hand, high CO_2 emissions imply relatively weak environmental stringency, thus promoting the production of environmentally unfriendly products in a country and its GVC participation in relative industries. On the other hand, high CO_2 emissions hurt the ecosystem, forcing a country to take measures to reduce emissions, such as shutting down polluting factories, which will thwart its production in related industries and the level of GVC participation.

These facts lead to the following questions: (1) How do GVC participation, CO_2 emissions, and economic growth affect each other? (2) What are the influencing mechanisms? (3) How can a country

[2] On average, these countries accounted for 84.54%, 92.09%, 89.27%, and 88.58% of the global CO_2 emissions, GDP, imports, and exports, respectively, for the period of study. GDP, import value, and export value were measured in constant 2010 USD.



(a) GVC participation degree (b) Per capita CO₂ emissions

Fig. 3. GVC participation degrees (%) and per capita CO_2 emissions (tons/person) by country income group, 2005–2015.
Data Sources: The carbon emissions data come from Trade in Value Added Database (2018 edition); the population size data used to compute per capita carbon emissions come from the World Bank Database.
Notes: 1. H, UM, LM, and L stand for high-income, upper-middle-income, lower-middle-income, and low-income groups. 2. According to the World Bank Analytical Classification 2015, no country in our sample belonged to the low-income group in 2015.

achieve environmentally-friendly growth in the context of the international vertical division and cooperation? It is expected that people prefer environmentally-friendly growth, not economic growth at the expense of the environment, or a system that is environmentally friendly with higher poverty. However, at present, cleaner production cannot be the spontaneous or preferred behavior of most producers around the world, especially in developing and undeveloped countries and regions. This is largely due to the inaccessibility and high cost of clean energy and clean production technologies. Therefore, the answers to these questions are crucial for policymakers to design effective green development policies and strategies.

To explore these questions, we applied the panel vector autoregression (PVAR) model, using data for 63 countries and regions from 2005 to 2015, and empirically analyzed the dynamic relationships between GVC participation, CO_2 emissions, and economic growth, mainly focusing on the impact of GVC participation on sustainable growth (i.e., environmentally-friendly growth). The PVAR model is widely used to analyze the relationships between endogenous variables using panel data (Love and Zicchino, 2006; Jawadi et al., 2016; Magazzino, 2016a; Magazzino, 2016b; Antonakakis et al., 2017; Magazzino, 2017), fitting with our research.

Although we were unable to study more countries and regions over a longer period due to data limitations and our research focus does not cover spatial correlation or GVC position,[3] this study makes three primary contributions. First, to our best knowledge, it is the first study examining the aforementioned dynamic relationships. Previous research focused separately on the impact of GVC participation on CO_2 emissions, the impact of GVC participation on gross domestic product (GDP), or the impact of GDP on CO_2 emissions. The studies failed to explore fully the dynamic relationships and influencing mechanisms of the three variables and the effects of GVC participation on sustainable growth. Our empirical results not only confirm the impacts of GVC participation on CO_2 emissions and GDP, and the effect of GDP on CO_2 emissions, but also unveil the reverse effects of CO_2 emissions and GDP on GVC participation, and the reverse effect of CO_2 emissions on GDP. Second, unlike previous studies, we considered the heterogeneous effects of GVC participation in diverse industries. Third, developing and developed countries have been playing divergent roles in GVCs and CO_2 emissions, so we examined the heterogeneity in the relationships between high- and low-income countries. Our empirical results show that the dynamic relationships vary across industry and income groups. We further explored the influencing mechanisms through heterogeneity analyses.

The remaining sections of this article are organized as follows. Section 2 reviews the relevant literature and develops testable hypotheses. Section 3 introduces the PVAR model and describes the variables and data. Section 4 presents the baseline results and several robustness checks. Section 5 provides further discussion on the dynamics between GVC participation, CO_2 emissions, and economic growth. Section 6 summarizes the main conclusions of the study and discusses policy implications. Limitations and future research are proposed in Section 7.

2. Literature review and hypotheses development

2.1. GVC–CO_2 nexus

Research on the GVC–CO_2 relationship, some of which supports the promoting effect of GVC participation on CO_2 emissions, is scarce. López et al. (2013) studied Spain–China trade in 2005 and found that the pollution haven hypothesis explained 29,667 Kt of CO_2 emissions, 24.1% of which was caused by GVC participation. Hertwich (2020) found that increases in GVC participation drove the rise of carbon-in-transit. Meng et al. (2018) suggested a correlation between GVC participation and CO_2 emissions without empirical analysis. Yao et al. (2021) posited that countries with high GVC are more energy-efficient and able to manufacture products with fewer energy inputs, and hence cause fewer emissions. Wang et al. (2019) empirically estimated the impact of GVC participation on per capita CO_2 emissions, using panel data of 62 countries from 1995 to 2011. They found an inverted-U relationship between GVC and CO_2 and attributed it to the combined results of scale, technique spillover, composition, and competition effects. Lv et al. (2019) also established a nonlinear effect of GVC participation on the carbon emissions embodied in export trade.

Despite the lack of research focused on the impact of CO_2 emissions on GVC participation, we argue that CO_2 emissions can affect GVC participation through the following two channels: (1) *Carbon transfer effect.* Ben-David et al. (2018) pointed out that multinationals that have headquarters in countries with strict environmental policies launch their activities in countries with poor environmental laws. Zhang et al. (2017) showed that low production costs and lower environmental regulations in developing countries lead developed countries to outsource their polluting production processes. The effect of carbon transfer leads to

[3] Please refer to limitations and future research of Section 7 for details.

international production specialization. Horizontal specialization enhances inter-industry trade across countries, while vertical specialization stimulates GVC participation. Nearly 70% of the increases in international trade can be attributed to GVC specialization (Yi, 2003). Developed countries with high CO_2 emissions will participate in GVCs to transfer emissions out. Duan et al. (2021) posited that high-income countries transfer their emissions offshore to low-income countries by outsourcing only dirty production stages instead of entire production processes. Some developing countries have enacted relatively loose environmental regulations in search of economic growth (Arce González et al., 2012; Yasmeen et al., 2019). Relatively low CO_2 standards and hence relatively high CO_2 emissions will bring opportunities for developing countries to participate in GVCs to make use of their comparative advantages in international markets. (2) *Environmental protection effect.* Companies worldwide have started redefining their business models to overcome environmental challenges and reach sustainable goals (WTO, 2018). A growing number of citizens focus on coordinated development between the environment and economic growth and play increasingly important roles in making decisions on environmental treatments (Do Paço et al., 2009; Glucker et al., 2013). The environmental protection effect pushes countries to participate in clean GVC activities and retreat from dirty GVC activities. Drake-Brockman (2018) emphasized the importance of sustainable GVC-linked investments where low-carbon opportunities are identified.

This discussion leads us to the following hypothesis:

H1. : CO_2 emissions respond to GVC participation and vice versa, and this varies by country.

2.2. GVC–GDP nexus

There are few studies on this relationship and they reported mixed findings. Ignatenko et al. (2019) analyzed 189 countries from 1990 to 2013 and found a positive impact of participation in GVCs on income per capita and productivity. Kowalski et al. (2015) reported that participation in GVCs raised the value added and productivity. However, Rodrik (2018) criticized the contribution of participation in value chains on output and productivity growth. Fagerberg et al. (2018) established that GVC participation failed to raise output growth by observing 125 countries during 1997–2013.

A few studies focused on the differentiated effects of GVC participation on output across countries and sectors. For example, Kummritz (2015) demonstrated the positive impact of GVC participation on domestic value added and that this impact was significant only for middle- and high-income countries. The results of Fagerberg et al. (2018) imply that small countries and countries with low capabilities are at a disadvantage in terms of benefitting from value chains. Formai and Vergara Caffarelli (2015) found that participation in GVCs presented differentiated impacts on total factor productivity and labor productivity growth across sectors by analyzing 50 countries from 1990 to 2009. Kordalska et al. (2016) provided estimations for 20 industries (13 manufacturing and seven service industries) in 40 countries. They estimated significantly positive results of backward GVC participation, mainly for the manufacturing industries.

Existing literature rarely paid attention to the reverse effect of GDP on GVC participation, but we argue that GDP can affect GVC participation in return because of three aspects: *(1) Productivity effect.* Countries that move up in GVCs gain larger benefits from international specialization and global production fragmentation (Liu et al., 2018). High-income countries usually participate in high-tech and capital-intensive industries' GVCs and stay at the upper ends of GVCs due to their comparative advantages at technological innovation and productivity. By outsourcing the production of comparative disadvantages via GVCs, a country can focus on the production in which it has comparative advantages and thus further improve productivity. In addition, high-income countries' comparative advantages are relatively non-substitutable in international markets. By participating in GVCs, a country can benefit from exports of advanced technologies to the rest of the world. Thus, as income rises, countries are willing and able to participate in the upper ends of GVCs. *(2) Technique spillover effect.* Low-income countries are eager to participate in GVCs to benefit from technique spillover effects (Borck and Coglianese, 2009; Zhou et al., 2020) from high-come countries. *(3) Substitution effect.* Since the comparative advantages of low-income countries usually lie in low costs and/or weak environmental supervision (Krueger, 1977; Chichilnisky, 1994; Erdogan, 2014; Ee et al., 2018), they could generally participate in the labor- and natural-resource intensive industries' GVCs and stay at the lower ends of GVCs. Moreover, their comparative advantages can be substituted relatively easily.[4] Therefore, as income drops, countries' willingness to participate in GVCs increases but their participation may decline.

Thus, we put forward the following hypothesis:

H2. : GVC participation affects GDP and vice versa, and the effect may vary by country and industry.

2.3. CO_2–GDP nexus

The relationship between CO_2 emissions and GDP has long been a concern of scholars. Early studies (see Holtz-Eakin and Selden, 1995; World Bank Development Report, 1992; Selden and Song, 1994; Grossman and Krueger, 1991, 1995) found that the environmental degradation–income relationship presented an inverted U-shape, which is well known as the environmental Kuznets curve (EKC) proposed by Grossman and Krueger (1991). Pollution increases up to a certain level as income goes up; after that, it decreases. This relationship has been tested by many recent studies. For instance, Charfeddine (2017) averred that the EKC hypothesis holds for CO_2 emissions. Ang (2007), using data of France for 1960–2000, found that CO_2 emissions and output had a quadratic relationship in the long run. The empirical results of Jaunky (2011) provided evidence of EKC for Greece, Malta, Oman, Portugal, and the U.K. Zhang and Zhang (2018) verified the validity of the EKC hypothesis for China. You and Lv (2018) found strong evidence for the inverted U-shaped EKC relationship between CO_2 emissions and income by analyzing panel data of 83 countries for 1985–2013. Antweiler et al. (2001) and Coxhead (2003) illustrated this non-linear relationship between pollution and income from scale, composition, and technique spillover effects. Dinda (2004) summarized the possible explanations for EKC as: (1) an economy develops from a clean agrarian economy to a polluting industrial economy to a clean service economy and (2) people with higher incomes have higher preferences for environmental quality.

However, higher national incomes do not necessarily lead to greater efforts to contain the emission of pollutants. The empirical results of Holtz-Eakin and Selden (1995) and Shafik (1994) show that pollutant emissions monotonically increase with income levels. Magazzino and Cerulli (2019) used a responsiveness scores approach and panel data of Middle Eastern and North African (MENA) countries over the period 1971–2013 and found that the GDP per capita showed positive responsiveness scores on CO_2 emissions. The empirical results of Jaunky (2011), based on panel data of 36 high-income countries for the period 1980–2005, reveal that a 1% increase in GDP generated an increase of 0.68% in CO_2 emissions in the short term and 0.22% in the long term, which is inconsistent with EKC. The evidence provided by Halkos and Tsionas (2001) indicates a monotonic relationship between environmental degradation and income, and thus, rejects the EKC hypothesis.

[4] With the recent deterioration of the "demographic dividend" in China, the advantage of labor costs no longer exists. Developed countries have moved their businesses to Southeast Asian countries that have lower labor costs. This compelled Chinese enterprises to retreat from the GVCs (Song and Wang, 2017).

Another strand of research unveiled an N-shaped rather than an inverted U-shaped relationship between pollution and output (e.g., Moomaw and Unruh, 1997; De Bruyn et al., 1998; Galeotti and Lanza, 1999; Millimet et al., 2003; Wang et al., 2019). Friedl and Getzner (2003) found a cubic relationship between GDP and CO_2 emissions for Austria for the period 1960–1999. Zheng et al. (2014) reiterated the cubic relationship by analyzing a panel data set of 30 provincial units in China from 1998 to 2010.

Accordingly, we propose the following hypothesis:

H3a. : GDP can significantly affect CO_2 emissions and the effect varies by country.

Magazzino (2016c) pointed out that the Toda and Yamamoto's Granger non-causality test (Toda and Yamamoto, 1995) showed a bidirectional causality between CO_2 emissions and economic growth in Italy over the period 1970–2006. Dinda and Coondoo (2006) employed bi-variate analysis and found bidirectional causality between CO_2 emissions and income for North America. Wang et al. (2016) established that increased CO_2 emissions in China during the period 1990–2012 led to augmented economic growth, though the impact was marginal. However, Magazzino (2016a) found that an increase in CO_2 emissions had a detrimental effect on the real GDP by studying the data of the South Caucasus area and Turkey from 1992 to 2013. Magazzino (2016b) explored the nexus between CO_2 emissions, economic growth, and energy use for ten Middle Eastern countries during 1971–2006, using a PVAR technique. For the six GCC (Gulf Cooperation Council) countries, the response of economic growth (real GDP) to CO_2 emissions was negative in the estimated coefficients and impulse responses. For the other four non-GCC countries, CO_2 emissions appeared to not have had any impacts on growth. Chontanawat (2020) found no evidence of causality running from CO_2 emissions to GDP in ASEAN for the period 1971–2015.

Admittedly, the mixed nature of these empirical findings can be attributed to the econometric methods, research periods, and variables selected by researchers. However, we believe that it is essentially due to two effects. *(1) Production effect*. When CO_2 emissions are relatively low, some countries, especially low-income ones, will sacrifice the environment to promote production. They may even introduce relatively lower environmental standards in striving for opportunities to expand production. In this case, as CO_2 emissions increase, GDP rises as well. *(2) Environmental protection effect*. When CO_2 emissions reach a certain level, measures must be taken to ensure sustainable growth. Countries, especially high-income ones, will reduce or shut down high-emission production. Under these circumstances, as CO_2 emissions grow, GDP may drop. In the early decades following the reform and opening policy in 1978, China emphasized the extreme importance of economic development (Liu et al., 2018). The extensive production mode with high energy consumption and high pollution promoted China to become the "world factory", which stimulated the rapid growth of China's economy. At that time, the production effect played a dominant role. Given resource depletion and environmental degradation, the focus of economic development has shifted into quality in recent decades. In 2012, China entered the state of "new normal" (Song and Wang, 2017), in which the economic growth rate is slowing and more attention is paid to the environment. At this stage, the environmental protection effect dominates.

Based on the discussion above, we propose:

H3b. : CO_2 emissions have a reverse impact on GDP and the effect varies by country.

Based on the literature review above, we found that previous research (1) ignored the potential reverse impacts of CO_2 emissions on GVC participation, GDP on GVC participation, and CO_2 emissions on GDP; (2) did not disentangle the relationships between GVC participation, CO_2 emissions, and GDP; and (3) did not pay sufficient attention to analyzing the way GVC participation in different sectors affects these relationships or ascertaining the heterogeneity of these relationships between different income groups. To fill these gaps, this study used the PVAR model to analyze the dynamic relationships between GVC participation (in different sectors), CO_2 emissions, and GDP with the full, high-income, and low-income samples and explored the underlying mechanisms.

3. Model and methods

3.1. Model specification

The PVAR model was first proposed in Holtz-Eakin et al. (1988). It is a combination of the VAR model and panel data. The VAR model (Sims, 1980) treats all variables in the system as endogenous, which facilitates studies of bilateral or multi-lateral time-series causality between variables. PVAR models have been used in multiple applications across various fields of research (Love and Zicchino, 2006; Jawadi et al., 2016; Antonakakis et al., 2017; Magazzino, 2017).

To ensure environmentally-friendly economic growth, all countries and regions worldwide need to jointly tackle the problem of CO_2 emissions. Thus, we applied panel data in this study, from which individual heterogeneity can be observed. The PVAR model is superior to other methods because it follows the VAR model of treating all variables in the system as endogenous, which facilitates analyzing the dynamic relationships between them, while also allowing for unobserved individual heterogeneity by introducing the VAR in panel data settings, which is conducive to obtaining efficient estimates.

We followed a similar strategy of Abrigo and Love (2016) and Magazzino (2016a,b, 2017) and specified the model as:

$$Y_{it} = \sum\nolimits_{j=1}^{p} A_j Y_{it-j} + u_i + e_{it}\ (i = 1, \ldots, N; t = 1, \ldots, T), \tag{1}$$

where Y_{it} represents a three-variable vector {GVC, LNGDPPC, LNCO2PC}. GVC, LNGDPPC, and LNCO2PC represent GVC participation degree, the logarithm of GDP per capita, and the logarithm of per capita CO_2 emissions, respectively. Let i index the cross-sectional observations and t the time period, respectively. In this study, $N = 63$ and $T = 11$. Y_{it-j} represents a j-period lag term of Y_{it}. The (3×3) matrices A_j are the parameters to be estimated. u_i and e_{it} are (1×3) vectors of dependent variable-specific panel fixed-effects and idiosyncratic errors.

We also examined the relationships between GVC participation in different industries, CO_2 emissions, and economic growth. We selected 12 industries and divided them into four industry groups according to their characteristics (see Section 3.2 for details). Thus, we had four additional regressions based on Model (1). Further, we analyzed the heterogeneous relationships between GVC, LNCO2PC, and LNGDPPC in high- and low-income countries, and thus we had two more regressions based on Model (1).

There is a restriction on applying the VAR procedure to panel data; that is, the underlying structure is the same for each cross-sectional unit (Love and Zicchino, 2006). To overcome the restriction on parameters, we allowed for "individual heterogeneity" by introducing fixed effects, denoted by u_i in Model (1).

As the fixed effects are correlated with the regressors due to the presence of lagged dependent variables in the right-hand side of the system of equations (Love and Zicchino, 2006), estimates would be biased even with a large N (Nickell, 1981). Theoretically, the bias approaches zero as T gets larger. However, Judson and Owen (1999) found significant bias in their research even when $T = 30$.

To further understand the dynamic relationships between our variables of interest, we presented impulse–response functions (IRFs) and forecast-error variance decompositions (FEVDs) based on the PVAR estimates. An IRF describes the reaction of one variable to a shock in another variable in the system. Referring to Lütkepohl (2007), we applied orthogonal impulse response functions (OIRFs) based on the Cholesky decomposition. The identifying assumption is that the variables that appear earlier in the system are more exogenous and the ones that appear later are more endogenous. In other words, the variables that come earlier in the ordering affect the variables that follow.[5] The literature review in Section 2 has demonstrated the current period impacts of GVC participation on CO_2 emissions, GVC participation on GDP, and GDP on CO_2 emissions. Therefore, we reasonably assumed the order of the three variables from relatively exogenous to relatively endogenous as GVC, LNGDPPC, and LNCO2PC.[6] Besides the OIRFs that present the year-by-year impulse–response dynamics, we also presented the cumulative impulse–response dynamics.

We then calculated the FEVDs to assess the importance of each variable in explaining the other variables. A FEVD shows the percentage of the variation in one variable that is explained by the shock in another variable (Abrigo and Love, 2016). We used the identification scheme employed in calculating the IRFs.

3.2. Variables and data

We collected data on per capita CO_2 emissions (CO2PC) and per capita GDP (GDPPC), expressed in constant 2010 USD, for 63 countries and regions from 2005 to 2015 from the World Bank database. The GVC participation degree (GVC) related data were obtained from the Trade in Value Added Database (2018 edition), developed by the Organization for Economic Co-operation and Development (OECD) and World Trade Organization (WTO).

3.2.1. GVC participation

The GVC participation degree consists of two parts: forward GVC participation degree (FGVC) and backward GVC participation degree (BGVC). Koopman et al. (2014) divided gross exports into final goods and intermediates and further divided intermediates into (1) finished and consumed goods in the importing country (FCIC); (2) goods that are processed and exported back to the exporting country (PEEC); and (3) goods processed and exported to a third country (PETC). Each part (or subpart) can be decomposed into domestic value added (DVA) and foreign value added (FVA) (see Fig. 4).

Referring to Koopman et al. (2014), and Wang et al. (2019), the FGVC, BGVC, and GVC participation degrees of country i at time t can be defined by Formulas (2)–(4), respectively.

$$Forward\ Particip.\ Degree\ in\ GVC_{it} = \frac{DVA\ embodied\ in\ foreign\ exports_{it}}{Gross\ exports_{it}} = \frac{DVA_{PETC\,it}}{Gross\ exports_{it}}, \tag{2}$$

$$Backward\ Particip.\ Degree\ in\ GVC_{it} = \frac{FVA_{it}}{Gross\ exports_{it}} = \frac{\left(FVA_{Final\ goods} + FVA_{FCIC} + FVA_{PEEC} + FVA_{PETC}\right)_{it}}{Gross\ exports_{it}}, \tag{3}$$

$$Particip.\ Degree\ in\ GVC_{it} = FGVC_{it} + BGVC_{it} = \frac{DVA_{PETC\,it} + \left(FVA_{Final\ goods} + FVA_{FCIC} + FVA_{PEEC} + FVA_{PETC}\right)_{it}}{Gross\ exports_{it}}. \tag{4}$$

The GVC–CO_2 and GVC–GDP relationships are determined by four effects—scale, technique spillover, composition, and competition effects. First, GVC participation will stimulate GDP growth and CO_2 emissions through the scale effect. The in-depth intra-industry specialization across countries drives the formation of GVCs and lowers the thresholds to international markets. Countries, especially developing and less developed ones, obtain more development opportunities through participating in GVCs. It will expand their production scales (i.e., the scale effect) but also enhance energy consumption, thus stimulating CO_2 emissions. Second, GVC participation will promote production but reduce CO_2 emissions because of the technique spillover effect. Countries that actively and deeply participate in GVCs are more likely to benefit from the spillover effect of advanced technologies of trade partners. Advanced technologies enable countries to undertake cleaner production, which stimulates GDP and reduces CO_2 emissions. Third, the composition effect is related to the economic structure driven by comparative advantages. To some extent, higher GVC participation degrees indicate deeper and wider intra-industry specialization, thus making the proportion of environmentally unfriendly production greater in countries that have comparative advantages in polluting products, while making countries whose comparative advantages lie in environmentally-friendly products more specialized in clean production.

Fourth, countries with high GVC participation degrees are relatively dependent on international markets and are likely to face fierce international competition. If a country enhances its international competitiveness through lower environmental standards, its polluting production may expand, and thus, both GDP and CO_2 emissions will increase. However, if a country gains competitiveness via R&D and innovation, its GDP will grow and emissions will decrease. Thus, the impact of GVC participation will be positive on GDP but ambiguous on CO_2 emissions due to the competition effect. Moreover, as an economy develops, people's preference for a high-quality environment grows. Environmentally-friendly production will finally survive in international competition. Therefore, we believe that the competition effect is conducive to promoting production while reducing emissions in the long run. In sum, the net impacts of GVC participation on CO_2 emissions and GDP are ambiguous.

We can obtain the GVC participation degree for an industry by replacing all the variables in (2) to (4) with industry-level values. To further analyze the relationships between GVC participation, CO_2 emissions, and economic growth, we collected data on GVC participation degrees of 12 industries from the Trade in Value Added Database (2018 edition) developed by OECD and WTO. We divided the industries into four groups based on their contributions to domestic CO_2 emissions and value added, following three steps: First, we obtained data on CO_2 emissions by industry from the Air and Climate Database (2018 edition) and value added by industry from the Trade in Value-Added Database (2018 edition), respectively, developed by the OECD and the WTO. By matching the two databases, we obtained measures of CO_2 emissions and value added for 12 industries in 32 out of 63 countries and regions from 2012 to 2015. Second, we computed the mean of CO_2 emissions as well as the mean of value added of these 32 countries from 2012 to 2015 by industry. A scatter plot of selected industries is shown in Fig. 5. Third, we split Fig. 5 into four quadrants based on the median values of CO_2 emissions (vertical axis) and value added (horizontal axis). Industries

[5] See Hamilton (1994) and Abrigo and Love (2016) for the derivation and discussion of IRFs.

[6] The VAR model in this study under these assumptions is similar to the structural VAR (SVAR) model with zero short-run restrictions, also known as Cholesky, recursive, or orthogonal identifications (Stock and Watson, 2001).

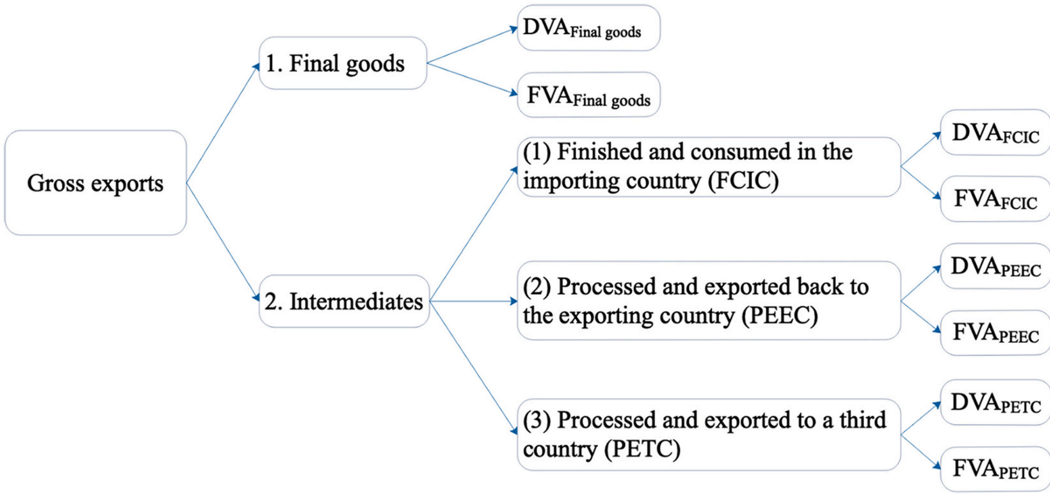


Fig. 4. The decomposition of gross exports.
Note: DVA and FVA stand for domestic value added and foreign value added, respectively.

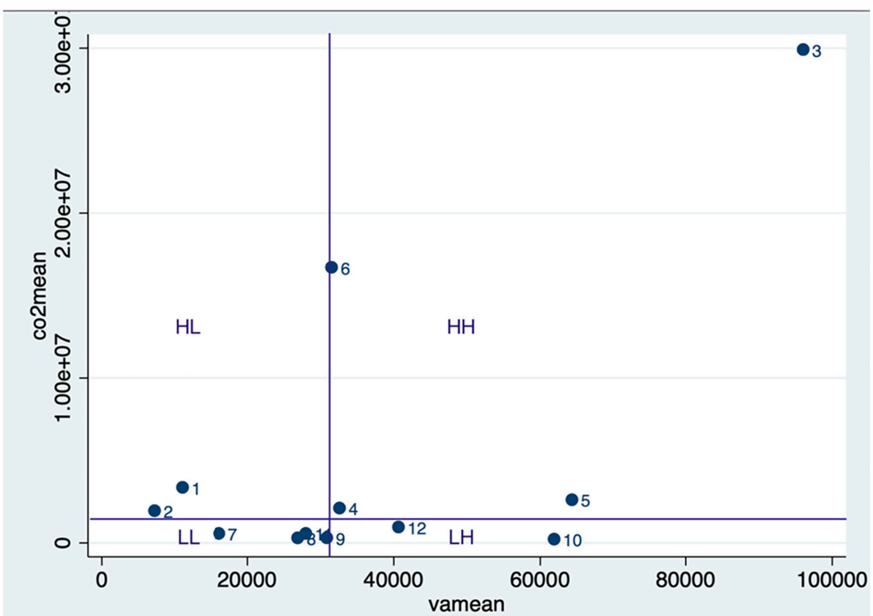


Fig. 5. Scatter plot of the mean of CO_2 emissions (vertical axis) and mean of value added (horizontal axis) of 12 industries in 32 countries from 2012 to 2015.
Data Sources: CO_2 emissions data by industry were collected from the Air and Climate Database (2018 edition) and value-added data by industry were obtained from the Trade in Value Added Database (2018 edition), respectively, developed by the Organization for Economic Co-operation and Development and World Trade Organization.

Table 1
Industry groups.

No.	Industry	Group
3	Manufacturing	HH
4	Construction	
5	Wholesale and retail trade; repair of motor vehicles	
6	Transportation and storage	
1	Agriculture, forestry, and fishing	HL
2	Mining and quarrying	
7	Accommodation and food services	LL
8	Information and communication	
9	Financial and insurance activities	
11	Education	
10	Real estate activities	LH
12	Human health and social work	

that fall in the first quadrant were classified into the"HH" group, that is, the high-CO_2 emissions and high value-added group. Similarly, industries falling in the second, third, and fourth quadrants were classified into the "HL," "LL," and"LH" groups, respectively. See Table 1 for details of the industry groups.[7]

Owing to diverse industry characteristics, we expected heterogeneous GVC–CO_2 and GVC–GDP relationships by industry group. Theoretically, the response of CO_2 emissions to GVC participation was expected to be stronger in high-CO_2 industry groups, and that of GDP to GVC participation was expected to be stronger in high value-added industry groups. However, since the aforementioned four effects work simultaneously, the expected empirical results would be ambiguous.

[7] We refer to these four groups as "HH," "HL," "LH," and "LL," but we remind readers that this distinction is relative and is based on the median level of the mean values of CO_2 emissions and value added by industry across 32 countries from 2012 to 2015.

3.2.2. Per capita CO_2 emissions

Although previous research has hardly studied the effects of CO_2 emissions on GVC participation and GDP, we argued that CO_2 emissions will affect GVC participation because if participating in GVCs helps reduce CO_2 emissions, holding other factors constant, countries will tend to enhance their GVC participation degrees and vice versa. The CO_2–GDP relationship is more complicated. If CO_2 emissions decrease as the economy develops, countries will embrace economic growth. However, if economic development promotes CO_2 emissions, a country may or may not sacrifice economic growth to protect the environment; it depends on its level of economic development and public environmental awareness.

3.2.3. Per capita GDP

The impact of GDP on CO_2 emissions has been analyzed extensively (see Section 2 for details). However, research on the effect of GDP on GVC participation is rare. We proposed that this effect is ambiguous because, on the one hand, higher GDP indicates higher productivity and greater international influence. A country with high GDP is more capable of participating in GVCs. On the other hand, countries that actively and deeply participate in GVCs are more likely to be affected by shocks in international markets. If there are serious adverse shocks in the international economy, it is the countries with high GDP that are more likely to cut their linkages with GVCs because they are more capable of being self-sufficient.

In addition, we divided 63 countries and regions into two groups: the high-income group includes 39 high-income ones, and the low-income group comprises the rest.[8] Considering the heterogeneity of countries in terms of natural resource endowments, comparative advantages, production styles, environmental protection awareness, and responses to international shocks, we expect that the aforementioned dynamic relationships vary across countries with different incomes.

Table 2 reports the summary statistics of all variables. Single country (region) statistics are available upon request. The mean values of all variables are positive. LNGDPPC and LNCO2PC have negative values of skewness, indicating that the distribution is left-skewed, with more observations on the right tail. However, the variables show similar values for the mean and median, indicating that a normal distribution emerges. Moreover, 10-trim values are near to the mean, and standard deviation to the pseudo standard deviation (PSD), which are in line with the fact that the inter-quartile range (IQR) shows the absence of outliers in our sample. The correlation matrix indicates that our series are significantly correlated at the 1% level (Table 3).

4. Empirical results

4.1. Diagnostic tests

Before applying the PVAR approach, we carried out a series of panel unit root tests including Levin et al. (2002), Harris and Tzavalis (1999), Breitung (2000), Im et al. (2003), Fisher-type (Choi, 2001), and Pesaran (2007). All tests except the CIPS test confirm that our variables are (trend) stationary. The CIPS test of some variables failed to reject the presence of cross-section dependence, including at the first-difference level. We applied Pesaran's (2004) cross-sectional dependence (CSD) test, which also failed to reject the presence of cross-sectional dependence in some cases. Although the spatial issue is beyond the scope of this research, we addressed the issue in the robustness check section.

Further, the results of the Dumitrescu-Hurling panel causality tests (Dumitrescu and Hurlin, 2012) reveal the bidirectional causality between each pair of variables of primary interest. The optimal lag chosen for the PVAR model is based on balancing the following aspects: the model has a small value of the Modified Akaike Information Criterion (MAIC), Modified Bayesian Information Criterion (MBIC), or Modified Hannan-Quinn Information Criterion (MQIC), and passes the Hansen's (1982) over-identifying test. Based on these selection criteria, we specified a 1-period lag order in the baseline regressions and the regressions grouped by income, and a 2-period lag order in the regressions containing GVC participation in different industry groups.[9]

4.2. PVAR analysis

4.2.1. Baseline regression results

Table 4 presents the results of the PVAR(1) model which considers the overall GVC participation. We found the following: (1) All three variables are significantly and positively correlated with their past values, which is in line with their trends. (2) The 1-period lag of GVC has significantly negative impacts on LNCO2PC and LNGDPPC. As GVC increases by 1%, CO2PC will decrease by 0.012%, more than the reduction in GDPPC (0.007%). (3) The 1-period lag of LNGDPPC will significantly and negatively affect GVC. The GVC will decrease by 6.4% when GDPPC increases by 1%. The impact of LNGDPPC on LNCO2PC one year ahead is positive but insignificant. (4) The 1-period lag of LNCO2PC will significantly and negatively influence LNGDPPC, while positively but insignificantly affecting GVC. As per capita CO_2 emissions increase by 1%, the GDP per capita will decrease by 0.18%, and vice versa.

4.2.2. Results by industry group

Table 5 presents the major PVAR(2) regression results when GVC participation in different industry groups is considered.[10] Panels I–IV show the results of HH, HL, LL, and LH groups, respectively. We found the following: (1) The 1-period lag of GVC participation in HH and HL industry groups will significantly and negatively affect LNCO2PC, while the coefficients are negative but insignificant in LL and LH. Moreover, the 1-period lag of GVC participation in HH, LH, and LL groups is significantly negatively correlated with LNGDPPC, and the coefficient of LL is smaller, while the coefficient of the HL group is insignificant. Furthermore, the coefficients are insignificant when the 2-period lag values of GVC participation are considered.

(2) The 1-period lag of LNGDPPC is positively correlated with GVC participation in all groups, while the 2-period lag of LNGDPPC is negatively correlated, although the coefficients are insignificant in the HL and LH groups. (3) The 1-period lag of LNCO2PC is positively correlated with GVC participation in the HH, HL, and LH groups, while the 2-period lag of LNCO2PC is negatively correlated, although the coefficients are insignificant in the HH group. The 1-period lag of LNCO2PC is significantly negatively correlated with GVC participation in the LL group and the coefficient of the 2-period lag is negative but insignificant.

4.2.3. Results by income group

Table 6 presents the PVAR(1) regression results when countries with different incomes are considered. We found the following: (1) The 1-period lag of GVC shows negative impacts on LNGDPPC and LNCO2PC in both groups, while the coefficients of the low-income group are insignificant and smaller. (2) The 1-period lag of LNGDPPC is positively but insignificantly correlated with GVC in the high-income group, while significantly negatively correlated with GVC in the low-income group.

[8] Countries and regions, whose average income during 2005 to 2015 was above the average of high-income standards announced by the World Bank over the same time period, were classified as the high-income group, while other countries and regions were classified as the low-income group.

[9] The results of unit root tests, causality tests, the MAIC, MBIC, and MQIC values are available upon request.

[10] As far as industries are considered, we only showed the results of our main focus, i.e., the impacts of GVC participation in different industry groups on LNGDPPC and LNCO2PC, and the reverse impacts of LNGDPPC and LNCO2PC on GVC participation in different industry groups.

Table 2
Descriptive statistics.

Variable	Obs.	Mean	Median	SD	Variance	Min	Max	Skewness	Kurtosis	IQR	Range	CV	SE	10-Trim	PSD
GVC	693	45.369	44.3	9.25	85.561	23.5	79.4	0.615	3.865	10.5	55.9	0.204	0.351	44.884	7.778
GVC_HH	693	25.719	24.625	8.122	65.964	8.2	50.075	0.591	2.985	10.9	41.875	0.316	0.309	25.185	8.074
GVC_HL	693	18.763	17.55	8.77	76.915	3.15	52.15	0.982	4.166	10.6	49	0.467	0.333	17.880	7.852
GVC_LL	693	12.481	10.675	7.389	54.597	3.225	46.25	2.21	9.06	6.95	43.025	0.592	0.281	11.305	5.148
GVC_LH	693	9.007	8.05	4.399	19.353	2.25	25.1	0.867	3.281	6.1	22.85	0.488	0.167	8.551	4.519
LNGDPPC	693	9.733	9.91	1.089	1.187	6.419	11.626	−0.732	3.051	1.575	5.207	0.112	0.041	9.837	1.167
LNCO2PC	693	1.741	1.874	0.803	0.644	−1.565	3.212	−1.031	4.527	0.805	4.777	0.461	0.031	1.806	0.597
By income group															
GVC_H	429	46.73	44.5	9.779	95.634	25.5	79.4	0.771	3.624	10.500	53.9	0.209	0.472	46.014	7.778
LNGDPPC_H	429	10.428	10.518	0.529	0.279	9.262	11.626	−0.181	2.442	0.785	2.364	0.051	0.026	10.435	0.581
LNCO2PC_H	429	2.109	2.079	0.453	0.205	1.21	3.212	0.383	2.564	0.572	2.002	0.215	0.022	2.089	0.424
GVC_L	264	43.158	44.15	7.846	61.563	23.5	61	−0.233	2.537	10.250	37.5	0.182	0.483	43.36	7.593
LNGDPPC_L	264	8.604	8.883	0.775	0.6	6.419	9.597	−0.995	3.039	1.041	3.178	0.090	0.048	8.703	0.771
LNCO2PC_L	264	1.142	1.338	0.882	0.779	−1.565	2.75	−0.431	3.073	1.322	4.315	0.772	0.054	1.174	0.979

Notes: 1. GVC, GVC_HH, GVC_HL, GVC_LL, GVC_LH, GVC_H, and GVC_L stand for the overall global value chain participation degree and degrees in the HH, HL, LL, and LH industry groups as well as high (H) and low(L) income groups, respectively. 2. LNGDPPC, LNGDPPC_H, and LNGDPPC_L are the logarithm of GDP per capita in the full, high-income, and low-income sample, respectively. 3. LNCO2PC, LNCO2PC_H, and LNCO2PC_L stand for the logarithm of per capita CO_2 emission in the full, high-income, and low-income sample, respectively. 4. As far as industry groups are concerned, we focus on the dynamic relationships between GVC participation in each group, the overall per capita CO_2 emissions, and the overall per capita GDP. 5. IQR, CV, and PSD refer to Inter-Quartile Range, Coefficient of Variation, and Pseudo Standard Deviation, respectively.

Table 3
Matrix of correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) GVC	1.000						
(2) GVC_HH	0.838***	1.000					
(3) GVC_HL	0.600***	0.723***	1.000				
(4) GVC_LL	0.762***	0.837***	0.812***	1.000			
(5) GVC_LH	0.651***	0.734***	0.620***	0.690***	1.000		
(6) LNCO2PC	0.194***	0.207***	0.125***	0.174***	0.016	1.000	
(7) LNGDPPC	0.116***	0.208***	0.228***	0.202***	−0.145***	0.766***	1.000
Variables	(8)	(9)	(10)	(11)	(12)	(13)	
(8) GVC_H	1.000						
(9) LNCO2PC_H	−0.013	1.000					
(10) LNGDPPC_H	0.050	0.389***	1.000				
(11) GVC_L				1.000			
(12) LNCO2PC_L				−0.143**	1.000		
(13) LNGDPPC_L				0.184***	0.750***	1.000	

Notes: 1. GVC, GVC_HH, GVC_HL, GVC_LL, GVC_LH, GVC_H, and GVC_L stand for the overall global value chain participation degree and degrees in the HH, HL, LL, and LH industry groups as well as high (H) and low(L) income groups, respectively. 2. LNGDPPC, LNGDPPC_H, and LNGDPPC_L are the logarithm of GDP per capita in the full, high-income, and low-income sample, respectively. 3. LNCO2PC, LNCO2PC_H, and LNCO2PC_L stand for the logarithm of per capita CO_2 emission in the full, high-income, and low-income sample, respectively. 4. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
PVAR(1) model regression results.

	(1)	(2)	(3)
Vars.	GVC	LNGDPPC	LNCO2PC
L.GVC	0.410***	−0.007***	−0.012***
	(0.075)	(0.002)	(0.003)
L.LNGDPPC	−6.426***	0.959***	0.075
	(1.838)	(0.043)	(0.074)
L.LNCO2PC	3.042	−0.183***	0.918***
	(2.111)	(0.041)	(0.072)

Obs. 567 (N = 63, $T = 9$).
Instruments: l(1/3).(GVC LNGDPPC LNCO2PC).
Hansen's J: 24.186 [0.149].
Notes: 1. Robust standard errors are in parentheses and p-values in brackets; 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The 1-period lag of LNCO2PC is positively correlated with GVC in both groups, while the coefficient in the high-income group is insignificant and smaller. (3) The 1-period lag of LNCO2PC is negatively correlated with LNGDPPC in both groups, while the coefficient is insignificant in the low-income group. The 1-period lag of LNGDPPC has an insignificant correlation with LNCO2PC in both groups.

4.3. IRF analysis

To further illustrate the dynamic relationships between the three variables and to examine causality, we simulated their OIRFs. The estimates in Tables 4–6 simply reflect reduced-form relationships between the variables. The OIRF analyzes the impact of a standard deviation shock[11] of the random disturbance term of a variable on the current and future states of other variables. The running sums of the OIRFs over the steps within each impulse–response pair are the cumulative OIRFs. In giving the variable a standard deviation shock, we used the Monte Carlo method to simulate the shock 200 times and obtained orthogonal

[11] A standard deviation shock is considered to be positive by default.

Table 5
PVAR(2) model regression results by industry group.

Panel I: HH	*(1)*	*(2)*	*(3)*
Vars.	*GVC_HH*	*LNGDPPC*	*LNCO2PC*
L.GVC_HH		−0.023***	−0.017*
		(0.007)	(0.010)
L2.GVC_HH		−0.004	0.004
		(0.004)	(0.004)
L.LNGDPPC	9.342*		
	(5.249)		
L2.LNGDPPC	−7.036**		
	(3.539)		
L.LNCO2PC	0.9		
	(2.893)		
L2.LNCO2PC	−3.409		
	(2.154)		
Instruments: l(1/4).(GVC_HH LNGDPPC LNCO2PC)			
Hansen's J chi2(18) = 25.928323 [0.101]			
Panel II: HL	*(1)*	*(2)*	*(3)*
Vars.	*GVC_HL*	*LNGDPPC*	*LNCO2PC*
L.GVC_HL		−0.008	−0.019*
		(0.005)	(0.010)
L2.GVC_HL		0.001	−0.001
		(0.002)	(0.005)
L.LNGDPPC	7.128		
	(6.240)		
L2.LNGDPPC	−2.554		
	(3.850)		
L.LNCO2PC	5.214*		
	(2.766)		
L2.LNCO2PC	−7.999***		
	(2.320)		
Instruments: l(1/4).(GVC_HL LNGDPPC LNCO2PC)			
Hansen's J chi2(18) = 21.312039 [0.264]			
Panel III: LL	*(1)*	*(2)*	*(3)*
Vars.	*GVC_LL*	*LNGDPPC*	*LNCO2PC*
L.GVC_LL		−0.008***	−0.003
		(0.002)	(0.005)
L2.GVC_LL		0.002	0.003
		(0.002)	(0.004)
L.LNGDPPC	3.821***		
	(1.400)		
L2.LNGDPPC	−3.764***		
	(1.286)		
L.LNCO2PC	−2.933***		
	(0.741)		
L2.LNCO2PC	−0.564		
	(0.579)		
Instruments: l(1/3).(GVC_LL LNGDPPC LNCO2PC)			
Hansen's J chi2(9) = 17.510961 [0.041]			
Panel IV: LH	*(1)*	*(2)*	*(3)*
Vars.	*GVC_LH*	*LNGDPPC*	*LNCO2PC*
L.GVC_LH		−0.030***	−0.023
		(0.010)	(0.015)
L2.GVC_LH		−0.002	0.003
		(0.005)	(0.007)
L.LNGDPPC	3.284		
	(2.896)		
L2.LNGDPPC	−0.56		
	(2.275)		
L.LNCO2PC	3.197**		
	(1.361)		
L2.LNCO2PC	−4.056***		
	(0.969)		
Instruments: l(1/4).(GVC_LH LNGDPPC LNCO2PC)			
Hansen's J chi2(18) = 26.724276 [0.084]			

Notes: 1. Robust standard errors are in parentheses and p-values in brackets; 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; 3. Obs. 504 ($N = 63$, $T = 8$).

Table 6
PVAR(1) model regression results by income group.

High income	(1)	(2)	(3)
Vars.	GVC_H	LNGDPPC_H	LNCO2PC_H
L.GVC_H	0.286***	−0.005*	−0.012***
	(0.110)	(0.003)	(0.004)
L.LNGDPPC_H	8.276	0.712***	0.100
	(5.789)	(0.172)	(0.204)
L.LNCO2PC_H	3.955	−0.190***	0.860***
	(2.763)	(0.048)	(0.076)
Obs. 351($N = 39$, T = 9)			
Instruments: l(1/3).(GVC_H LNGDPPC_H LNCO2PC_H)			
Hansen's J chi2(18) = 19.826745 ($p = 0.343$)			
Low income	(1)	(2)	(3)
Vars.	GVC_L	LNGDPPC_L	LNCO2PC_L
L.GVC_L	0.455***	−0.003	−0.002
	(0.100)	(0.002)	(0.004)
L.LNGDPPC_L	−10.637***	0.936***	−0.080
	(2.277)	(0.042)	(0.072)
L.LNCO2PC_L	6.300**	−0.050	1.071***
	(3.205)	(0.063)	(0.101)
Obs. 216 ($N = 24$, T = 9)			
Instruments: l(1/3).(GVC_L LNGDPPC_L LNCO2PC_L)			
Hansen's J chi2(18) = 19.446107 ($p = 0.365$)			

Notes: 1. Robust standard errors are in parentheses and *p*-values in brackets; 2. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

impulse response graphs and cumulative orthogonal impulse response graphs.[12]

4.3.1. Baseline IRF results

Figs. 6.1 and 6.2 show the year-by-year and cumulative impulse response graphs, respectively. The first rows show the responses of LNCO2PC, LNGPDPC, and GVC to a standard deviation shock of LNCO2PC. We found that LNGDPPC has a significantly negative response to a standard deviation shock of LNCO2PC. The cumulative response of LNGDPPC to the shock in LNCO2PC is increasingly negative over the ten-year horizon.[13] A standard deviation shock in LNCO2PC produces a sustained positive impact on GVC, and hence the cumulative response turns out to be increasingly positive.

The second rows show the responses of the three variables to a standard deviation shock of LNGDPPC. LNCO2PC positively responds to a standard deviation shock of LNGDPPC year-by-year, and the cumulative response is increasingly positive over the ten-year horizon. GVC has a negative year-by-year response to the shock on LNGDPPC and the response turns to become positive around the tenth year, thus showing a U-shape. The cumulative response is negative and converges to a negative value in the long run.

The third rows present the responses of the three variables to a standard deviation shock of GVC. A standard deviation shock of GVC increases LNCO2PC in the current period, but the year-by-year response of LNCO2PC then turns negative. The cumulative response of LNCO2PC to the shock in GVC is increasingly negative over the ten-year horizon. The year-by-year response of LNGDPPC to a standard deviation shock of GVC is positive at first, soon turns negative, and then changes to positive again in the fifth period. The cumulative response of LNGDPPC to the shock of GVC turns from negative to positive around the tenth year.

[12] The results obtained from a larger number of repetitions did not produce a significant difference.

[13] Considering that the accuracy of the prediction decreases over time and that our sample covers only eleven years, it is reasonable that the impulse–response graphs in this study show the impulse–response dynamics for ten years (Figs 6.1 and 6.2) or eight years (Figs 7.1 and 7.2). The impulse–response graphs for longer periods are available upon request.

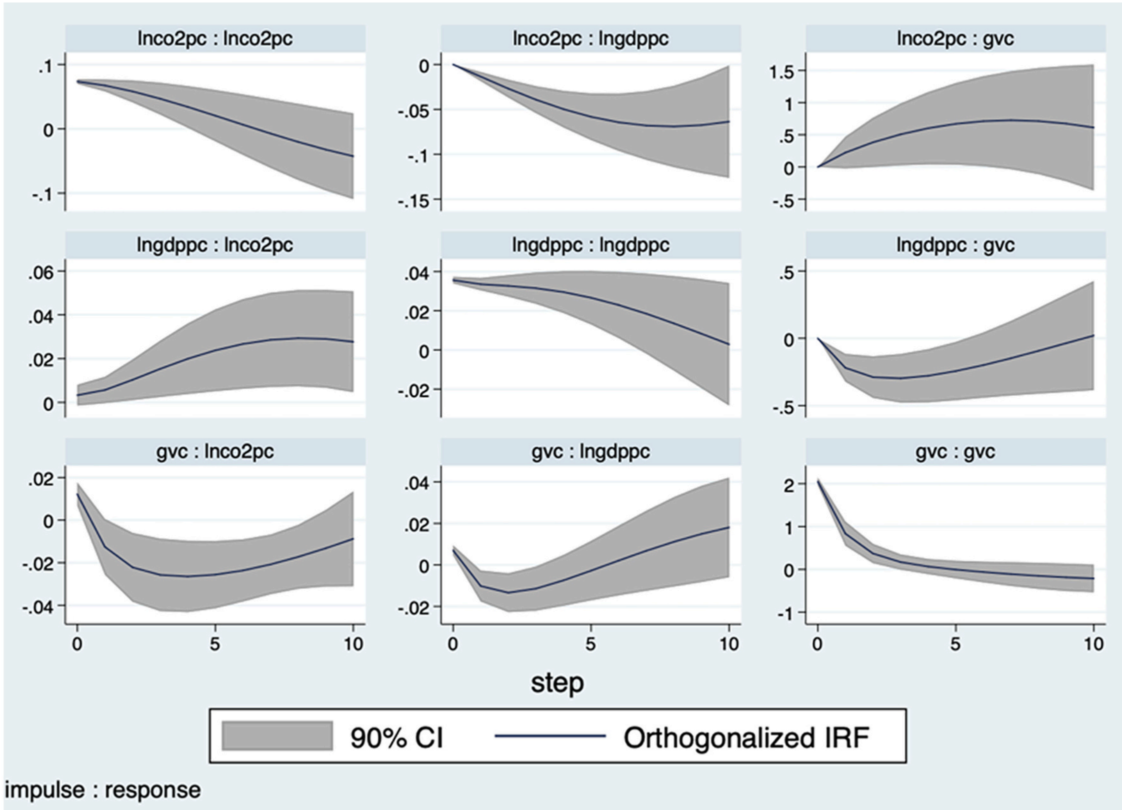


Fig. 6.1. Orthogonalized impulse response.

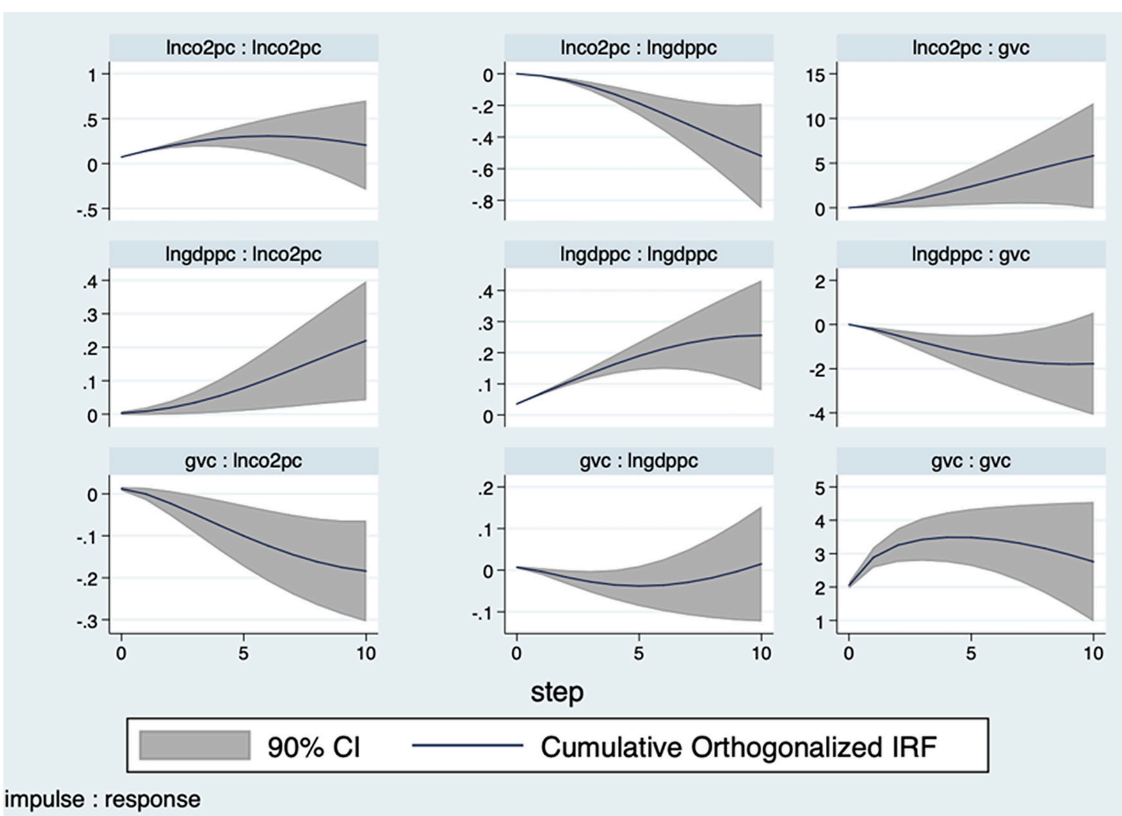
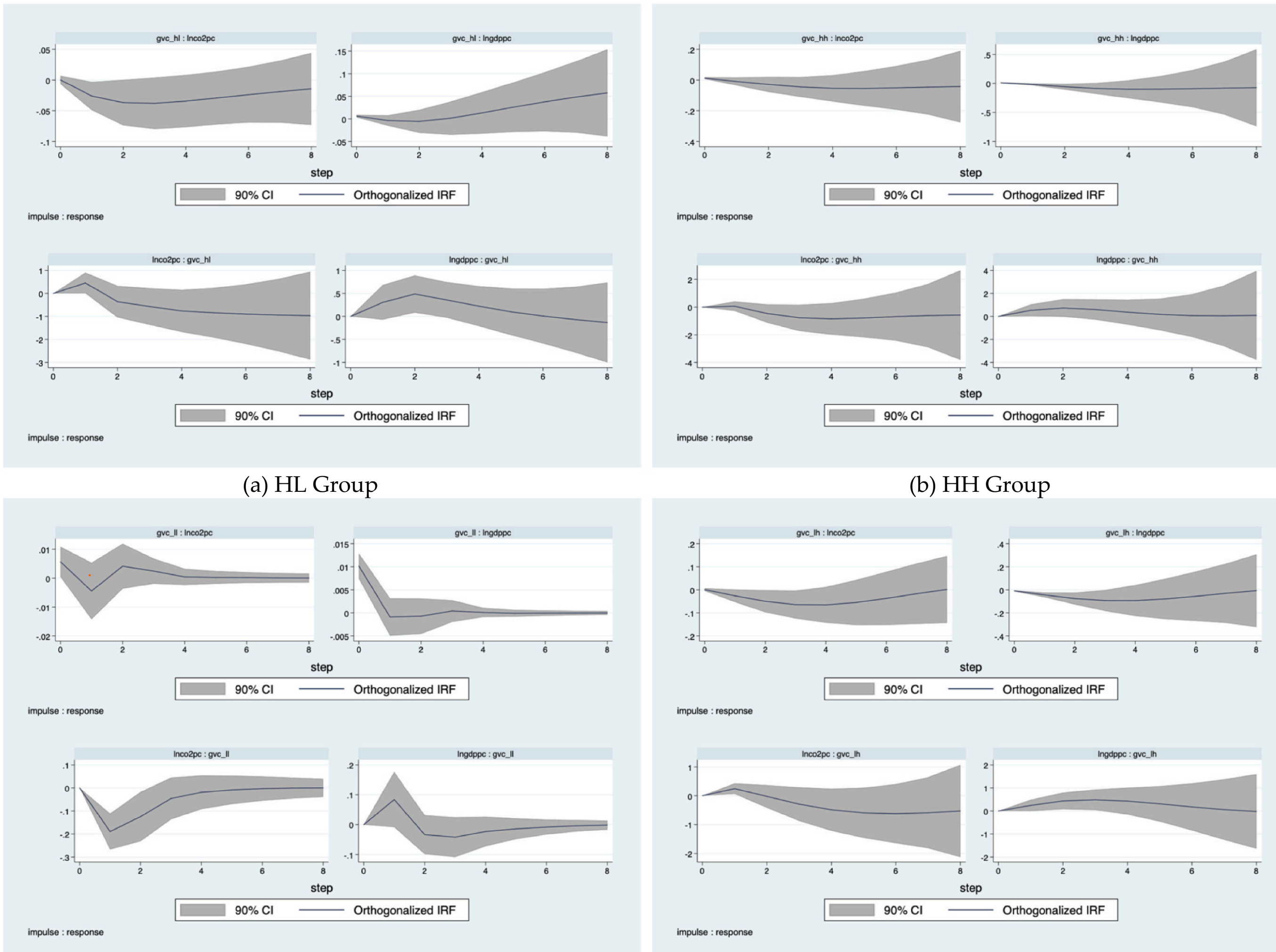


Fig. 6.2. Cumulative orthogonalized impulse response.



(a) HL Group (b) HH Group (c) LL Group (d) LH Group

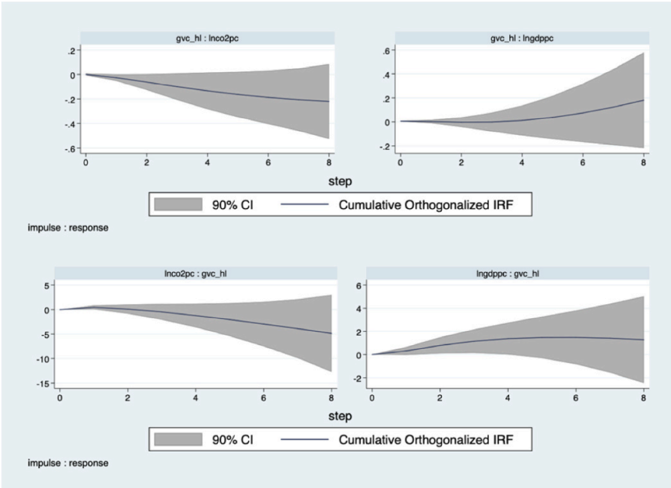
Fig. 7.1. Orthogonalized impulse response by industry group.

4.3.2. *IRF results by industry group*

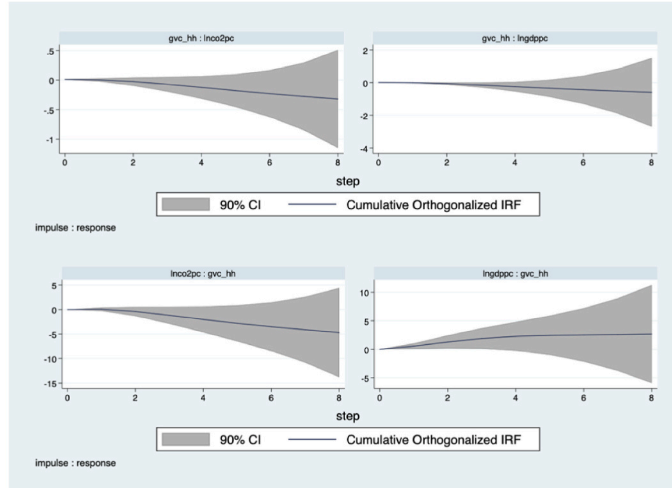
Figs. 7.1 (a) to (d) and 7.2 (a) to (d) show the major year-by-year and cumulative impulse response graphs of industry groups, respectively, for the relationships of primary interest (see footnote 10). We found the following: (1) The year-by-year response of LNCO2PC to a standard deviation shock of GVC participation in the HL group is consistently negative, and thus, the cumulative response is increasingly negative during the ten years. The year-by-year response of LNGDPPC turns from negative to positive in the second year and the cumulative response is increasingly positive during the ten-year horizon. The year-by-year responses of LNCO2PC and LNGDPPC to a standard deviation shock of GVC participation in the HH and LH groups are continuously negative, and the cumulative responses are increasingly negative during the ten years. The cumulative response of LNGDPPC of the HH group is relatively strong, compared to the LH group. The year-by-year responses of LNCO2PC and LNGDPPC to a standard deviation shock of GVC participation in the LL group are positive at first, followed by a brief period of negative responses, and then fade away. The cumulative responses are positive and stable in the long run. (2) With a standard deviation shock of LNCO2PC, the year-by-year responses of GVC participation in the HL, HH, and LH groups are positive and increasing at first, and then gradually decreasing to become negative. The negative year-by-year response of the HL group is the largest in the long term, followed by the HH and LH groups. The cumulative responses of GVC participation in these three groups are positive in the beginning and then become increasingly negative in the long term. The response of GVC participation in the LL group is generally negative and the impulse–response curve presents a U-shape. Consequently, the cumulative response is increasingly negative at first and converges to a negative value in the long run. (3) With a standard deviation shock of LNGDPPC, the year-by-year responses of GVC in the HH and LH groups are continuously positive and inversely U-shaped, and the cumulative responses are increasingly positive and then tend to become relatively stable in the long run. The year-by-year responses of GVC in the HL and LL groups are at first positive and increasing, and then decreasing to become negative. Differently, the year-by-year positive response of the LL group is relatively small and lasts for a relatively short time, compared to the HL group. Thus, the cumulative response of GVC in the HL group is persistently positive, while it is positive at first and becomes negative in the long term in the LL group.

4.3.3. *IRF results by income group*

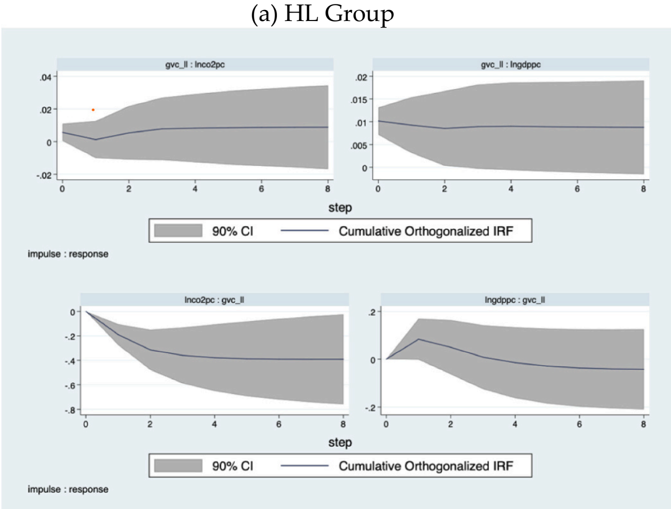
Figs. 8.1(a) and (b) and 8.2 (a) and (b) show the year-by-year and cumulative impulse response graphs of income groups, respectively. We found the following: (1) With a standard deviation shock of GVC, the year-by-year and cumulative responses of LNCO2PC turn from positive to negative, while the year-by-year and cumulative responses of LNGDPPC turn from negative to positive in the high-income group. In



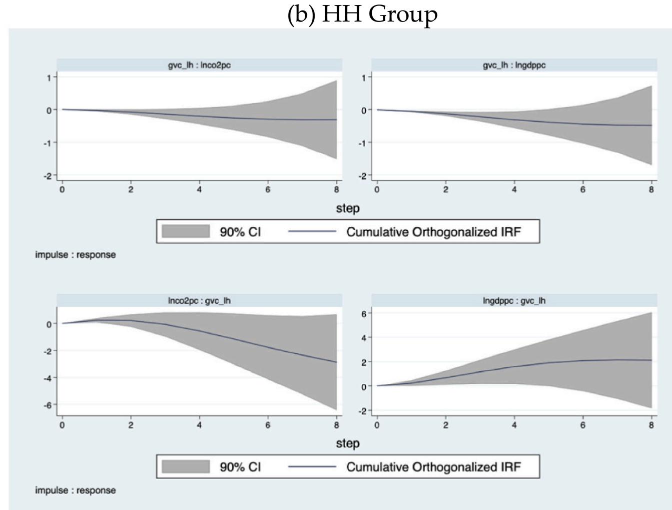
(a) HL Group



(b) HH Group

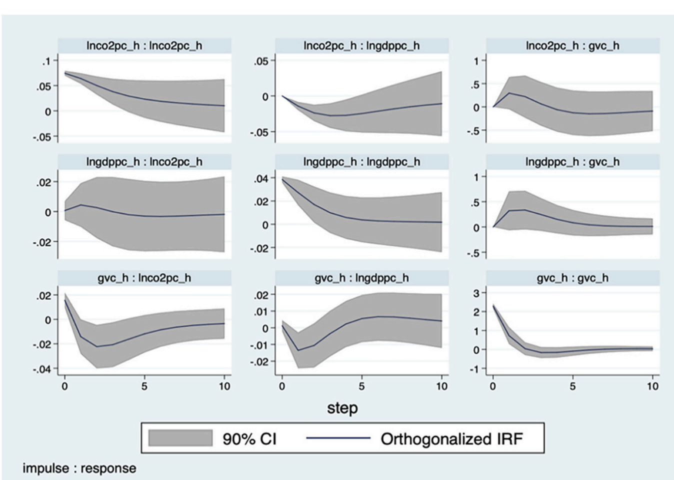


(c) LL Group

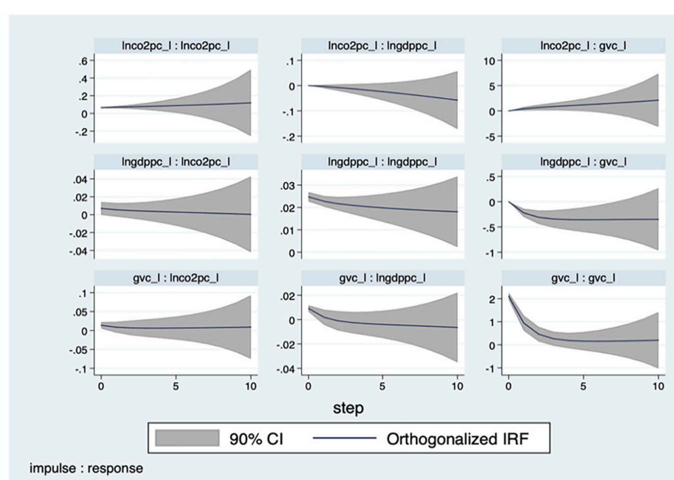


(d) LH Group

Fig. 7.2. Cumulative orthogonalized impulse response by industry group.

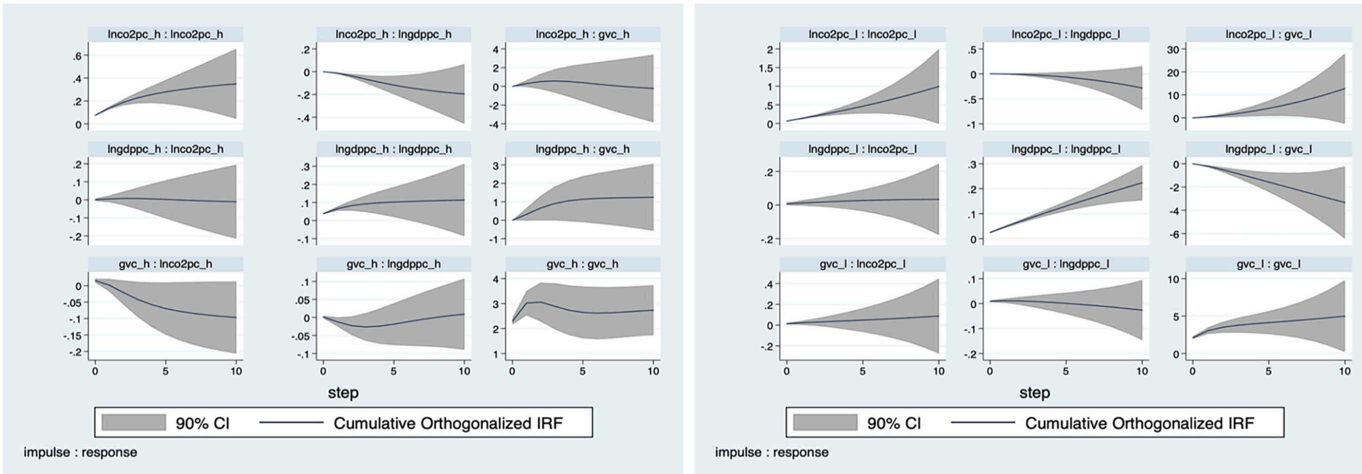


(a) High-income Group



(b) Low-income Group

Fig. 8.1. Orthogonalized impulse response by income group.



(a) High-income Group (b) Low-income Group

Fig. 8.2. Cumulative orthogonalized impulse response by income group.

the low-income group, the year-by-year and cumulative responses of LNCO2PC are continuously positive, while the year-by-year and cumulative responses of LNGDPPC turn from positive to negative. (2) In the high-income group, the year-by-year and cumulative responses of GVC to a standard deviation shock of LNCO2PC are initially increasingly positive and then drop to become negative. The year-by-year response of GVC to a standard deviation shock of LNGDPPC is increasingly positive at first and then decreases to zero, and the cumulative response is increasingly positive. In the low-income group, the year-by-year and cumulative responses of GVC to a standard deviation shock of LNCO2PC are increasingly positive, while the responses to a standard deviation shock of LNGDPPC are increasingly negative. (3) In the high-income group, the year-by-year and cumulative responses of LNCO2PC to a standard deviation shock of LNGDPPC are inverted U-shaped and are negative in the long term. The year-by-year response of LNGDPPC to a standard deviation shock of LNCO2PC is increasingly negative at first and the negative value drops to zero in the long run; thus, the cumulative response is increasingly negative. In the low-income group, the year-by-year and cumulative responses of LNCO2PC to a standard deviation shock of LNGDPPC are increasingly positive, while the reverse responses are increasingly negative.

4.4. *FEVD analysis*

To compare the effect sizes, which reflect the relative importance of different shocks on each of the three variables, we performed a variance decomposition of the PVAR model. We repeated the Monte Carlo simulation 200 times to simulate the first eight forecast periods of the variance decomposition. Tables 7–9 show the results of periods one, four, and eight.

Table 7
Forecast-error variance decomposition.

Response var.		Impulse var.		
	Period	GVC	LNGDPPC	LNCO2PC
	1	100%	0%	0%
GVC	4	88.277%	3.821%	7.901%
	8	65.198%	5.345%	29.458%
	1	3.707%	96.293%	0%
LNGDPPC	4	6.281%	60.614%	33.105%
	8	2.345%	28.138%	69.518%
	1	2.667%	0.196%	97.136%
LNCO2PC	4	8.405%	2.216%	89.379%
	8	15.947%	12.048%	72.005%

Table 8
Forecast-error variance decomposition by industry group.

Panel I: HH		Impulse var.		
Response var.	Period	GVC_HH	LNGDPPC	LNCO2PC
	1		0%	0%
GVC_HH	4		24.036%	16.306%
	8		17.714%	38.613%
	1	4.140%		
LNGDPPC	4	15.093%		
	8	19.459%		
	1	2.781%		
LNCO2PC	4	12.938%		
	8	30.154%		
Panel II: HL		*Impulse var.*		
Response Var.	*Period*	*GVC_HL*	*LNGDPPC*	*LNCO2PC*
	1		0%	0%
GVC_HL	4		10.860%	15.471%
	8		6.801%	46.912%
	1	2.688%		
LNGDPPC	4	0.581%		
	8	8.211%		
	1	0.001%		
LNCO2PC	4	16.618%		
	8	23.064%		
Panel III: LL		*Impulse var.*		
Response var.	*Period*	*GVC_LL*	*LNGDPPC*	*LNCO2PC*
	1		0%	0%
GVC_LL	4		0.894%	4.734%
	8		0.967%	4.770%
	1	6.840%		
LNGDPPC	4	4.278%		
	8	4.273%		
	1	0.714%		
LNCO2PC	4	1.204%		
	8	1.202%		
Panel IV: LH		*Impulse var.*		
Response var.	*Period*	*GVC_LH*	*LNGDPPC*	*LNCO2PC*
	1		0%	0%
GVC_LH	4		22.058%	6.640%
	8		18.813%	34.569%
	1	2.844%		
LNGDPPC	4	38.882%		
	8	48.314%		
	1	0.012%		
LNCO2PC	4	27.978%		
	8	26.289%		

Table 9
Forecast-error variance decomposition by income group.

High-income		*Impulse var.*		
Response var.	*Period*	*GVC_H*	*LNGDPPC_H*	*LNCO2PC_H*
	1	100.000%	0.000%	0.000%
GVC_H	4	93.310%	4.447%	2.243%
	8	91.944%	4.872%	3.183%
	1	0.103%	99.897%	0.000%
LNGDPPC_H	4	6.956%	58.726%	34.318%
	8	6.366%	39.580%	54.054%
	1	4.224%	0.007%	95.768%
LNCO2PC_H	4	9.147%	0.178%	90.675%
	8	10.744%	0.343%	88.913%
Low-income		*Impulse var.*		
Response var.	*Period*	*GVC_L*	*LNGDPPC_L*	*LNCO2PC_L*
	1	100.000%	0.000%	0.000%
GVC_L	4	77.723%	3.598%	18.680%
	8	39.708%	5.274%	55.018%
	1	12.070%	87.930%	0.000%
LNGDPPC_L	4	4.043%	86.172%	9.784%
	8	2.332%	50.413%	47.255%
	1	4.121%	1.052%	94.827%
LNCO2PC_L	4	1.617%	0.528%	97.855%
	8	0.958%	0.259%	98.783%

4.4.1. Baseline FEVD results

Observing Table 7, we found that: (1) The variation of each of the three variables is largely due to their disturbances, and the importance of these disturbances decreases over time. (2) Eight periods ahead, the variations of GVC and LNGDPPC explain approximately 16% and 12%, respectively, of the variation in LNCO2PC, increasing at longer periods. LNCO2PC in turn contributes to the GVC and LNGDPPC, again increasing at longer periods. After eight periods, LNCO2PC explains around 29.5% and 69.5% of the total variations in GVC and LNGDPPC, respectively. (3) LNGDPPC explains only about 5.3% of the variation in GVC eight periods ahead, and the effect is stable over time. The contribution of GVC to the variation in LNGDPPC is as low as 3.7% one period ahead, and the magnitude grows to nearly 6.3% four periods ahead and then decreases to 2.3% eight periods ahead, thereby displaying an inverted U-shape.

4.4.2. FEVD results by industry group

Table 8 presents the major variance decomposition results by industry group for the relationships of primary interest (see footnote 10). We mainly found the following: (1) Eight periods ahead, GVC in HH and LH explains 19.4% and 48.3% of the variation of LNGDPPC, greater than the variation explained for short periods, while GVC in HL and LL explains only 8.2% and 4.3% of the variation in LNGDPPC, respectively. (2) The contributions of GVC in HH and HL to the variation in LNCO2PC eight periods ahead are 30.2% and 23.1%, respectively, and are increasing over time, while those of GVC in LL and LH are 1.2% and 26.3%, respectively, in a decreasing manner. (3) Observing the eighth period, we found that LNCO2PC accounts for 46.9% and 38.6% of the variation in GVC in HL and HH, respectively, followed by LH (34.6%) and LL (4.8%). LNGDPPC explains 18.8% and 17.7% of the variation in GVC in LH and HH, respectively, while it explains only 6.8% and 0.97% of the variation in GVC in HL and LL, respectively.

4.4.3. FEVD results by income group

Table 9 presents the variance decomposition results by income group. We mainly found the following: (1) GVC explains 10.7% of the variation in LNCO2PC eight periods ahead in the high-income group in an increasing manner, while it explains only 0.96% of the variation inLNCO2PC in the eighth period in the low-income group in a decreasing manner. Moreover, the contribution of GVC to the variation in LNGDPPC eight periods ahead in the high-income group is 6.4% and is generally increasing over time, while in the low-income group, the contribution is 2.3% in a decreasing manner. (2) Observing the eighth period, we found that LNCO2PC accounts for 3.2% and 55.02% of the GVC variation in the high- and low-income groups, respectively. LNGDPPC explains 4.9% and 5.3% of the GVC variation in the high- and low-income groups, respectively. (3) Observing the eighth period, we found that the contributions of LNGDPPC to the variations in LNCO2PC in the high- and low-income groups are 0.343% and 0.259%, respectively. Moreover, LNCO2PC accounts for 54.054% and 47.255% of the variations in LNGDPPC in the high- and low-income groups.

4.5. Robustness checks

We performed three robustness checks. First, we checked the sensitivity of our impulse responses and variance decompositions to the ordering of the three variables. Second, we assessed the potential of spatial correlation by spatial clustering of the errors. Third, we examined the sensitivity of our results to specifying a lag length of one period rather than two. These results for robustness checks are available on request.

4.5.1. Reorder of variables in the model

The impulse response results of the panel VAR could be affected by the order of variables in the model. To check the robustness of our results with the order of {GVC, LNGDPPC, LNCO2PC}, we tried the other five possible orders and found the following: (1) At the aggregate level, the results of the PVAR regressions, year-by-year impulse-response (OIRF) dynamics, cumulative impulse-response (COIRF) dynamics, and forecast-error variance decompositions (FEVDs) are generally in line with those shown in this paper. (2) As GVC participation in different industry groups is considered, the PVAR regression results are consistent. The OIRF and COIRF dynamic results are robust for all groups except for the LL group. As the order changes, the results of the LL group are slightly different from those we presented in this paper and the differences occur in the first or second periods. Further, the results of FEVD are mostly robust, and slight differences are mainly found in the HL and LL groups. (3) As income groups are considered, the PVAR regression results are consistent. The OIRF and COIRF dynamic results are robust for all groups, especially for the high-income group. The results of FEVD are also mostly robust, and slight differences are mainly found in the low-income group.

4.5.2. Spatial dependence

Given some evidence of cross-sectional dependence, one solution is to apply a recently developed spatial panel VAR modeling approach introduced by Civelli et al. (2018) for a two-variable case. However, as noted by Civelli et al. (2018, p. 81), "…the spatial terms are not exogenous by construction because they are correlated with the current innovations to the endogenous variables." The issue of causality is problematic in spatial lag models and not readily solvable with instrumental variables (Gibbons and Overman, 2012).[14] Because our focus is not estimating the spatial spillovers among countries, and the ordering of causality among countries in impulse response analysis and variance decompositions would be somewhat arbitrary, adding significant complexity to the ordering of the innovations in the three variables, we do not estimate a spatial panel model.

But to mitigate the effects of spatial correlation that may affect the baseline results, we attempted to account for cross-sectional dependence by using a clustered standard error approach that grouped 63 countries and regions by their continents. The approach mitigates the potential effects of spatial correlation on estimated standard errors and increases the efficiency of the slope estimates in the baseline results. We found the

[14] Time-lagged spatial variables may not better capture the relationships between spatial units than current-period variables. The time-lagged variables may simply be more exogenous econometrically but not reflect true causality.

following: (1) At the aggregate level, though the scale of some coefficients changed, the results of the PVAR regressions and FEVDs are generally robust. The changes in ORIF mainly take place in the medium run and thus the convexity of ORIF only slightly differs, while the CORIF is relatively more robust. (2) As the industry groups are considered, besides the changes in the scale of coefficients of PVAR(2) regressions, a few coefficients' significance and/or signs have changed for the HH, HL, and LH groups. The ORIFs, CORIFs, and FEVDs of these groups are slightly different as well. (3) When considering income groups, the scale of coefficients from PVAR(1) regressions changed. Except for the effect of the 1-period lag of LNGDPPC on GVC that turned from insignificantly positive to significantly negative in the high-income group, the signs of other coefficients are generally robust. The ORIFs and CORIFs are consistent in the low-income group, while slightly different in the high-income group, especially in the short- and medium-run. The FEVD results are slightly different as well, especially in the high-income group. The results showed that high-income countries are more likely to exhibit spatial correlation.

4.5.3. *Specifying a different lag length*

Referring to GVC participation in different industry groups, we presented results based on 2-period lags. While the results of MAIC, MBIC, and MQIC showed that the 1-period lag regressions are preferred in the HL and LL groups, the results of MBIC and MQIC showed that the 1-period lag is preferred in the HH group and the result of MQIC revealed that the 1-period lag is preferred in the LH group. Therefore, we tried the PVAR(1) regressions as well as ORIF, CORIF, and FEVD in industry group analyses and did not find significant differences.

In sum, our results are generally robust and the aforementioned hypotheses (H1, H2, H3a, and H3b) are verified by our results.

5. Discussion

5.1. *The effects of GVC on LNCO2PC and LNGDPPC*

The empirical results show that: (1) GVC will reduce LNCO2PC, consistent with Yao et al. (2021), and increase LNGDPPC in the long term, in line with Kowalski et al. (2015) and Ignatenko et al. (2019), though it may decrease LNGDPPC in the short term. They are the combined results of the scale, technique spillover, composition, and competition effects, as discussed in Wang et al. (2019). Some of the effects are positively associated with LNCO2PC and LNGDPPC, while others are negatively associated. In the long run, GVC's negative impact on LNCO2PC and the positive impact on LNGDPPC dominate. Additionally, the deeper the GVC participation degree, the more a participant country will be affected by international markets. When a GVC-participating country suffers adverse shocks, the negative impacts will spread to other GVC participants, and vice versa. During the period of interest, the economies of most countries in the sample were severely affected by the 2008 global financial crisis, and many of them took a long time to recover. To a certain degree, this probably explains the short-run adverse effect of GVC on LNGDPPC.

(2) GVC participation in different industries will affect LNCO2PC heterogeneously, similar to the results of Wang et al. (2019). GVC participation in high-CO_2 industries (HH and HL) shows higher impacts on LNCO2PC than in low-CO_2 industries (LH and LL). GVC participation in different industries will also affect LNGDPPC heterogeneously, consistent with Kordalska et al. (2016) and Formai and Vergara Caffarelli (2015). GVC participation in high value-added industries shows higher impacts on LNGDPPC. This result was expected because high-CO_2 industries are relatively sensitive to CO_2-related shocks, and low value-added industries have smaller impacts on a country's GDP, and vice versa.

Specifically, in the long run, GVC participation in high-CO_2 industries (HH and HL) will reduce LNCO2PC, and that in low value-added industries (HL and LL) will enhance LNGDPPC. GVC participation in HL industries may be the best scenario because it will reduce LNCO2PC while enhancing LNGDPPC. Moreover, GVC participation in LH industries can reduce LNCO2PC but worsen LNGDPPC. This result proves that the scale, technique spillover, composition, and competition effects play heterogeneous roles in different industries, which is reasonable considering the various production characteristics of industries.

(3) The responses of LNCO2PC and LNGDPPC to GVC vary by income. The responses in the high-income group are stronger than those in the low-income group, which is in line with the findings of Kummritz (2015) and Fagerberg et al. (2018). Further, in the high-income group, the response of LNCO2PC is generally negative and that of LNGDPPC turns from negative to positive. In the low-income group, the response of LNCO2PC is generally positive and that of LNGDPPC turns from positive to negative. In other words, in the long run, through participating in GVCs, high-income countries could benefit in terms of higher LNGDPPC and lower LNCO2PC, while both economic and carbon emission conditions worsen in low-income countries.

High-income countries usually have comparative advantages in high-tech and capital-intensive commodities. With participation in GVCs, high-income countries can focus on producing these commodities by transferring labor-intensive and energy-intensive production abroad, as discussed by Duan et al. (2021). The composition and scale effects lead to a reduction in LNCO2PC but may result in the increase or decrease of LNGDPPC. Further, according to Ivarsson and Alvstam (2010), Zhang and Gallagher (2016), and Reddy et al. (2020), GVCs make the spread of technologies worldwide easier and faster; to keep comparative advantages in intensive international competition, high-income countries are motivated to continuously innovate and upgrade technologies, which is conducive to their economies and natural environments. In brief, the responses of LNCO2PC and LNGDPPC to GVC are the comprehensive results of scale, composition, technique spillover, and competition effects.

Low-income countries generally have comparative advantages in labor- and energy-intensive commodities. By participating in GVCs, the scale and composition effects expand the production of these commodities, which stimulates economic growth while exacerbating carbon emissions. The positive effects of technology spillovers on economic growth and carbon reduction might not occur in low-income countries. First, measures, such as patent protection, have prevented high-income countries from spilling over technologies to low-income countries (Sanyal, 2004; Saggi, 2007). Second, the R&D, education, and infrastructure of low-income countries are usually in poor condition, which may not support the effective application of advanced technologies. Moreover, the competition effect may force low-income countries to reduce their high-polluting production to meet international environmental standards, but they may not be capable of expanding environmentally-friendly production. Therefore, low-income countries may not be able to directly benefit from participating in GVCs for a considerable period.

5.2. *The effects of LNCO2PC and LNGDPPC on GVC*

(1) LNCO2PC will positively affect GVC, which can be due to the carbon transfer effect (Zhang et al., 2017; Ben-David et al., 2018) and environmental protection effect (Do Paço et al., 2009; Glucker et al., 2013). On the one hand, countries may use GVC participation as an effective measure to deal with CO_2 emissions (Wang et al., 2019). On the other hand, the increased production, or the lower environmental standards, which result in higher LNCO2PC, may be conducive to GVC participation, especially in low-income countries. LNGDPPC will negatively affect GVC. As discussed, GVC participation may stimulate or reduce GDP growth. If the stimulation effect dominates, countries will take measures to enhance GVC participation, otherwise, they will reduce GVC participation. A possible explanation for the negative effect of LNGDPPC on GVC is that the unfavorable aspects of GVC participation are gradually emerging as the anti-globalization sentiment increases

(Meyer, 2017; Branicki et al., 2021).

(2) GVC participation in different industries shows heterogeneous responses to changes in LNCO2PC and LNGDPPC. As LNCO2PC increases, GVC participation in high-CO_2 industries (HH and HL) as well as low-CO_2, high value-added industries (LH) will increase at first and then decrease in the long run. The positive response may result from the negative effect of GVC participation in these industries on LNCO2PC. The consequent negative response implies, to a certain extent, that GVC participation in these industries may be an effective but not optimal way to reduce LNCO2PC in the long run. A possible reason is an adverse effect of participating in GVCs. Increased participation in GVCs raises the dependence on international markets and the susceptibility to global economic fluctuations. Therefore, in the long run, countries tend to find better CO_2 solutions to replace GVC participation, such as clean energy and clean technologies. Moreover, GVC participation in low-CO_2, low value-added (LL) industries will decrease as LNCO2PC increases, because it will aggravate CO_2 emissions, as discussed above.

LNGDPPC positively affects GVC in all the groups during a relatively short period, and thereafter, negatively affects them over a relatively long period, thus showing an inverted U-shape. Further, the positive responses of GVC in the high value-added groups (HH and LH) are relatively larger and last relatively longer. The responses of GVC in the low value-add groups (HL and LL) become negative relatively earlier and the negative scales are relatively larger. Considering that the cumulative effects of GVC in high value-added groups on LNGDPPC are negative while the cumulative responses of GVC in those groups to LNGDPPC are positive, we believe that high value-added industries (HH and LH) mainly receive non-economic benefits (e.g., carbon reductions) from GVC participation, which is in line with the negative effects of GVC participation in HH and LH on LNCO2PC discussed above.

The cumulative response of GVC participation in HL industries to LNGDPPC is positive. This result is in line with our expectations since GVC participation in HL industries can promote economic growth and meanwhile reduce CO_2 emissions as discussed above. The cumulative effect of GVC in LL on LNGDPPC is positive while the cumulative response of GVC in LL industries to LNGDPPC turn from positive to negative. It implies that although GVC participation promotes the economic growth of LL industries, it brings about adverse effects on non-economic fields, such as CO_2 emissions, which is in line with the positive cumulative effect of GVC participation in LL on LNCO2PC discussed above. As economies develop, countries will pay more attention to the environment.

(3) The responses of GVC to the changes of LNCO2PC and LNGDPPC are different across income groups. The impact of LNCO2PC on GVC turns from positive to negative in the high-income group. This result again confirms our argument that GVC participation can be effective but might not be optimal in reducing CO_2 emissions. The impact of LNGDPPC on GVC is generally positive. As economies develop, high-income countries will benefit more from GVCs because they will be more powerful to take advantage of the global market. As the positive effects of GVC participation overcome the adverse effects, high-income countries will enhance GVC participation.

The response of GVC to LNCO2PC is generally positive in low-income countries, although GVC participation will enhance their LNCO2PC. This situation is largely because GVC participation can bring about economic benefits to low-income countries (Gereffi, 1999; Humphrey and Schmitz, 2002), which explains the short-term increase of GVC with LNGDPPC to a certain degree. Low-income countries tend to give priority to economic growth (Liu et al., 2018) even at the expense of the environment. However, in the long run, when the negative effects of GVC on LNGDPPC play leading roles in low-income countries (Fagerberg et al., 2018), GVC participation declines as LNGDPPC increases. This result shows that as their economies develop to a certain extent, low-income countries will reduce GVC participation to avoid the negative impacts on their economies and environments. Higher LNGDPPC will provide low-income countries with more opportunities to introduce better measures, such as advanced technologies and clean energy, to protect the environment while developing their economies. Moreover, low-income countries may lose their low-cost comparative advantages from economic growth but have not yet developed new comparative advantages. In this case, it seems that their GVC participation degrees will be lower as economies develop since their GVC positions may be replaced by other low-income countries (Song and Wang, 2017).

5.3. The dynamics between LNCO2PC and LNGDPPC

Similar to those who have confirmed the existence of an EKC (Grossman and Krueger, 1991; Ang, 2007; Charfeddine, 2017; You and Lv, 2018), the response of LNCO2PC to LNGDPPC is found to be generally positive over time and presents an inverted U-shaped relationship. It indicates that in the early stage of economic growth, the scale effect dominates the effect of LNGDPPC on LNCO2PC. In this stage, the energy consumption required by economic development will stimulate LNCO2PC. As time goes by, economic development will promote technological progress, industrial composition adjustment, and environmental protection awareness, thus inhibiting CO_2 emissions. We may reasonably speculate that economic growth will result in CO_2 reduction if observed over a longer period. Referring to the effect of LNCO2PC on LNGDPPC, we found that it is generally negative, in line with the findings of Magazzino (2016a) on the South Caucasus area and those of Magazzino (2016b) on GCC countries, and presents a U-shaped curve. This result implies that reducing production may lower CO_2 emissions in the short run, but it is not an optimal carbon reduction measure and will not be chosen if better feasible measures are available to fix carbon-related issues.

When different income groups are considered, the dynamic relationships vary substantially. In the high-income group, the response of LNCO2PC to LNGDPPC presents an inverted U-shape, which is consistent with the baseline result. It also turns from positive to negative over time, thereby confirming our speculation discussed above. In the low-income group, the response of LNCO2PC to LNGDPPC is increasingly positive, thus showing that the technique spillover and competitive effects may not be fully utilized by low-income countries. These countries tend to prioritize economic growth; therefore, the negative impacts of the scale and composition effects on the environment dominate. The effects of LNCO2PC on LNGDPPC are generally negative in both groups, however, the effect presents a U-shape in the high-income group, while it is decreasingly negative in the low-income group. We have discussed that reducing production can reduce emissions, but it is not the best way. Clean technology and clean energy are better measures to reduce emissions (Soytas et al., 2007; Sbia et al., 2014; Magazzino, 2016d). However, their applications require that economies advance to a certain stage of development. Low-income countries may have not crossed those thresholds and must sacrifice production if they choose to reduce carbon emissions.

6. Conclusions and policy implications

This study applied the PVAR approach, using data for 63 countries and regions over the period 2005–2015, to analyze the dynamic relationships between GVC participation, CO_2 emissions, and economic growth and the underlying mechanisms of these relationships. Special attention was paid to the impacts of GVC participation on CO_2 emissions and GDP, in an attempt to unveil the relationship between GVC participation and sustainable growth. The empirical results support all hypotheses proposed. The major findings are: First, GVC participation is conducive to environmentally-friendly growth. The year-by-year and cumulative responses of per capita GDP to a standard deviation shock of GVC are positive in the long run, while those of per capita CO_2 emissions are negative. The FEVD results show that GVC participation explains 6.3% of the per capita GDP variation four periods ahead, and 16% of the variation of per capita CO_2 emissions eight periods ahead. These results are attributed to the mixed results of scale, technique spillover, composition, and competition effects. Second, we found evidence of heterogeneous effects between different industry groups. GVC participation in high-CO_2 emission industries has greater impacts on CO_2 emissions, and that in high value-added industries have greater impacts on GDP. GVC participation in high CO_2 emission and low value-added industries contributes to economic growth and carbon reductions. GVC participation in other industries contributes either to economic growth or carbon reductions. Heterogeneous characteristics of industries make the aforementioned four effects work differently. Third, high-income countries benefit more from GVC participation in terms of economic growth and CO_2 reductions. Several factors prevent low-income countries from thoroughly benefiting from GVC participation, such as comparative disadvantages in capital-intensive and high-tech production, inefficient application of advanced technologies, and weak reactions to adverse shocks from international markets.

Other findings include: First, GVC participation has a long-run positive response to per capita CO_2 emissions and a negative response to per capita GDP. The variation of per capita CO_2 emissions explains a larger share of GVC variations, especially in high-CO_2 groups. These results may imply that participating in GVCs is a feasible measure to deal with emissions, but that countries would reduce GVC participation as they become increasingly developed, probably due to the side effects brought by high dependencies on international markets. Second, the impact of per capita CO_2 emissions on GVC participation varies by industry and income, so does per capita GDP. Specifically, per capita CO_2 emissions present a larger impact on GVC participation in high-CO_2 industries, and per capita GDP presents a larger impact on GVC participation in high value-added industries, which is to be expected considering the industries' characteristics. Moreover, both per capita CO_2 emissions and per capita GDP have larger impacts on the GVC participation of low-income countries. A possible reason is that these countries have relatively lower GVC participation degrees, and hence are easier to have larger changes. Another possible reason is that low-income countries may not have better alternatives to deal with economic or environmental shocks. Third, per capita CO_2 emissions increase as per capita GDP increases, and an increase in per capita CO_2 emissions will lead to a decrease in per capita GDP. This dynamic relationship varies by income. The impact of per capita GDP on per capita CO_2 emissions presents an inverted U-shape and is negative in the long term in high-income countries, while it is increasingly positive in low-income countries. The impact of per capita CO_2 emissions on per capita GDP is negative, and presents a U-shape in high-income countries, while it is increasingly negative in low-income countries. The impact of per capita GDP on per capita CO_2 emissions, in line with existing studies, is the comprehensive result of four effects. Countries would rather reduce production to deal with CO_2 emissions, which reflects the growing public awareness of the environment and the lack of better alternative measures to tackle emissions, especially in low-income countries.

Accordingly, important policy implications emerge as follows: First, countries should take measures to actively participate in GVCs, such as lowering tariffs and non-tariff barriers, encouraging international communication, enhancing mutual understanding, etc. Meanwhile, countries should pay attention to the knock-on effects of trading partners suffering negative shocks from events such as financial crises, wars, or a pandemic. Lowering or withdrawing from GVCs is not the optimal solution to deal with the adverse effects. While integrating into international markets, countries must not neglect the development of their domestic markets. It is critical to maintain some independence in the domestic economy and not rely too heavily on trading partners. China's domestic and international dual-cycle development strategy could be a case for reference. Second, during the process of participating in GVCs, high-income countries should continue to strengthen their comparative advantages in technology and capital-intensive production and lower technological thresholds, promoting technology spillovers to low-income countries. Low-income countries should improve domestic human capital and infrastructure to efficiently utilize the technique spillover effects. In addition, low-income countries should optimize domestic production composition, shifting their competitiveness from low environmental standards to high-quality clean products. Third, countries should not blindly favor GVC participation in industries with high value added and low carbon emissions. In cases where GVC participation lowers CO_2 emissions, the effect of carbon reduction is more pronounced when countries participate in the GVCs of high-carbon emission industries. Similarly, countries should be aware that the domestic economy is more likely to be affected by adverse shocks on the international market when they participate in the GVC of high value-added industries.

Finally, reducing production is not the optimal solution to tackle environmental problems. Instead, improving energy efficiency and promoting energy diversity are better solutions (Omri, 2013; Magazzino, 2016d)). Specifically, countries should increase investments in R&D and education, encouraging independent innovation in energy-saving technologies (Magazzino and Cerulli, 2019); actively use clean and renewable energy, such as solar, wind, and nuclear energy; and enhance public awareness of low-carbon production and consumption. Governments should set clear carbon reduction targets (Magazzino, 2015). For example, China proposed that CO_2 emissions will peak around 2030, the proportion of non-fossil energy in primary energy consumption will increase to about 20% by 2030, and CO_2 emissions per GDP will drop by 60–65% compared with 2005 in 2030. Moreover, policymakers can supervise environmental pollution behaviors through legislation and regulations, such as carbon tax. They can also allocate special funds to financially motivate low-carbon behaviors, like subsidies for purchasing electric vehicles.

7. Limitations and future research

This study is not without limitations. First, although the results of the unit root tests in this study generally support (trend) stationarity, there were a few exceptions when allowing for cross-sectional dependence. Tobler's first law of geography pointed out that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970). To check the robustness of our results, we considered spatial interdependence by spatially clustering the errors, assuming that unobserved components in outcomes for units (countries) within clusters (continents) are correlated, but we did not estimate spatial spillovers. Second, countries' positions on the GVCs are different, which implies they are responsible for different phases of production and thus in turn lead to different CO_2 emissions and economic growth. This is an issue unexplored in this paper. Third, this study is limited by data availability.

Future research could attempt to account for cross-sectional dependence where it occurs by constructing a spatially correlated matrix (Zhu et al., 2022) and estimating spatial spillovers (e.g., the spatial panel VAR model as used in Civelli et al. (2018)), though the issue of identifying causal relationships across space remains a challenge. Further improvements could include incorporating the position index of a country's industries within GVCs (Koopman et al., 2014; Liu et al., 2018; Ye et al., 2020), and covering more countries and regions over a longer period.

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