



Complex network analysis of carbon emission transfers under global value chains

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Abstract

Accompanied with the increasing complicated global value chain (GVC) networks is the carbon emission transfers among countries. Utilizing the complex network analysis alongside quadratic assignment procedure (QAP), this paper detects the community structure and influencing forces of the emission transfers under GVCs. The results imply that the bipolar structure of the network transformed gradually to tripolar owing largely to the surging of carbon emissions from China. Evidence on the existence of environmental Kuznets curve (EKC) in the emission transfers from high-income countries to low-income countries, and a U-shape relationship transfers in the reverse direction, suggesting that growing carbon emissions from both low- and high-income countries transferred to other high-income countries gradually. Gaps in technology, especially in patent applications, between source and destination countries played an important role therein.

Keywords Carbon emission transfer · Global value chains · Complex network · Quadratic assignment procedure · Environmental Kuznets curve (EKC) · Technology gaps

JEL Classification F14 · F18 · Q56 · R15

Introduction

The Leaders Summit on Climate in April 2021 put the carbon emission restrictions again in the spotlight. Thus far, more than 127 countries have promised to realize carbon neutrality by mid-twenty-first century. As a matter of fact, the rapid development of global value chain (GVC) networks intensify the multinational carbon emission transfers, making it more cumbersome and difficult to account and harmonize the carbon responsibilities. The time one country or

area specializes in one or more production stages in GVCs, carbon emissions embodied in the exported value added are transferred to other countries at the same time. According to studies, roughly a quarter of carbon emissions in the world were associated with trade (Andrew and Peters 2013), whereas more than 80% of which occurs in GVCs (UNCTAD 2013). Increasingly, value added flows within GVCs intensify the carbon emission transfers among countries or regions, thus bringing more difficulties in coordinating the responsibilities for carbon emissions. This study on the complex network analysis of carbon emission transfers under GVCs attempts to explore the key influencing factors and figure out the efficient carbon reduction measures for the sake of promoting carbon neutrality, which is an urgent and tricky issue for developing countries, in particular, China.

Extant efforts on the decomposition of GVC and carbon emissions embodied in trade on the basis of multi-regional input–output (MRIO) models provide a solid foundation for our study (Peters 2008; Kanemoto et al. 2012; Pei et al. 2016; Meng et al. 2018). This branch of studies can be generally classified into three strands: the first strand, represented by Meng et al. (2013) and Liu et al. (2015), placed emphasis on China’s inter-regional carbon emissions

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embodied in commodities for domestic final consumption and those for export based on technical coefficients matrix; the second strand, such as Meng et al. (2018) and Yan et al. (2020), explored the carbon emissions embodied in final goods and intermediate trade in value-added with the application of accounting frameworks proposed by Koopman et al. (2014); the third strand, like Assamoi et al. (2020) and Xiao et al. (2020), calculated the carbon emission intensity (CEI) embodied in simple and complex GVC trade according to decomposition framework put forward by Wang et al. (2017), which was actually developed from Koopman et al. (2014). By using the method in Wang et al. (2017), our study bears more similarity with the third strand but foci on the carbon emission transfer networks under GVC instead of CEI. The measurement of the carbon content in trade is to track one country's emission footprints (Zafrilla et al. 2014; Kanemoto et al. 2016; Meng et al. 2018), carbon leakage (Levinson 2009; Aichele and Felbermayr 2015), responsibility distribution (Bastianoni et al. 2004; Lenzen et al. 2007), and so on. As concluded in most studies, the carbon emissions embodied in trade flows increased dramatically accounting for more than one quarter of global carbon emissions (Andrew and Peters 2013; Xiao et al. 2020; Liu et al. 2021). Particularly, carbon emission transfers through trade flows from developing economies to developed economies attracts growing attention (Ding et al. 2018; Kondo 2018; Zheng 2021). Moreover, the trade imbalance appeared to aggravate such transfers, allowing rich economies to further offshore their pollution to poor economies. Similarly, the studies on the pollution haven effect reveal that high-income countries are net pollution importers while low-income countries are net exporters (Serrano and Dietzenbacher 2010; Zhang et al. 2017).

With the development of global production sharing, a growing number of studies engage in tracing the changes in carbon intensity (Xiao et al. 2019, 2020; Zhao and Liu 2020) or accounting carbon emissions embodied in the value-added chains (Pei et al. 2016; Meng et al. 2018; Liu et al. 2021). This line of studies have substantial theoretical and methodological overlap with those on consumption-based accounting of value-added trade in Wang et al. (2017), providing a more comprehensive picture of carbon emissions under GVC participation. From the perspective of consumption-based carbon content of trade in value-added, developed countries turn out to have higher carbon emissions collectively than developing countries, which however bear a greater proportion of emission responsibilities (Banerjee 2021; Zheng 2021). Such unfair responsibility distribution to some extent reveals that the developed nations benefit from GVCs through offshoring environmentally intensive production activities to less developed countries (Babiker 2005; Arto and Dietzenbacher 2014).

Besides the accounting framework, some scholars classify the impacts of different influencing factors on carbon emissions into three effects: scale effects, technical effects, and composition effects (Kreickemeier and Richter 2014). This stream of research has a strong grounding and originates from the work of Grossman and Krueger (1995) on economic growth and the environment. Mostly, in mainstream literature, the scale effects arising from the economic augmentations play a negative role in environment protection (Kreickemeier and Richter 2014); composition effects from economic structure or industrial changes are mixed, as Antweiler et al. (2001) found that the composition effects of trade made poor countries dirtier while made rich countries cleaner; yet recent literature prefers the negative role of composition effects (Yan and Yang 2010; Kreickemeier and Richter 2014); technical effects from technology advancements act as a notably driving force in the positive effects of foreign trade on environmental change (Frankel and Rose 2005). Furthermore, Grossman and Krueger (1995) also developed the famous environmental Kuznets curve (EKC) hypothesis, the inverted-U relationship between economic development and different pollution.

Though a large number of studies foci on carbon emission content of trade and GVC participation, there are still some gaps in relevant literature. Firstly, ignoring the sophistication of production sharing activities, research on the carbon emissions embodied in value added from GVC participation is far from enough. Secondly, in striking contrast with the growing attention on carbon emission transfers among countries, few studies notice the asymmetry and community features of the transfers. Thirdly, the determinant of the emission transfers during GVC activities are still limited in the scope of trade, but actually are closely related to the overall production activities as the value-added gains from GVC constitute an increasingly important part of GDP.

Therefore, this paper engages in properly accounting the carbon emission transfers under GVCs, delving into the community structure and influencing factors of the emission transfer networks. By doing so, the contributions of this study are summarized as follows: (1) This paper expands the studies on carbon emissions by identifying the critical part of carbon emissions embodied in the value added from GVC activities. The application of decomposition framework put forward by Wang et al. (2017) is conducive to tell apart the similarities and differences of the carbon emission transfer networks induced separately by simple and complex GVC activities. (2) This work facilitates the comprehensive understanding of the emission transfer networks through the construction of top networks and community detection. Explicit attentions have been paid to the emission transfers among all the investigated countries, as well as the variation in community scale and community members. (3) Re-testing of the scale effects, technical effects, and composition effects

is carried out in the context of the transfer networks under GVCs, and with the quadratic assignment procedure (QAP) method, instead of traditional approaches such as ordinary least square (OLS) regression. By doing this, the purpose of this paper is not only to figure out the effects of income disparity, technology gaps, and structural differences on the emission transfers, but also to direct the public attention to the environmental externalities accompanied with manufacturing offshoring, thus trying to explore the way out for low-income countries to improve their states.

The rest of this paper is arranged as follows. The “**Methodology and data**” section puts forward the GVC decomposition framework and measurement of carbon emissions, as well as the details of complex network analysis and QAP methods. Data sources and processing of different indicators are also presented in this section. Description and community detection of the networks are portrayed in the “**Results and discussion**” section, the “**QAP results and analysis**” section is the QAP results and analysis, and the “**Conclusions and implications**” section concludes.

Methodology and data

Following the extant literature on GVC decomposition and measurement, such as Koopman et al. (2014) and Wang et al. (2017), we can gauge the real carbon emissions embodied in value added from one country’s GVC activities. Assume a world with G countries and N sectors, complex linkages among sectors across these countries can be well organized into input–output tables, matrix form is as follows:

$$\begin{bmatrix} A_{11} & A_{12} & \dots & A_{1G} \\ A_{21} & A_{22} & \dots & A_{2G} \\ \vdots & \vdots & \ddots & \vdots \\ A_{G1} & A_{G2} & \dots & A_{GG} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_G \end{bmatrix} + \begin{bmatrix} \sum_j^G Y_{1j} \\ \sum_j^G Y_{2j} \\ \vdots \\ \sum_j^G Y_{Gj} \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_G \end{bmatrix} \quad (1)$$

where, A is a $GN \times GN$ matrix, submatrix $A_{ij}(i, j = 1, 2, \dots, G)$ denotes the input coefficients of intermediate use in country j from country i to produce one unite of gross output, including domestic value-added ($i = j$)

and imported input ($i \neq j$); $(X_i)_{GN \times 1}^T$ is $GN \times 1$ vector, representing gross outputs, X_i , a $N \times 1$ vector, denotes output vector of each sector in country i ; Y_{ij} is a $N \times 1$ vector of final goods produced in country i and consumed in country j , and it indicates that final goods are consumed at domestic market instead of abroad when $j = i$. Intermediate inputs are endogenous while final products are exogenous in this input and output model. Let $B = (I - A)^{-1}$, after rearranging, we obtain the following:

$$\begin{bmatrix} B_{11} & B_{12} & \dots & B_{1G} \\ B_{21} & B_{22} & \dots & B_{2G} \\ \vdots & \vdots & \ddots & \vdots \\ B_{G1} & B_{G2} & \dots & B_{GG} \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_G \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_G \end{bmatrix} \quad (2)$$

where, block matrix B_{ij} is the widely known Leontief inverse, denoting the amount of gross output in country i required by per unite increase in final demand of country j .

Value added from GVC activities

Define V_i , an $1 \times N$ row vector, as the direct value-added coefficients, \hat{V}_i as a $N \times N$ block diagonal matrix of country i with direct value-added coefficients of N sectors along the diagonal, total value added in gross outputs can be derived as below:

$$Va' = \begin{bmatrix} \hat{V}_1 & 0 & \dots & 0 \\ 0 & \hat{V}_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \hat{V}_G \end{bmatrix} \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1G} \\ X_{21} & X_{22} & \dots & X_{2G} \\ \vdots & \vdots & \ddots & \vdots \\ X_{G1} & X_{G2} & \dots & X_{GG} \end{bmatrix} = \begin{bmatrix} \hat{V}_1 \sum_j^G B_{1j} Y_{j1} & \hat{V}_1 \sum_j^G B_{1j} Y_{j2} & \dots & \hat{V}_1 \sum_j^G B_{1j} Y_{jG} \\ \hat{V}_2 \sum_j^G B_{2j} Y_{j1} & \hat{V}_2 \sum_j^G B_{2j} Y_{j2} & \dots & \hat{V}_2 \sum_j^G B_{2j} Y_{jG} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{V}_G \sum_j^G B_{Gj} Y_{j1} & \hat{V}_G \sum_j^G B_{Gj} Y_{j2} & \dots & \hat{V}_G \sum_j^G B_{Gj} Y_{jG} \end{bmatrix} \quad (3)$$

Following the framework proposed by Wang et al. (2017), the gross value added can be decomposed into two parts, non_GVC activities and GVC activities, according to whether the value added crossing national borders for production purposes or not (Koopman et al. 2008; Wang et al. 2017). Better understanding of such decomposition can be perceived by rearranging formula (3).

$$Va' = \hat{V}(I - A)^{-1}Y = \underbrace{\hat{V}(I - A^d)^{-1}Y^d}_{\text{i) Produced and consumed domestically}} + \underbrace{\hat{V}(I - A^d)^{-1}Y^f}_{\text{ii) Embodied in the trade of final products}} + \underbrace{\hat{V}(I - A^d)^{-1}A^f(I - A^d)^{-1}Y^d}_{\text{iiia) Simple GVC activities}} + \underbrace{\hat{V}(I - A^d)^{-1}A^f[(I - A)^{-1}Y - (I - A^d)^{-1}Y^d]}_{\text{iiib) Complex GVC activities}} \quad (4)$$

where, the superscripts d and f are domestic and foreign, respectively, for instance, A^d denotes domestic input coefficients matrix, Y^d represents the final goods produced and consumed domestically, while Y^f indicates the final goods produced domestically and consumed abroad (Wang et al. 2017). As shown in formula (4), the production of the value added produced and consumed domestically, as the first part, or crossing borders for consumption purposes, as the second part, are identified as non-GVC activities; while the production of the value added crossing borders for production purposes, as the last two parts in the formula, is considered to be GVC activities. According to the times of crossing national borders, the GVC activities can be divided further into simple part and complex part, the former cross national

borders only once and the latter traverse national borders at least twice.

Carbon emissions embodied in value added from GVC activities

Similarly, define emission intensity F_i , an $I \times N$ row vector, as the carbon emissions per unite of output in country i , \hat{F}_i as a $N \times N$ block diagonal matrix of country i with direct emission coefficients of N sectors along the diagonal. Then total emissions of each sector in country i can be expressed as formula (5):

$$\begin{bmatrix} \hat{F}_1 & 0 & \dots & 0 \\ 0 & \hat{F}_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \hat{F}_G \end{bmatrix} \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1G} \\ X_{21} & X_{22} & \dots & X_{2G} \\ \vdots & \vdots & \ddots & \vdots \\ X_{G1} & X_{G2} & \dots & X_{GG} \end{bmatrix} = \begin{bmatrix} \hat{F}_1 \sum_j^G B_{1j} Y_{j1} & \hat{F}_1 \sum_j^G B_{1j} Y_{j2} & \dots & \hat{F}_1 \sum_j^G B_{1j} Y_{jG} \\ \hat{F}_2 \sum_j^G B_{2j} Y_{j1} & \hat{F}_2 \sum_j^G B_{2j} Y_{j2} & \dots & \hat{F}_2 \sum_j^G B_{2j} Y_{jG} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{F}_G \sum_j^G B_{Gj} Y_{j1} & \hat{F}_G \sum_j^G B_{Gj} Y_{j2} & \dots & \hat{F}_G \sum_j^G B_{Gj} Y_{jG} \end{bmatrix} \quad (5)$$

Following the accounting system proposed by Meng et al. (2018), we calculate the carbon emissions embodied from the production sharing activities between countries. The logic of the measurement is that production-based emissions of sectors in one specific country are embodied in downstream sectors of other countries, and finally absorbed abroad. Utilizing the similar intuition as we applied to decompose gross value added in Eq. (4), we can trace the carbon emissions embodied in the value added from GVC activities as follows:

$$EGVC_{ij} = \underbrace{\hat{F}_i(I - A_{ii})^{-1}A_{ij}(I - A_{ii})^{-1}Y_{ii}}_{(1) EGVC_Simple} + \underbrace{\hat{F}_i(I - A_{ii})^{-1}A_{ij}[B_{ij}Y_{ij} - (I - A_{ii})^{-1}Y_{ii}]}_{(2) EGVC_Complex} \quad (6)$$

where, $EGVC_{ij}$ represents the amount of carbon emissions embodied in the GVC activities between country i and j , which is conceptually different from the EEG_F , carbon emissions embodied in gross exports in Meng et al.(2018), and $EEBT$, emissions embodied in bilateral trade in Peters and Hertwich (2008). As in formula (6), $EGVC$ can be split further into generally two parts: (1) Carbon emissions embodied in the value added in exported intermediate goods and finally absorbed by the direct importer (country j); this part is from simple GVC activities, named $EGVC_S$ and (2) Carbon emissions embodied in the value added in exported intermediate goods and finally absorbed by a third country; this part is from complex GVC activities, named $EGVC_C$.

Utilizing the similar intuition as we deduced the GDP gains from production sharing activities, $EGVC$ can be regarded as the environmental cost of GVC activities.

Then, the following logic of our research is simple: With the application of GVC decomposition framework and complex network analysis, we aim to calculate the carbon emissions embodied in GVC activities, and figure out the characteristics of carbon emission transfer networks, including the position of each country, the community structure, and the sectoral differentiation. Moreover, in light of the assumptions commonly referred in literature on the potential economic effects on environment (Grossman and Krueger 1995), such as the scale effects, technical effects, and composition effects, we investigate the driving factors of the emission transfer networks with the utilization of QAP to re-test the assumptions.

Definitions of top networks

Most existing relevant literature on trade networks prefer to use either binary networks or weighted networks. In the binary networks, a tie exists between country i and country j when there is bilateral trade between i and j or the trade volume exceed a specified threshold value (Clark and Beckfield 2009). Differently, each tie between countries in the weighted networks is weighted by a designated proxy of the trade volume (Fagiolo et al. 2008). These two types of networks pay equal importance to the relationship between countries and ignore the power-law distribution as the foreign trade between one country or region with its partners is not identical (Garas et al. 2010). Mostly, international trade of a country concentrates its relations with a few trade partners. According to dependency theories, such concentration is notable not only in developing countries but also in

developed countries. Recently, a few studies came to realize the differential importance of trade relations, and proposed top networks, in which there is a tie between country i and country j if j is i 's top emission source or destination; or else, there is no tie between these two countries (Yan and Yang 2010); thus, both trade relationships and concentrations of countries are taken into consideration. Likewise, in this study, we construct the networks based on top carbon emission transfers induced by the GVC activities among countries. In particular, we stress the top carbon emission networks where a tie exists between i and j , if i is j 's top emission source or destination.

Nodes in the top networks represent different economies when we discuss carbon emissions at national level. Nodes can also be manufacturing sectors in different economies (i.e., different country-sector pairs) when we focus on sectoral emission transfers in the framework of GVCs. Edges in the networks denote carbon emission transfers in the production sharing between economies or sectors. Carbon emission transfer networks can be classified into weighted and unweighted networks, directed and undirected ones. The former classification is based on whether the volume of each edge is taken into consideration; if edges in the networks are weighted by the volume between vertices, this network is a weighted network, otherwise an unweighted network; similarly, if the edges between vertices have directions, the network is directed, otherwise undirected. Given the purpose of this study, directed and weighted networks are utilized to reveal both the direction and amount of carbon emissions transfers under GVCs.

Besides, many networks consist of district communities, which is one of the important features of complex networks. In this study, we detect the community structure of the carbon emission transfer networks with the application of Gephi, a powerful software for visualization and community detection. The method for community detection in Gephi is the fast unfolding algorithm based on modularity optimization. More specifically, modularity coefficient is constructed to measure the density of links within communities (Newman 2004), as shown in formula (7). After processing, gigantic networks are decomposed into a number of independent communities or clusters, which consist of different sets of highly connected nodes (Blondel et al. 2008).

$$Q_t = \frac{1}{2m} \sum_{i,j} \left[X_{ij} - \frac{\sum_j X_{ij} \sum_i X_{ji}}{2m} \right] \delta(c_i, c_j) \tag{7}$$

where, Q_t denotes modularity coefficient, an index between $[-1, 1]$. The higher the value of Q_t the better quality of the detection. X_{ij} is the weighted edge between vertices i and j ; $m = \frac{1}{2} \sum_{ij} X_{ij}$ represents the gross weight of edges in the networks; δ is a function of different communities, node i

belongs to community c_i while j belongs to c_j , if $c_i = c_j$, then δ equals 1 and 0 otherwise.

The fast unfolding algorithm for community detection is proceeded with two iterated phases: firstly, each node is treated as a single community in the network; there will be a variation in modularity when adding node i into its neighboring community c_j designated by node j , and we define the variation in Q_t as ΔQ_t , as shown in formula (8):

$$\Delta Q_t = \left[\frac{\sum_{in} + 2\sum_{in} X_{i,in}}{2m} - \left(\frac{\sum_{all} + \sum_j X_{ij}}{2m} \right)^2 \right] - \left[\frac{\sum_{in}}{2m} - \left(\frac{\sum_{all}}{2m} \right)^2 - \left(\frac{\sum_j X_{ij}}{2m} \right)^2 \right] \tag{8}$$

where, ΔQ_t represents the variation in Q_t , \sum_{in} denotes the total weights of edges in i 's neighboring community, $\sum_{in} X_{i,in}$ indicates the total weights of edges from i to nodes in its neighboring community, \sum_{all} is the total weights of all edges among nodes in the network, m is the same as in formula (7). During the iteration, node i will be designated to neighboring community if ΔQ_t is positive and achieve its maximum value, or remain in community c_i . Such process will be performed thousands of times to realize modularity optimization and stable communities. Secondly, a new network made up of detected communities is identified through this iteration phase. Weights of edges between any two communities in the new network depends on the summation of edges between nodes in this two communities, while edges between nodes in the same community perform self-loops in the new network.

In addition to visualization and community detection, degree centrality is employed with the help of UCINET 6 to evaluate the position of each economy in the network. Degree centrality is a simple but powerful tool to measure the connections between different nodes. In our study of carbon emission transfer networks under GVCs, weighted degree centrality of each node equals to the simple average of in-degree and out-degree centrality; the former measures incoming edges while the latter the outgoing edges, as shown in formula (9):

$$WDC(n_i) = \frac{IDC(n_i)_{in} + ODC(n_i)_{out}}{2} = \left(\frac{\sum_j X_{ji}}{g-1} + \frac{\sum_j X_{ij}}{g-1} \right) / 2 \tag{9}$$

where, $IDC(n_i)_{in}$ and $ODC(n_i)_{out}$ represents the in-degree and out-degree centrality of node i , respectively, $WDC(n_i)$ denotes the weighted degree centrality of i , g is the number of nodes in the network. Degree centralities of all the nodes have been normalized for the sake of comparability of different years.

Multilateral dependencies

On the basis of GVC framework, some literature carried out empirical investigations on the driving factors of carbon emissions embodied in the sharing production activities (Assamoi et al. 2020; Duan et al. 2021), which bears much similarity with the group of research on international trade and climate change (Kreickemeier and Richter 2014). Traditionally, the environmental outcomes of economic growth have been divided into three effects, that is scale effects, composition effects, and technical effects (Grossman and Krueger 1995), which is widely used in relevant literature on the international trade and environment nexus (Liu and Zhao 2021). Mostly, studies reach an agreement that scale effects of growing traditional trade volume increase the carbon emissions, in contrast, technological advancement (technical effects) tends to decrease emissions (Yan and Yang 2010). While the outcomes of composition effects caused by trade or industry structure change turn out to be mixed in literature (Grossman and Krueger 1995; Antweiler et al. 2001; Yan and Yang 2010). Moreover, composition effects and technical effects are sometimes treated as whole, named reallocation effects in some works (Melitz and Trefler 2012; Kreickemeier and Richter 2014).

Compared with traditional trade, production sharing within the framework of GVCs has been highly fragmented among different economies and lay solid basis on the comparative advantages (Kowalski et al. 2015; Meng et al. 2020). Such worldwide specialization is thought to bear more characteristics of efficiency-improving, not only in productivity and technique change, but also in energy and environment (Ehab and Zaki 2021). Under this circumstance, we wonder whether the assumptions of three traditional effects still hold in the context of GVCs. Such query motivates our study to investigate the driving factors of the carbon emission transfer networks from the scale effects, technical effects, and composition effects with the utilization of QAP, a nonparametric permutation test that proved to be superior to OLS in network analysis (Krackhardt 1988), thus commonly utilized in the studies on the determinant factors of trade networks in particular (Liu et al. 2020; Zhao et al. 2021).

Data source

World input–output tables (WIOTs) for GVC decomposition and carbon emissions data in environmental accounts for carbon intensity are two vital datasets in this study. We try to collect MRIO tables and calculate carbon emission intensity of manufacturing industries from 2000–2014. The MRIOs released by World Input–Output Database (WIOD) have been commonly utilized to decompose GVC in recent literature (Koopman et al. 2014; Meng et al. 2018; Wang et al. 2017). This paper use the latest version released in

2016 covering 43 economies and 56 sectors during the calendar year 2000 to 2014. Moreover, WIOD released carbon emission data as well as original energy sources like coal, gasoline, and oil, in its environmental accounts, which involves 40 economies and 35 sectors from 2000 to 2009 (Genty et al. 2012). In order to prolong the time span to 2014, we collect the sectoral emission data in 2009–2014 from the Eora database (Lenzen et al. 2013), and merge with the emission data from WIOD as in Xiao et al. (2019) did in their study. Moreover, to improve the consistency of the merged data of WIOD and Eora of 2010–2014, this paper sets the original emission data of 2000–2009 from WIOD as benchmark, and then calculates the estimated emission data from 2010 to 2014 according to formula (10):

$$C_i = \frac{C_{09}}{C_{merge_09}} * C_{merge_i} \quad (10)$$

where, i ranges from 2010 to 2014, C_i is the carbon emissions for one country, C_{09} denotes the WIOD emission data of this country in 2009, C_{merge_09} and C_{merge_i} are the carbon emissions from merge database of this country in 2009 and i , respectively. Finally, we obtain carbon emission intensity of 13 manufacturing industries¹ and 39 economies (as shown in Table 1) from 2000 to 2014.

Results and discussion

Spatial distribution

The spatial distribution of carbon emissions embodied in value added from GVC activities can be seen directly from Fig. 1. In 2000, carbon emissions of manufacturing industries in Russia amounted to 72.42 million metric tons (Mt), accounting for 17.93% of EGVC worldwide. Two thirds of these emissions were from simple GVC activities and approximately 60% from sector 13 (basic metals and fabricated metal). Second to Russia was the USA; EGVC was 48.56 Mt, accounting for 12.02% of total, around 32.07% from sector 10 (Chemicals and chemical products) and 26.30% from sector 13. EGVC in countries such as China,

¹ The classification of manufacturing industries has been matched between WIOTs released in 2013 and 2016, covering 17 sectors: C5 food, beverages, and tobacco; C6 manufacture of textiles, wearing apparel, and leather products; C7 wood and products of wood and cork; C8 pulp, paper, printing, and publishing; C9 coke, refined petroleum, and nuclear fuel; C10 chemicals and chemical products; C11 rubber and plastics; C12 other non-metallic mineral; C13 basic metals and fabricated metal; C14 electrical and optical equipment; C15 machinery, not elsewhere classified; C16 transport equipment; C17 manufacturing, not elsewhere classified, recycling.

Table 1 Net carbon emission transfers under GVCs in 2000 and 2014 (million metric tons, Mt)

Country (abbr.)	EGVC		EGVC_S		EGVC_C	
	2000	2014	2000	2014	2000	2014
Australia (AUS)	3.11	-0.25	1.45	-0.29	1.65	0.04
Austria (AUT)	0.51	-0.52	0.41	0.09	0.09	-0.61
Belgium (BEL)	1.37	-1.17	1.18	0.34	0.20	-1.51
Bulgaria (BGR)	0.06	-0.08	-0.07	-0.06	0.13	-0.02
Brazil (BRA)	-0.80	-6.26	-0.69	-4.69	-0.11	-1.56
Canada (CAN)	1.42	-1.08	4.07	1.58	-2.65	-2.66
China (CHN)	1.27	29.63	0.46	13.04	0.82	16.59
Cyprus (CYP)	-0.02	-0.09	0.03	-0.05	-0.05	-0.04
Czech Rep. (CZE)	0.78	0.22	0.33	0.51	0.45	-0.29
Germany (DEU)	-6.05	-12.60	-2.27	-2.35	-3.78	-10.24
Denmark (DNK)	-0.69	-1.24	-0.10	-0.20	-0.59	-1.04
Spain (ESP)	-1.53	-3.22	-0.55	-0.73	-0.98	-2.49
Estonia (EST)	-0.13	0.22	-0.08	0.09	-0.05	0.13
Finland (FIN)	0.05	-0.32	0.17	0.02	-0.12	-0.33
France (FRA)	-4.22	-6.51	-1.17	-1.34	-3.05	-5.17
United Kingdom (GBR)	-0.68	-1.84	-0.22	-0.81	-0.46	-1.03
Greece (GRC)	-0.37	-0.43	-0.29	-0.24	-0.07	-0.19
Hungary (HUN)	-0.67	-1.04	-0.15	0.12	-0.52	-1.16
Indonesia (IDN)	2.87	12.25	1.61	5.13	1.26	7.12
India (IND)	-0.09	-0.20	-0.30	-1.93	0.21	1.73
Ireland (IRL)	-0.21	0.66	0.23	0.72	-0.44	-0.05
Italy (ITA)	-3.96	-5.86	-2.04	-1.67	-1.92	-4.18
Japan (JPN)	-3.99	-10.59	-3.55	-5.49	-0.44	-5.11
South Korea (KOR)	-0.62	-4.17	0.09	0.27	-0.71	-4.44
Lithuania (LTU)	-0.16	0.16	-0.13	0.06	-0.03	0.10
Luxembourg (LUX)	0.00	-0.07	0.00	-0.03	-0.01	-0.04
Latvia (LVA)	-0.12	-0.16	-0.09	-0.04	-0.02	-0.12
Mexico (MEX)	-5.58	-6.21	-1.66	-0.62	-3.91	-5.59
Malta (MLT)	-0.08	1.30	-0.04	0.23	-0.04	1.07
Netherlands (NLD)	0.50	-1.73	0.58	0.21	-0.08	-1.94
Poland (POL)	1.62	1.12	0.49	0.05	1.13	1.07
Portugal (PRT)	-0.59	-0.53	-0.28	-0.15	-0.31	-0.37
Romania (ROU)	0.48	-0.59	0.16	-0.37	0.31	-0.22
Russian Federation (RUS)	28.00	38.00	14.11	12.97	13.89	25.03
Slovakia (SVK)	0.54	0.32	0.14	0.31	0.40	0.00
Slovenia (SVN)	-0.14	-0.21	-0.03	0.03	-0.11	-0.25
Sweden (SWE)	-0.79	-0.83	-0.05	-0.10	-0.74	-0.73
Turkey (TUR)	-0.42	-4.30	-0.39	-1.39	-0.03	-2.91
United States (USA)	-10.20	-16.60	-12.05	-15.85	1.85	-0.75

Source: Calculated by the authors

Germany, and Japan exceeded 20 Mt, accounting for 7.04%, 6.23%, and 5.35% of world's total, respectively.

In 2014, the EGVC of China surged to 235.39 Mt, about 23.36% of global EGVC, 35.07% from sector 12 (Other non-metallic mineral) and 27.31% from sector 13. Flowing behind was Russia, EGVC of which rose to 125.12 Mt, 12.42% of total, 54.03% from sector 13. EGVC from the USA (80.27 Mt) was almost twice than that separately

from Indonesia (IDN, 50.58 Mt), India (IND, 40.15 Mt), and Germany (40.05 Mt). EGVC_S and EGVC_C varied widely among countries, and most of them show obvious increase except some decline in Australia, Belgium, Cyprus, France, Netherlands, and Romania, especially in Australia and Cyprus, declined by more than 50%.

The net emission transfers of countries are calculated by deducting the imported emissions from the exported

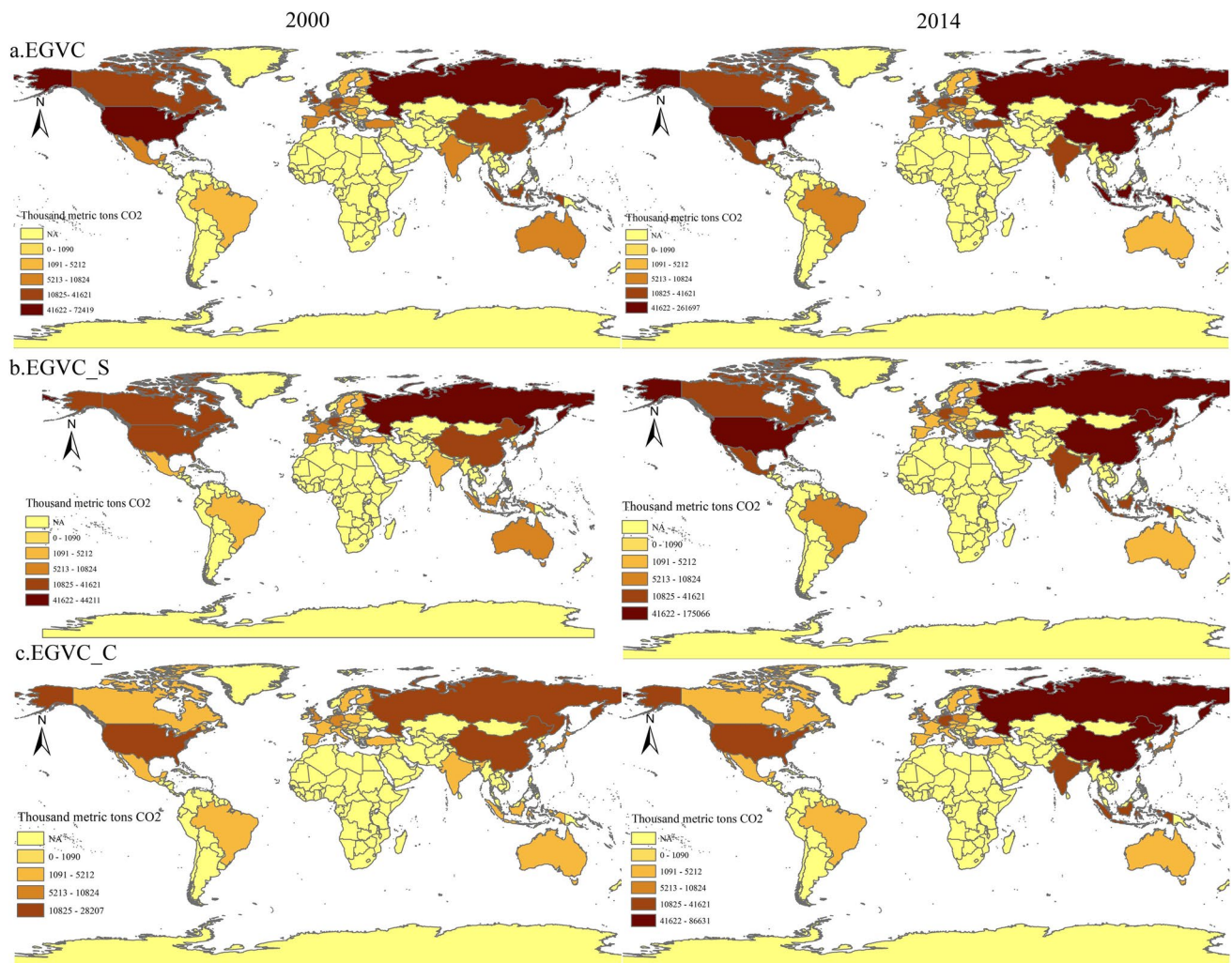


Fig. 1 Spatial distribution of carbon emissions embodied in GVC activities in 2000 and 2014. Source: Mapped by the authors. Notes: For better comparability, the legend is designated according to EGVC in 2000 and applied to all the maps

emissions under GVCs. As displayed in Table 2, some countries were net emission exporters initially in 2000 and became net importers gradually in 2014, such as Netherlands, Austria, Belgium, Canada, and Australia; some countries, like the USA, Germany, Japan, Brazil, Turkey, and Korea, which were net importers in the beginning continued to enlarge the imported emissions through GVCs. Contrarily, some other countries remained to be net emission exporters all the time, most notably, net exported emissions of Russian, China, and Indonesia, amounted to 38 Mt, 29.63 Mt, and 12.25 Mt, respectively. When analyzing further with the net emission transfers from simple to complex GVC activities, even though the USA and Germany were both net importers, the USA imported increasing amount

of emissions through the simple GVC activities while Germany imported more through complex GVC activities. Also, China, Russian, and Indonesia exported larger quantity of carbon emissions during complex GVC participation.

Community detection

For the sake of more intuition about the community structure, we not only visualize the top networks but also tabulate the member countries and their normalized weighted degree centrality (WDC_n) within each community. As displayed in Fig. 2², the top emission network of EGVC in 2000 consisted of two big and one small communities, dominated by

² Complete networks including all the emission transfers under GVCs in 2000 and 2014 are presented in Appendix Fig. 7 and 8, respectively.

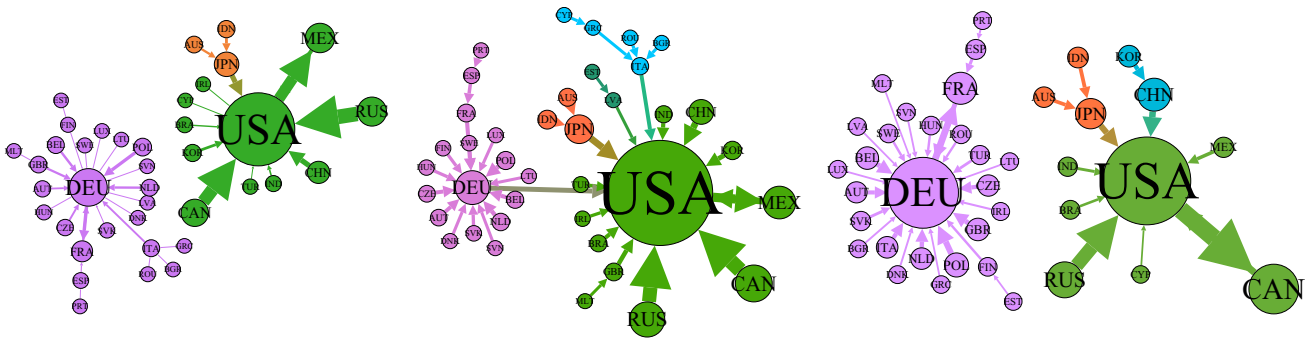


Fig. 2 Top carbon emission transfer networks under GVCs in 2000. Source: Drawn by the authors. Notes: Nodes represent countries; nodes with the same color belong to the same community; the bigger the nodes the higher WDC_n of the country

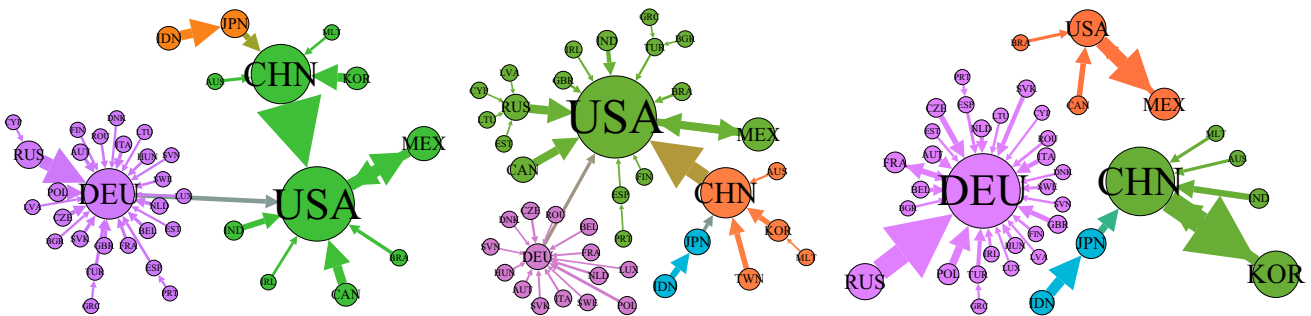


Fig. 3 Top carbon emission transfer networks under GVCs in 2014. Source: Drawn by the authors. Notes: Nodes represent countries; nodes with the same color belong to the same community; the bigger the nodes the higher WDC_n of the country

Germany, the USA, and Japan, respectively. The Japan community had only two member countries and attaches to the USA community; hence, there were actually two core communities. In the USA community, tight connections mainly sourced from some high centrality countries like Russia, Canada, Japan, and China, and WDC_n of which were 0.247, 0.217, 0.168, and 0.13, respectively, as shown in Appendix Table 8. Mexico (0.253, WDC_n, same as below) was the principal destination of the tie with the USA. In contrast, connections of the Germany community distributed more evenly, and generally concentrated in EU countries, such as France (0.108), Poland (0.054), Belgium (0.039), and Italy (0.039). In the case of EGVC_S and EGVC_C networks, though some small communities with core countries like Italy, Latvia, and China had been detected, and the bipolar structure consisting of the United States and Germany communities remained stable.

As shown in Fig. 3 and Appendix Table 9, community structure of the emission networks in 2014 undergone the transition from bipolar to tripolar mainly due to the growing connections of China with other countries. In the EGVC network, as a major member country in the USA community, China, WDC_n of which gone up to 0.746, second only

to the USA, developed into the top destination of EGVC from East Asian countries (or areas) like Korean (0.127), Japan (0.218), and Australia (0.135). Germany community covered most of the European countries including Russia (0.21), top connection of which had transferred from the USA to Germany. In the case of EGVC_S and EGVC_C, tripolar character of the network was more evident. Except the USA and Germany community, the third big community led by China emerged, the size of which even occasionally surpassed that of incumbent communities dominated by Germany and the USA. In particularly in the EGVC_C network, the China community turned out to be the second large community, implying that the status of China in the network became increasingly important. In the meantime, the number of member countries within the USA community scaled down to three.

Sectoral analysis

In this subsection, we dive into the community structure of carbon emission transfer networks from the GVC activities of different manufacturing sectors. As Fig. 4 illustrated, in 2000, there were two big communities dominated by the

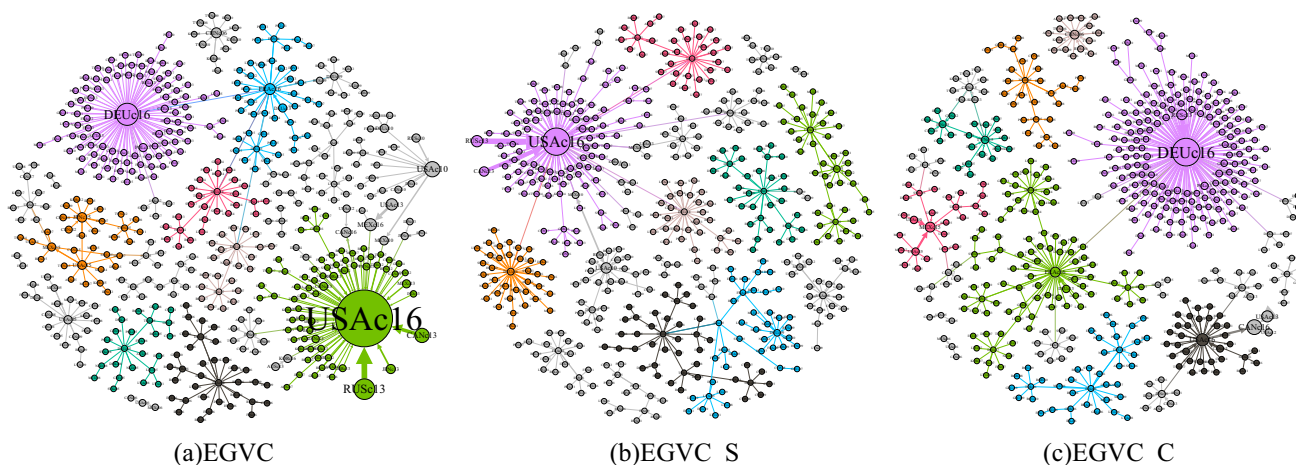


Fig. 4 Top carbon emission transfer networks of manufacturing industries under GVCs in 2000. a EGVC. b EGVC_S. c EGVC_C. Source: Drawn by the authors. Notes: Nodes represent country-sector

pairs; nodes with the same color belong to the same community; the bigger the nodes the higher WDC_n of the country-sector pair

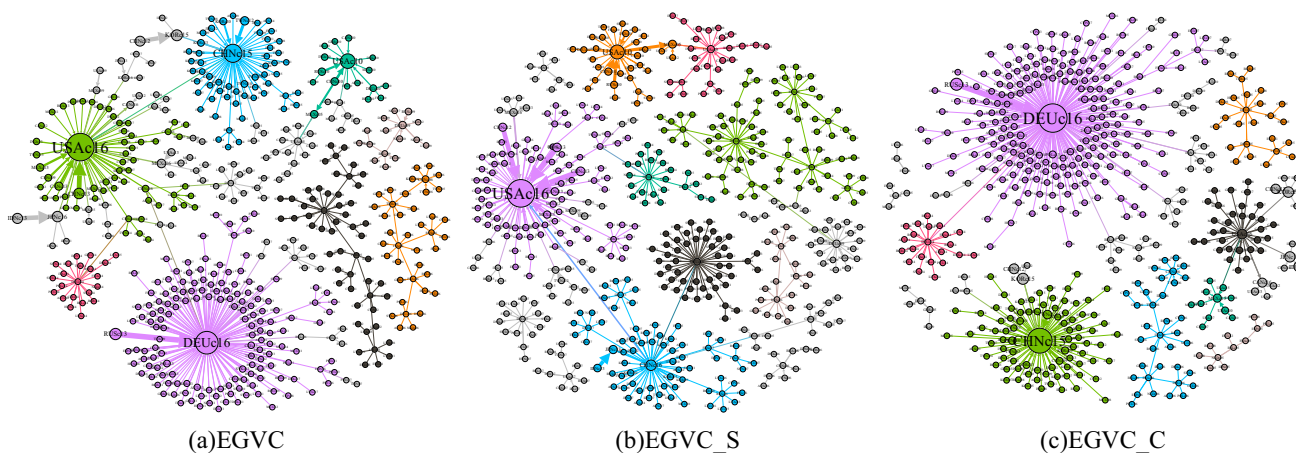


Fig. 5 Top carbon emission transfer networks of manufacturing industries under GVCs in 2014. a EGVC. b EGVC_S. c EGVC_C. Source: Drawn by the authors. Notes: Nodes represent country-sector

pairs; nodes with the same color belong to the same community; the bigger the nodes the higher WDC_n of the country-sector pair

sector 16 in the USA and Germany, implying that sector 16 in these two countries were the top destination of EGVC from upstream sectors in other countries, the main reason maybe that the production of transport equipment, for example ship and aircraft, demanded for a great deal of foreign value added thus importing large quantity of carbon emissions in the meantime. A case in example, more than 70% parts of Boeing 787 were imported from abroad suppliers. Moreover, the Germany community in the EGVC_S network agglomerated and concentrated on a bigger scale than the United community in the EGVC_S network. There were other communities dominated by manufacturing industries from developed countries, notably sector 10 and 15 in the

USA, sector 16 in France, sector 5 and 14 in Germany, and sector 6 in Italy, etc. By contrast, only a few small-scale communities are grouped by developing countries such as the community led by sector 6 in China. In the case of and EGVC_C, sector 16 in the USA and Germany dominated the biggest community and remained to be the top destinations, respectively Fig. 5.

In 2014, manufacturing sectors in developed countries were still at the core and the top destinations of emission transfers from other sectors in different countries. The community dominated by sector 16 in Germany scaled up while that by sector 16 in the USA downsized to some extent. Moreover, the community dominated by sector 15 in China

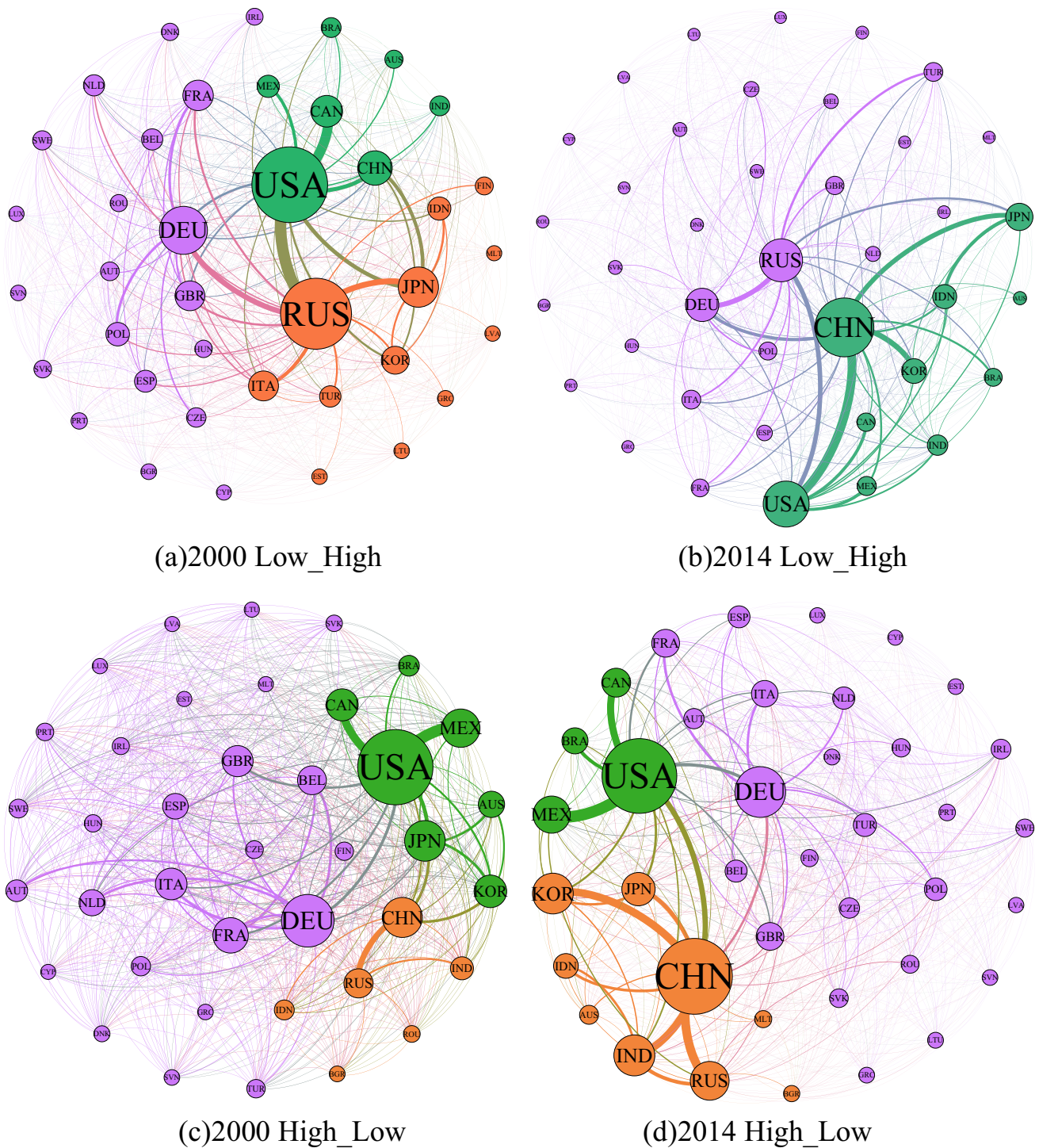


Fig. 6 The emission transfers between low per capita GDP countries to high per capita GDP countries under GVCs. a 2000 Low_High. b 2014 Low_High. c 2000 High_Low. d 2014 High_Low. Source: Drawn by the authors. Notes: Nodes represent countries; nodes with the same color belong to the same community; the bigger the nodes the higher WDC_n of the country; when the GDP per capita of the

sourcing country is lower than that of the destination country, the emission transfer is classified as Low_High type; when the GDP per capita of the sourcing country is higher than that of the destination country, the emission transfer is regarded as High_Low type; the Low_High and High_Low emission transfer networks of EGVC_S and EGVC_C were roughly the same with EGVC

expanded rapidly, overshadowed the other communities led by developed countries, for instance, the shrinkage of Netherlands-c5 community and the breakdown of France-c16 community. In addition, developing countries such as Turkey, Russia, and Mexico also began to play more and more important roles in different communities.

Emission transfers between “rich” and “poor”

The emission transfers between rich and poor economies are the controversial issues in extant literature, motivating us to explore the network structure of the emission transfers from low per capita GDP countries to high per capita GDP countries (Low_High) as well as high per capita GDP countries to low per capita GDP countries (High_Low). As portrayed in Fig. 6, the transfer networks of Low_High consisted of three communities dominated by the USA, Germany, and Russia, respectively, in 2000. The former two dominant countries were emission destinations for most member countries while the latter one was the main emission sources for not only its member countries like Japan, Korea, and Italy, but also the other developed countries like the USA, Germany, UK, and France. Gradually, there were only two communities, dominated by China and Russia, respectively, in 2014, suggesting that these two developing countries became the main emission exporter to the rest of the world, including the USA and Germany.

Compared with Low_High transfer networks, the network structure of High_Low was relatively stable. Three communities led by Germany, the USA, and China, respectively, remained unchanged from 2000 to 2014. Still, Germany and the USA acted as the major emission destinations while China as one of the main emission exporters and possessed closer relationship with Japan, Australia, Korea, as well as some developing countries, such as Russia, India, and Indonesia.

QAP results and analysis

After the elaboration of carbon emission transfer networks under GVCs, a question arises that what are the driving forces of the networks. To answer this question, we step further to figure out the scale effects, technical effects, and composition effects with the utilization of QAP. As in extant literature, gross domestic product per capita (*GDP_per_capita*) is widely used to measure the scale effects. In addition, the square of GDP per capita (*PGDP_square*) is taken into consideration to test the existence of EKC, which suggests the pollution reduction when the economic growth reaches a certain level. Besides, patent applications and the gross domestic expenditure on research and development (R&D) are used to measure technical effects; industrial structure

denoted by the share of manufacturing industries of GDP and factor endowment structure calculated by the ratio of gross fixed capital formation to labor are exploited to gauge the composition effects (Grossman and Krueger, 1995; Antweiler et al., 2001; Kreickemeier and Richter, 2014). During the empirical tests, we treat the emission transfer matrixes under GVCs as independent variables, including *EGVC*, *EGVC_S*, and *EGVC_G* and construct the difference matrixes of dependent variables like *GDP_per_capita*, *PGDP_square*, *Patent*, *R&D*, *Industry*, and *Factor*. To some extent, the different matrixes of *GDP_per_capita*, *Patent* and *R&D*, *Industry* and *Factor* can be interpreted as the income gap, technology gap, and structure gap, respectively, among source and destination countries.

In order to check the robustness and heterogeneity, we divide the manufacturing industries into two groups, the high- and medium-high-technology (HMT) and the low- and medium-low-technology (LMT), and then investigate separately the emission transfers within HMT and LMT. This Organization for Economic Co-operation and Development (OECD) classification³ is based largely on the importance of expenditures on R&D relative to the gross output or gross value added of industries. The HMT manufacturing industries include computers, aircraft, motor vehicles, electrical equipment, and most pharmaceuticals and chemicals. The LMT industries cover rubber, plastics, and basic metals, as well as food processing, textiles, clothing, and footwear, etc. Moreover, we also investigate the heterogenous effects of economic development, technology advancement, and composition change on the carbon emission transfers from low income countries to high income countries (Low_High), and high income to low income countries. Specifically, if the GDP per capita of the sourcing country is lower than the destination country, then the emission transfers between these two countries are treated as Low_High type, otherwise considered as High_Low type.

QAP correlation test

Correlation tests between the dependent and independent matrixes are carried out with the utilization of UCINET 6 before QAP regression. After 5000 times random permutation, we obtain the test results as shown in Table 2, the correlation between *EGVC*, as well as *EGVC_S* and *EGVC_C*, and *GDP_per_capita* was negative and statistically significant at the 1% level in 2000 and 2014, implying that scale effects of increasing GDP per capita accompanied with the reduction of the carbon emission transfers under GVC activities.

³ Source: <https://www.indexmundi.com/facts/indicators/TX.VAL.TECH.MF.ZS>

Table 2 Correlation tests of all the emission transfers

Dependent Variables	Scale effect	EKC effect	Technical effect		Composition effect	
	<i>GDP per capita</i>	<i>PGDP_square</i>	<i>Patent</i>	<i>R&D</i>	<i>Industry</i>	<i>Factor</i>
2000 EGVC	−0.126*** (0.000)	−0.088* (0.079)	0.215** (0.024)	0.27*** (0.005)	0.153* (0.076)	0.226*** (0.000)
2000 EGVC_S	−0.154*** (0.000)	−0.085** (0.042)	0.187** (0.045)	0.245*** (0.006)	0.118 (0.119)	0.227*** (0.000)
2000 EGVC_C	−0.122*** (0.000)	−0.075 (0.126)	0.229** (0.022)	0.265*** (0.006)	0.158* (0.079)	0.21*** (0.000)
2014 EGVC	−0.243*** (0.000)	0.33*** (0.001)	0.334*** (0.000)	−0.08*** (0.002)	−0.077 (0.133)	0.145* (0.088)
2014 EGVC_S	−0.269*** (0.000)	0.276*** (0.001)	0.295*** (0.003)	−0.109*** (0.000)	−0.063 (0.135)	0.129* (0.084)
2014 EGVC_C	−0.245*** (0.000)	0.338*** (0.002)	0.346*** (0.001)	−0.08*** (0.002)	−0.07 (0.163)	0.14 (0.107)

P-value in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively

The correlation between three emission transfer indexes and *PGDP_square* was interesting because the coefficients were negative initially and then became significant positive in 2014, suggesting the possible existence of U-shape relationship between carbon emission transfers and GDP per capita.⁴ That is to say, continued growth of GDP per capita after reaching turning point accompanied with increasing emission transfers under GVCs. Such result is somewhat counterintuitive but may be plausible when considering the income gaps between source and destination countries. The potential U-shape relationship signified that increasing income gaps accompanied with less emission transfers but after income gaps reaching a certain level, emission transfers would show an obvious increase.

Besides, the correlation between R&D and EGVC, EGVC_S, and EGVC_C were initially positive and turned significant but weak negative afterwards; a stronger and positive correlation was found between emission transfers and *Patent*, signifying the positive effects of technological advancement on emission transfers. The possible explanation maybe that technical advancement primarily possessed the typical characteristics of “dirty,” as the purpose of most new techniques was production expansion and efficiency promotion since the industrial revolution, which inevitably caused surging fossil energy consumption and finally increased the carbon emissions (Clapp 1994). In 2014, no

significant correlation was detected between emission transfers and *Industry*. Similarly, the positive correlation with *Factor* became less significant, thus resulting in insignificant composition effects.

When diving into the carbon emission transfers within HMT and LMT manufacturing industries separately, we obtain the correlation results as illustrated in Table 3. It can be seen from the table that no substantial differences were found between the correlation tests of overall emission transfers and those of HMT and LMT transfers except the slight changes in the results of *Factor* in 2014. Positive correlation between emission transfers within HMT manufacturing industries and *Factor* existed and remained at a higher significant level, whereas, our statistical tests failed to detect a significant positive correlation between the emission transfers and *Factor*. The mix results of HMT and LMT put forward an explanation for the weak yet significant positive correlation between emission transfers and *Factor*.

Results of further investigation on the High_Low and Low_High carbon emission transfers under GVCs are presented in Table 4, which differed widely from the test results in Table 2. The major reason for such distinct results may be that high-income countries generally act as net importers through outsourcing their pollution-intensive production to low-income countries; hence, the overall emission transfers were mainly low–high type. However, the high-low emission transfers from developed countries to developing countries were largely triggered by trade flow of capital-intensive or technology-intensive products instead of pollution-intensive products. Under this circumstance, economic and structural factors may influence differently these two types of carbon emission transfers. In the case of High_Low, the correlation between emission transfers and *GDP per capita* remained significant positive, while the weak negative correlation between emission transfers and *PGDP_square* turned out

⁴ Correlation coefficients with an absolute value of less than 0.1 is classified as small, therefore we pay more attention to the variables with the absolute value of coefficients more than 0.1 and at higher significant level. The absolute values of correlation coefficients in 2000 between *PGDP_square* and EGVC, EGVC_S, and EGVC_C were no more than 0.088, suggesting a very small correlation, and at relatively lower significant statistic level, so we leave it alone and only consider the significant positive correlation in 2014, namely the possible appearance of U-shaped relationship.

Table 3 Correlation tests of the emission transfers within HMT and LMT manufacturing industries

Dependent variables	Scale effect	EKC effect	Technical effect		Composition effect	
	GDP per capita	PGDP_square	Patent	R&D	Industry	Factor
2000 EGVC (HMT)	−0.128*** (0.000)	−0.078* (0.084)	0.256** (0.015)	0.24** (0.018)	0.123 (0.147)	0.213*** (0.000)
2000 EGVC_S (HMT)	−0.155*** (0.000)	−0.071* (0.062)	0.219** (0.023)	0.209** (0.015)	0.093 (0.181)	0.204*** (0.000)
2000 EGVC_C (HMT)	−0.124*** (0.000)	−0.066 (0.138)	0.276** (0.011)	0.243** (0.015)	0.117 (0.146)	0.196*** (0.000)
2014 EGVC (HMT)	−0.218*** (0.000)	0.274*** (0.009)	0.372*** (0.000)	−0.066** (0.011)	−0.073 (0.16)	0.208** (0.04)
2014 EGVC_S (HMT)	−0.251*** (0.000)	0.214** (0.019)	0.327*** (0.001)	−0.09*** (0.001)	−0.061 (0.15)	0.171** (0.046)
2014 EGVC_C (HMT)	−0.216*** (0.000)	0.277** (0.011)	0.388*** (0.000)	−0.063** (0.019)	−0.064 (0.2)	0.209** (0.044)
2000 EGVC (LMT)	−0.133*** (0.000)	−0.081* (0.097)	0.202** (0.031)	0.264*** (0.006)	0.159* (0.067)	0.221*** (0.000)
2000 EGVC_S (LMT)	−0.161*** (0.000)	−0.078* (0.054)	0.177** (0.042)	0.239*** (0.006)	0.123 (0.102)	0.223*** (0.000)
2000 EGVC_C (LMT)	−0.13*** (0.000)	−0.069 (0.135)	0.214** (0.028)	0.257*** (0.008)	0.166* (0.063)	0.205*** (0.000)
2014 EGVC (LMT)	−0.264*** (0.000)	0.338*** (0.001)	0.334*** (0.002)	−0.089*** (0.001)	−0.067 (0.165)	0.123 (0.128)
2014 EGVC_S (LMT)	−0.295*** (0.000)	0.287*** (0.002)	0.302*** (0.002)	−0.115*** (0.000)	−0.052 (0.186)	0.111 (0.122)
2014 EGVC_C (LMT)	−0.268*** (0.000)	0.346*** (0.001)	0.345*** (0.002)	−0.091*** (0.001)	−0.06 (0.198)	0.116 (0.148)

P-value in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively; HMT represent high- and high-medium-technology manufacturing industries, LMT represent low- and low-medium-technology manufacturing industries

to be positive but insignificant in 2014, indicating the disappearance of the EKC. Similar to *GDP_per_capita*, the correlation between emission transfers and *R&D* remained significant positive in both 2000 and 2014. However, *Industry* had a significant negative but weak correlation with emission transfers. In contrast, *Factor* possessed a significant positive correlation with emission transfers.

Compared with High_Low, the results of Low_High emission transfers bear more similarity with those of overall emission transfers. The U-shape relationship between Low_High transfers and GDP per capita came into being in 2014. The correlation between Low_High transfers and *Patent* was positive and turned significant gradually, yet that between emission transfers and *R&D* became significantly negative. A weak positive but significant correlation between emission transfers and *Industry* remained steady during this period of time, while the significant positive correlation between emission transfers and *Factor* turned out to be insignificant afterwards.

QAP regression

After the correlation test, QAP regression was carried out. Regression results of emission transfers under simple and complex GVC activities are indispensable to test the robustness. As illustrated in Table 5, the coefficients of *GDP_per_capita* were significant negative in 2000 and became weak positive but insignificant in 2014, suggesting that the scale effects of economic development played a role in decreasing the emission transfers under GVCs initially and then increased the transfers but not statistically significant. Contrarily, the EKC effects represented by the square of GDP per capita turned out to be weak in both years, significant positive in the beginning and then became insignificant negative, suggesting the disappearance of U-shape relationship and occurrence of an insignificant EKC between emission transfers and GDP per capita. The EKC hypothesis held that the more advanced the development stages, the higher awareness of protecting environment among general public and governments. Such “green” awareness therefore motivates stricter regulations on air pollution that brought about

Table 4 Correlation tests of High_Low and Low_High emission transfers

Dependent variables	Scale effect	EKC effect	Technical effect		Composition effect	
	GDP per capita	PGDP_square	Patent	R&D	Industry	Factor
2000 EGVC (High_Low)	0.088*** (0.009)	-0.062*** (0.000)	0.201** (0.024)	0.172*** (0.007)	-0.073** (0.049)	0.038** (0.034)
2000 EGVC_S (High_Low)	0.117*** (0.005)	-0.061*** (0.000)	0.177** (0.028)	0.155*** (0.006)	-0.062* (0.074)	0.048** (0.018)
2000 EGVC_C (High_Low)	0.059** (0.016)	-0.059*** (0.000)	0.209** (0.023)	0.174*** (0.007)	-0.078** (0.038)	0.028* (0.077)
2014 EGVC (High_Low)	0.122*** (0.000)	0.003 (0.456)	0.167** (0.026)	0.286*** (0.000)	-0.058*** (0.003)	0.144*** (0.01)
2014 EGVC_S (High_Low)	0.097*** (0.002)	0.02 (0.311)	0.173** (0.027)	0.317*** (0.000)	-0.043** (0.014)	0.124*** (0.01)
2014 EGVC_C (High_Low)	0.138*** (0.000)	-0.013 (0.457)	0.153** (0.026)	0.244*** (0.000)	-0.067*** (0.001)	0.154*** (0.009)
2000 EGVC (Low_High)	-0.346*** (0.000)	0.026 (0.125)	0.029 (0.142)	-0.007 (0.519)	0.117* (0.057)	0.092*** (0.005)
2000 EGVC_S (Low_High)	-0.31*** (0.000)	0.018 (0.149)	0.025 (0.139)	-0.003 (0.521)	0.091* (0.053)	0.073*** (0.007)
2000 EGVC_C (Low_High)	-0.361*** (0.000)	0.037* (0.087)	0.033 (0.165)	-0.012 (0.507)	0.146* (0.056)	0.112*** (0.002)
2014 EGVC (Low_High)	-0.628*** (0.000)	0.231*** (0.003)	0.311*** (0.008)	-0.396*** (0.000)	0.051* (0.075)	-0.032 (0.364)
2014 EGVC_S (Low_High)	-0.529*** (0.000)	0.176*** (0.002)	0.241*** (0.007)	-0.354*** (0.000)	0.034* (0.096)	-0.023 (0.376)
2014 EGVC_C (Low_High)	-0.654*** (0.000)	0.26*** (0.004)	0.345*** (0.009)	-0.393*** (0.000)	0.062* (0.072)	-0.036 (0.37)

P-value in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively; Low_High denote carbon emissions transferred from economies of lower GDP per capita to economies of higher GDP per capita; High_Low represents the carbon emissions transfer from rich economies to poor economies

Table 5 QAP regression

Variables	EGVC		EGVC_S		EGVC_C	
	2000	2014	2000	2014	2000	2014
Intercept	0.711*** (0.000)	1.429*** (0.000)	0.412*** (0.000)	0.698*** (0.000)	0.499*** (0.000)	1.262*** (0.000)
GDP_per_capita	-0.156*** (0.001)	0.026 (0.136)	-0.186*** (0.001)	0.005 (0.416)	-0.152*** (0.001)	0.026 (0.144)
PGDP_square	0.064* (0.087)	-0.064* (0.094)	0.073** (0.047)	-0.048 (0.122)	0.068* (0.068)	-0.059 (0.116)
Patent	0.109 (0.141)	0.197** (0.031)	0.094 (0.147)	0.17** (0.028)	0.129 (0.1)	0.21** (0.023)
R&D	0.263*** (0.008)	0.09 (0.144)	0.234*** (0.008)	0.08 (0.124)	0.252*** (0.009)	0.082 (0.185)
Industry	0.187** (0.02)	0.248*** (0.005)	0.141** (0.042)	0.192*** (0.008)	0.192** (0.021)	0.251*** (0.004)
Factor	0.247*** (0.001)	-0.163*** (0.001)	0.264*** (0.001)	-0.197*** (0.001)	0.23*** (0.001)	-0.162*** (0.001)
Adj_R2	0.189***	0.200***	0.171***	0.166***	0.185***	0.207***

P-value in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively

Table 6 QAP regression of carbon emission transfers within LMT and HMT manufacturing industries

Variables	EGVC(HMT)		EGVC_S(HMT)		EGVC_C(HMT)		EGVC(LMT)		EGVC_S(LMT)		EGVC_C(LMT)	
	2000	2014	2000	2014	2000	2014	2000	2014	2000	2014	2000	2014
Intercept	0.404*** (0.000)	0.636*** (0.000)	0.247*** (0.000)	0.365*** (0.000)	0.283*** (0.000)	0.528*** (0.000)	0.513*** (0.000)	1.25*** (0.000)	0.27*** (0.000)	0.577*** (0.000)	0.335*** (0.000)	1.099*** (0.000)
<i>GDP_per_capita</i>	-0.168*** (0.001)	0.024 (0.148)	-0.195*** (0.001)	0.014 (0.281)	-0.166*** (0.001)	0.025 (0.132)	-0.161*** (0.001)	0.028 (0.123)	-0.192*** (0.001)	0.014 (0.294)	-0.158*** (0.001)	0.027 (0.135)
<i>PGDP_square</i>	0.067* (0.098)	-0.053 (0.203)	0.074* (0.061)	-0.042 (0.185)	0.072* (0.084)	-0.044 (0.24)	0.069* (0.068)	-0.057 (0.119)	0.078** (0.048)	-0.04 (0.18)	0.072* (0.056)	-0.052 (0.164)
<i>Patent</i>	0.182* (0.051)	0.246** (0.016)	0.16* (0.059)	0.221** (0.02)	0.207** (0.04)	0.266*** (0.01)	0.096 (0.142)	0.197** (0.022)	0.085 (0.163)	0.174** (0.022)	0.116 (0.11)	0.21** (0.023)
<i>R&D</i>	0.191** (0.035)	0.136* (0.088)	0.16** (0.045)	0.103 (0.12)	0.183** (0.05)	0.132 (0.106)	0.264*** (0.005)	0.069 (0.213)	0.233*** (0.008)	0.062 (0.197)	0.251*** (0.01)	0.059 (0.256)
<i>Industry</i>	0.144* (0.068)	0.182** (0.038)	0.104 (0.117)	0.119* (0.097)	0.138* (0.087)	0.18** (0.045)	0.192** (0.018)	0.249*** (0.006)	0.145** (0.033)	0.196*** (0.006)	0.199** (0.018)	0.253*** (0.005)
<i>Factor</i>	0.236*** (0.001)	-0.139*** (0.002)	0.241*** (0.001)	-0.186*** (0.001)	0.22*** (0.001)	-0.134*** (0.006)	0.246*** (0.001)	-0.185*** (0.001)	0.263*** (0.001)	-0.226*** (0.001)	0.228*** (0.001)	-0.185*** (0.001)
Adj_R2	0.173***	0.199***	0.149***	0.160***	0.173***	0.207***	0.187***	0.206***	0.168***	0.179***	0.181***	0.214***

P-value in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively; LMT represent low- and low-medium-technology manufacturing industries; HMT represent high- and high-medium-technology manufacturing industries

carbon emission reductions (Priour 2009). The coefficients of *Patent* remained positive and were statistically significant in 2014, suggesting that the more patent applications in the emission sourcing countries than the destination countries, the more emission transfers between them. In comparison, the positive coefficients of *R&D* turned out to be insignificant gradually. The coefficients of both *Industry* and *Factor* were significant positive in 2000, but in 2014, coefficients of *Industry* remained significant positive and increased obviously, yet these of *Factor* grew into significant negative. Such mix estimates of industry structure and factor endowment resulted in the uncertain effects of composition change on emission transfers.

In the case of HMT and LMT manufacturing industries, the regression results are presented in Table 6. It can be seen from the table that estimates of *GDP_per_capita*, *PGDP_square*, *R&D*, *Industry*, and *Factor* are in consistent with these in Table 5, especially the emission transfers within LMT industries. The U-shape correlation between emission transfers and economic growth transformed to weak and insignificant EKC relation. The technique effects of growing gaps in patent applications and R&D expenditure still acted as a stimulus for more emission transfers under GVCs, in particular in HMT industries. Moreover, the composition effects were still uncertain because the change in the industry structure tended to increase the emission transfers while the change in the factor endowment gradually decreased rather than increased the emission transfers latterly.

When diving deeper into emission transfers from low income countries to relatively high income countries (Low_High) and these from high to low income countries (High_Low), we obtain striking different results. As illustrated in Table 7, in terms of Low_High emission transfers, the coefficients of *GDP_per_capita* were significant negative while those of *PGDP_square* were significant positive, suggesting the existence of U-shape correlation between emission transfers and economic development. Situations in High_Low emission transfers were just the opposite. The coefficients of *GDP_per_capita* were significant positive while those of *PGDP_square* were significant negative, implying a EKC relation between emission transfers and economic income gap. This diametrically opposite result indicated that carbon emissions sourced from both low-income and high-income countries transferred increasingly to high-income countries, and decreasingly flowed to low-income countries.

The coefficients of *Patent* were positive and statistically significant at 1% and 5% level in both Low_High and High_Low emission transfers, whereas the results of R&D turned out to differ widely which were weak negative in the case of Low_High yet were weak positive and significant in the case of High_Low transfers. These results were in favor of the view that technique effects or widening technology gap tended to increase the carbon emission transfers under

GVCs, especially in the High_Low transfers. Coefficients of *Industry* were significant positive in Low_High emission transfers while kept insignificant negative in High_Low transfers. Likewise, the results of *Factor* in Low_High transfers were nearly the same with those in Table 4, positive initially and turned significant negative afterwards, but remained weak negative and insignificant in High_Low transfers. These findings indicated that composition effects of the differences in industrial structure and factor endowment resulted in growing emission transfers at the beginning and then decreased the transfers from low income countries to high income countries⁵.

Conclusions and implications

Accompanied with the increasing complicated GVC networks is the carbon emission transfers among countries or regions. The comprehensive and systematic analysis of carbon emission networks under GVCs is not only helpful for better understanding of the core-periphery structure of the global transfers but also conducive to find out the efficient way to reduce the carbon emissions. In light of the gaps in extant literature on this issue, we tracked the carbon emissions embodied in the global manufacturing production sharing and detected the community structure of the emission transfer networks. Additionally, this study employed the QAP method to revisit the assumptions of scale effects, technical effects, and composition effects, as well as the EKC hypothesis to explore the driving forces of the emission transfer networks.

The carbon emissions embodied in GVC activities spatially distributed in Russia and the USA. The EGVC of developing countries represented by China, Indonesia, and India undergone a significant increase, which in striking contrast with the deduction of EGVC from several developed countries like Australia, Canada, and some EU members. The community detection revealed distinct core-periphery structure in the transfer networks. Under most circumstances, the USA and Germany acted as the two main destinations of the carbon emissions embodied in imported value added. However, this bipolar structure of the carbon emission networks from GVC activities transformed gradually to tripolar pattern, owing largely to the surging carbon emissions from China. Findings from QAP tests provide comprehensive explanation and understanding of the scale effects, technique

⁵ Moreover, according to our reviewer's helpful suggestions, we divide manufacturing industries further into labor-, capital-, and technology-intensive. Correlation tests and QAP results are roughly the same with the above estimation, and main findings in this paper still hold. Those results were not presented in this paper, but readily available for readers.

Table 7 QAP regression of carbon emission transfers between low income countries to high income countries

Variables	EGVC(High_Low)		EGVC_S(High_Low)		EGVC_C(High_Low)		EGVC(Low_High)		EGVC_S(Low_High)		EGVC_C(Low_High)	
	2000	2014	2000	2014	2000	2014	2000	2014	2000	2014	2000	2014
Intercept	27.423*** (0.000)	25.828*** (0.000)	10.886*** (0.000)	7.453*** (0.000)	16.537*** (0.000)	18.376*** (0.000)	-33.003*** (0.000)	17.811*** (0.000)	-16.686*** (0.000)	12.035*** (0.000)	-16.317*** (0.000)	5.776*** (0.000)
GDP_per_capita	0.074*** (0.009)	0.278*** (0.001)	0.105*** (0.006)	0.333*** (0.001)	0.044** (0.028)	0.214*** (0.002)	-0.378*** (0.001)	-0.145*** (0.001)	-0.337*** (0.001)	-0.147*** (0.001)	-0.397*** (0.001)	-0.127*** (0.001)
PGDP_square	-0.046** (0.037)	-0.054** (0.015)	-0.041** (0.05)	-0.042** (0.024)	-0.047** (0.032)	-0.062*** (0.004)	0.123*** (0.009)	0.057** (0.012)	0.097** (0.015)	0.042** (0.031)	0.151*** (0.01)	0.066** (0.016)
Patent	0.146** (0.031)	0.172** (0.025)	0.118** (0.03)	0.171** (0.02)	0.159** (0.027)	0.163** (0.029)	0.081** (0.044)	0.201*** (0.001)	0.071** (0.049)	0.15*** (0.001)	0.087** (0.049)	0.228*** (0.001)
R&D	0.098** (0.044)	0.075* (0.075)	0.098** (0.042)	0.055* (0.075)	0.092* (0.057)	0.089* (0.057)	-0.03 (0.29)	-0.082*** (0.003)	-0.027 (0.253)	-0.061*** (0.003)	-0.031 (0.361)	-0.093*** (0.003)
Industry	-0.041 (0.178)	-0.014 (0.391)	-0.031 (0.225)	-0.003 (0.486)	-0.046 (0.157)	-0.024 (0.305)	0.08* (0.064)	0.053** (0.019)	0.06* (0.075)	0.031* (0.075)	0.104* (0.063)	0.068** (0.014)
Factor	-0.005 (0.426)	0.032 (0.107)	0.004 (0.393)	-0.017 (0.236)	-0.012 (0.256)	0.074** (0.013)	0.189*** (0.001)	-0.513*** (0.001)	0.155*** (0.003)	-0.427*** (0.001)	0.223*** (0.001)	-0.539*** (0.001)
Adj_R2	0.055***	0.123***	0.049***	0.139***	0.054**	0.102***	0.160***	0.457***	0.121***	0.320***	0.189***	0.505***

P-value in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively; Low_High denote carbon emissions transferred from economies of lower GDP per capita (or poor) to economies of higher GDP per capita (or rich); High_Low represents the carbon emissions transfer from rich economies to poor economies

effects, composition effects, and EKC hypothesis from the perspectives of income disparity, technology gaps, and structural differences. Widening income disparity between source and destination countries turned out to decrease the transfers initially. Expanding technology gaps and the structure differences in factor endowments brought more emission transfers. Moreover, the EKC hypothesis was proved to be valid in the emission transfers from high-income countries to low-income countries, whereas a U-shape relationship was detected in the reverse emission transfers, indicating that growing carbon emissions from not only low-income countries but also high-income countries transferred to other high-income countries.

By doing so, this paper provides some policy implications: firstly, the polarization development of the emission transfer networks conveyed obvious characteristics of regional in scope, for instance, the community consisted of EU countries led by Germany, North American Free Trade Agreement (NAFTA) dominated by the USA, and East Asia grouped by China, making it possible for community members work closely to achieve carbon deduction as specific environmental regulations can be carried out regionally though intra-community cooperation and collaborative

supervision strategies. Secondly, growing emission transfers from both low-income and high-income countries to other high-income countries indicates that some high-income countries have to engage in pollution-intensive production during GVC participation, capturing value added at the cost of environment degradation. Going beyond this zero-sum game, both high-income and low-income countries should shoulder the responsibility for carbon neutrality and take effective measures to reduce carbon emissions instead of offshoring pollution to trade partners. Thirdly, strong patent protection stimulates patenting (Eaton and Kortum 1996), especially after the reform of the international patent system owing largely to the concern of technological transfers from developed countries to less-developed countries (LDCs). An increasing emphasis on strategic patenting in high-income developed countries allow for more manufacturing offshoring to low-income developing countries without worrying about leaks of key technology. Therefore, to avoid “pollution heaven” and escape from the low-end of GVCs is to motivate technological innovation, especially for developing countries.

Appendix

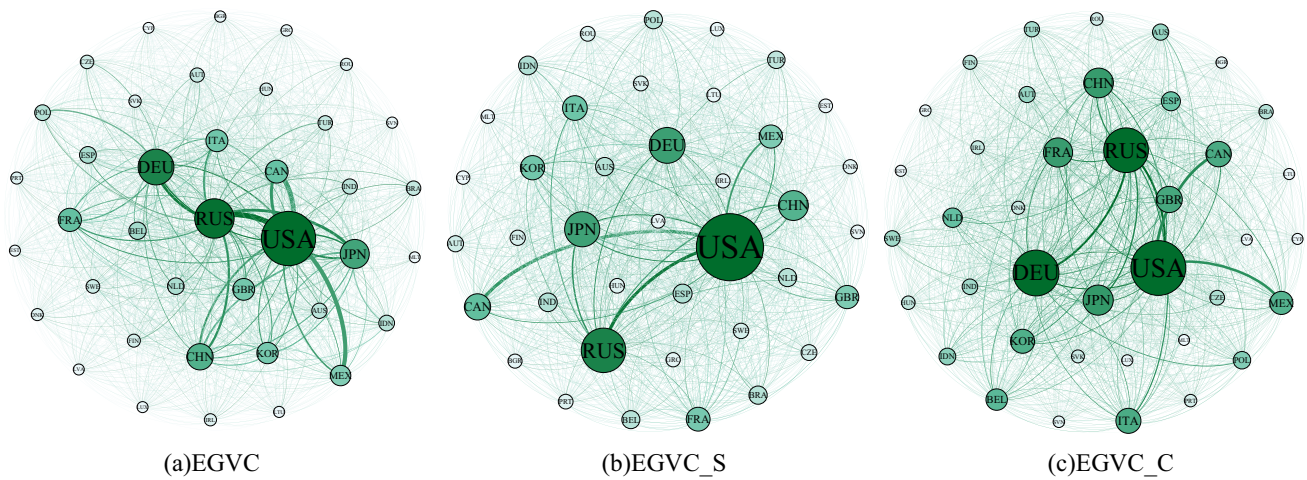


Fig. 7 The transfer networks of carbon emissions embodied in GVC activities in 2000. **a** EGVC. **b** EGVC_S. **c** EGVC_C. Source: Drawn by the authors. Notes: Nodes represent countries; the bigger the nodes the higher WDC_n of the country.

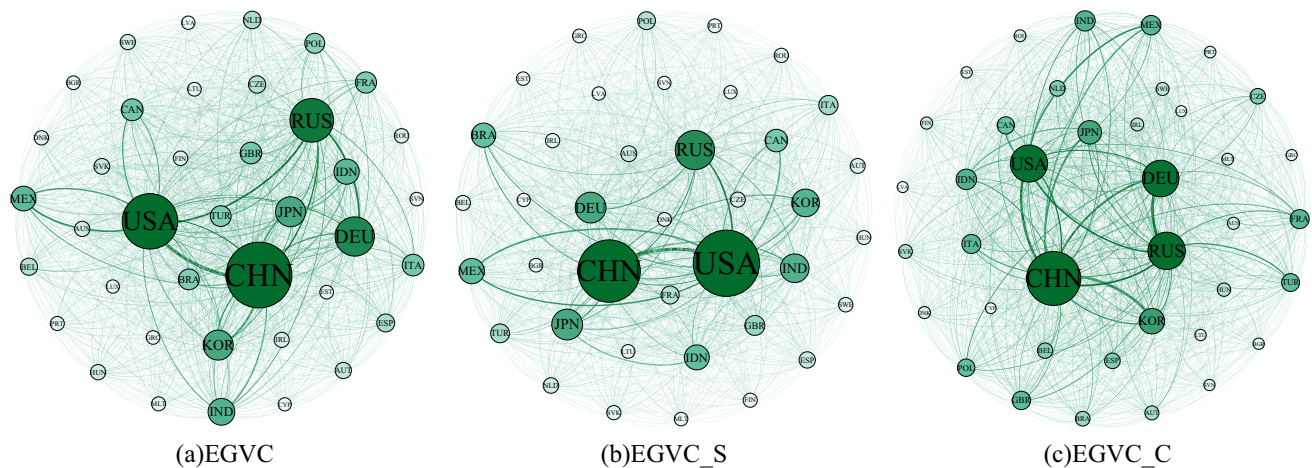


Fig. 8 The transfer networks of carbon emissions embodied in GVC activities in 2014. **a** EGVC. **b** EGVC_S. **c** EGVC_C. Source: Drawn by the authors. Notes: Nodes represent countries; the bigger the nodes the higher WDC_n of the country.

Table 8 Community structure of the emission transfer networks in 2000

	Community	Core country	Member countries
EGVC	0 (7.69%)	JPN (0.168)	AUS (0.037), IDN (0.046)
	1 (64.10%)	DEU (0.392)	AUT (0.029), BEL (0.039), BGR (0.002), CZE (0.031), DNK (0.003), ESP (0.02), EST (0), FIN (0.009), FRA (0.108), GBR (0.036), GRC (0.001), HUN (0.008), ITA (0.039), LTU (0), LUX (0.001), LVA (0.001), MLT (0), NLD (0.038), POL (0.054), PRT (0.004), ROU (0.006), SVK (0.012), SVN (0.002), SWE (0.008)
	2 (28.21%)	USA (1.000)	BRA (0.022), CAN (0.217), CHN (0.13), CYP (0), IND (0.025), IRL (0.005), KOR (0.044), MEX (0.253), RUS (0.247), TUR (0.012)
EGVC_S	0 (7.69%)	JPN (0.151)	AUS (0.032), IDN (0.043)
	1 (42.5%)	DEU (0.208)	AUT (0.018), BEL (0.024), CZE (0.019), DNK (0.002), ESP (0.013), FIN (0.006), FRA (0.031), HUN (0.005), LTU (0.000), LUX (0.001), NLD (0.027), POL (0.034), PRT (0.003), SVK (0.006), SVN (0.001), SWE (0.005)
	2 (30.77%)	USA (1.000)	BRA (0.022), CAN (0.243), CHN (0.108), GBR (0.031), IND (0.024), IRL (0.005), KOR (0.038), MEX (0.196), MLT (0), RUS (0.223), TUR (0.011)
	3 (12.82%)	ITA (0.025)	BGR (0.002), CYP (0), GRC (0), ROU (0.005)
	4 (5.13%)	LVA (0.001)	EST (0.000)
EGVC_C	0 (7.69%)	JPN (0.181)	AUS (0.042), IDN (0.045)
	1 (69.23%)	DEU (0.759)	AUT (0.051), BEL (0.071), BGR (0.004), CZE (0.054), DNK (0.004), ESP (0.034), FIN (0.016), FRA (0.206), GBR (0.071), GRC (0.001), HUN (0.015), IRL (0.007), ITA (0.057), LTU (0.001), LUX (0.002), LVA (0.001), NLD (0.057), POL (0.093), PRT (0.004), ROU (0.013), SVK (0.025), SVN (0.003), SWE (0.015), TUR (0.023)
	2 (17.95%)	USA (1.000)	BRA (0.018), CAN (0.457), CYP (0), IND (0.025), MEX (0.039), RUS (0.262)
	3 (5.13%)	CHN (0.218)	KOR (0.059)

The percentage values in the brackets after each community denotes the size of the community, that is the share of nodes within the community in the total number of nodes; the value in the bracket after each country is the normalized weighted degree centrality (WDC_n) of that country.

Source: Calculated by the authors.

Table 9 Community structure of the carbon emission transfer networks in 2014

	Community	Core country	Member countries
EGVC	0 (5.13%)	JPN (0.218)	IDN (0.146)
	1 (69.23%)	DEU (0.598)	AUT (0.025), BEL (0.02), BGR (0.002), CYP (0.000), CZE (0.038), DNK (0.002), ESP (0.012), EST (0.002), FIN (0.005), FRA (0.018), GBR (0.029), GRC (0.001), HUN (0.011), ITA (0.025), LTU (0.003), LUX (0.001), LVA (0.001), NLD (0.027), POL (0.063), PRT (0.003), ROU (0.006), RUS (0.21), SVK (0.022), SVN (0.002), SWE (0.008), TUR (0.021)
	2 (25.64%)	USA (1.000)	AUS (0.018), BRA (0.026), CAN (0.136), CHN (0.746), IND (0.071), IRL (0.011), KOR (0.127), MEX (0.322), MLT (0.008)
EGVC_S	0 (5.13%)	JPN (0.140)	IDN (0.100)
	1 (38.46%)	DEU (0.141)	AUT (0.01), BEL (0.008), CZE (0.014), DNK (0.001), FRA (0.007), HUN (0.004), ITA (0.009), LUX (0.000), NLD (0.016), POL (0.025), ROU (0.002), SVK (0.007), SVN (0.001), SWE (0.003)
	2 (46.15%)	USA (1.000)	BGR (0.001), BRA (0.023), CAN (0.136), CYP (0.000), ESP (0.006), EST (0.001), FIN (0.002), GBR (0.021), GRC (0.001), IND (0.057), IRL (0.009), LTU (0.001), LVA (0.000), MEX (0.253), PRT (0.002), RUS (0.146), TUR (0.014)
	3 (10.26%)	CHN (0.515)	AUS (0.013), KOR (0.08), MLT (0.002)
EGVC_C	0 (7.69%)	JPN (0.181)	AUS (0.042), IDN (0.045)
	1 (69.23%)	DEU (1.000)	AUT (0.04), BEL (0.033), BGR (0.005), CYP (0.000), CZE (0.062), DNK (0.003), ESP (0.021), EST (0.004), FIN (0.009), FRA (0.098), GBR (0.051), GRC (0.001), HUN (0.019), IRL (0.012), ITA (0.043), LTU (0.005), LUX (0.002), LVA (0.001), NLD (0.035), POL (0.103), PRT (0.004), ROU (0.011), RUS (0.356), SVK (0.04), SVN (0.003), SWE (0.013), TUR (0.036)
	2 (10.26%)	USA (0.365)	BRA (0.018), CAN (0.063), MEX (0.284)
	3 (12.82%)	CHN (0.901)	AUS (0.018), IND (0.077), KOR (0.529), MLT (0.018)

The percentage values in the brackets after each community denotes the size of the community, the share of the nodes within the community in the total number of nodes; the value in the bracket after each country is the normalized weighted degree centrality (WDC_n) of that country.

Source: Calculated by the authors.

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Data Availability The datasets used in this study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate The authors attest that this manuscript has not been published anywhere else and is not under consideration by any other journal. Ethical approval and informed consent do not apply to this study.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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