Environmental Science and Pollution Research (2020) 27:32062–32075
https://doi.org/10.1007/s11356-020-09130-3

RESEARCH ARTICLE

Carbon emission intensity embodied in trade and its driving factors from the perspective of global value chain

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Received: 13 November 2018 / Accepted: 29 April 2020 / Published online: 6 June 2020

Abstract

As a global problem, climate warming has received widespread attention recently. With trade development and labor division deepening, there exist large differences in carbon emission intensity (CEI) embodied in different trade patterns. Assessing environmental costs of different trade patterns is the core issue for policy makers. We decompose the overall CEI embodied in trade into CEI embodied in final goods trade, domestic trade, traditional intermediate trade, and global value chain trade. Using global multi-region input-output table provided by the WIOD database, we calculate the CEI embodied in different trade patterns during 1995–2014. Further, we analyze the influencing factors of CEI embodied in different trade patterns. We find that CEI embodied in domestic trade is lower than that of international trade. All kinds of embodied CEI in developing countries are higher than that in developed countries. Furthermore, the driving factors of the overall embodied CEI, including domestic trade and international trade, are population, PGDP, energy intensity, and trade. The expansion of industrialization can effectively reduce the CEI embodied in trade of developing countries. The increase of PGDP and industrialization can effectively reduce the CEI embodied in trade related to global value chain and traditional intermediate trade, while only the increase of PGDP can effectively reduce the CEI embodied in domestic trade and final goods trade. Population can reduce the embodied CEI in trade related to global value chain and traditional intermediate trade of developed countries. Economic development can almost promote the reduction of the CEI embodied in all trade patterns. Although industrialization has insignificant impact on the CEI embodied in final goods trade of the developed countries, it can reduce such CEI of developing countries.

Keywords Global value chain; Embodied carbon emission intensity; Input-output method; STIRPAT model

JEL classifications F18 · Q54 · Q56

Introduction

As one of the global problems, climate change has received widespread attention. The International Energy Agency (IEA 2012) points out that the global carbon emissions have risen from 21 billion tons in 1990 to 30.6 billion tons in 2010, and still maintain increasing trend. Responding to global climate change and reducing greenhouse gas (GHG) emissions have become a global consensus. The IAEA (2005) recommends using carbon emission intensity as overall performance indicator to estimate a country's performance. Many countries use carbon intensity indicators as emission mitigation targets. For example, China clearly states in the 13th Five-Year Plan that carbon intensity will fall by 18% in 2020; China and India promise to reduce carbon intensity by 60–65% and 33–35% in 2030, respectively (UNFCCC 2015). However, with the rapid development of trade and the deepening of the labor division, there exists large difference in CEI embodied in trade under different trade patterns. The environmental costs and effects of different trade patterns are different. In order to effectively achieve carbon mitigation targets, it is a key issue for policy makers to assess carbon emission intensity embodied in different trade patterns and formulate corresponding mitigation policies. However, relevant research is limited. In this study,

Responsible Editor: Philippe Garrigues

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we estimate CEI embodied in different trade patterns with world input-output table and explore its driving factors. It provides implications for countries to formulate GHG mitigation policies, participate in global division of labor as well as understanding the driving factors of CEI embodied in different trade patterns.

Both carbon emissions and carbon emission intensity are used as quantitative indicators of global GHG reduction. The former is the absolute quantity indicator, and the latter is the relative quantity indicator. Among them, the CEI refers to the amount of CO_2 emissions per unit of GDP (PGDP), which is a quantitative indicator in Chinese government's commitment to reduce emissions in the World Global Climate Conference or government documents. However, in some applications, especially when using input-output technology to measure the carbon emissions embodied in trade, carbon emission intensity or carbon emission coefficient is defined as CO_2 emissions per unit of output (e.g., Grether and Mathys 2008; Zhang 2009; Zhang et al. 2014; Duan and Jiang 2017; Meng et al. 2018). This is because the balance of the input-output table follows the total output equal to the total input. For the calculation of embodied carbon emissions and CEI, the existing research focuses on measuring the carbon emissions embodied in bilateral export trade or ones country trade to test the environmental effects of trade.

With the deepening of the global production fragmentation, Arce González et al. (2012), López et al. (2013a), López et al. (2013b), López et al. (2013c), and Zhang et al. (2017) measured the carbon emissions embodied in different trade patterns from the perspective of international production fragmentation, then testing the effects of pollution haven hypothesis in different trade patterns. Based on final demand, Su and Ang (2017) decomposed China's aggregate embodied intensities of CO_2 into the emissions intensities in rural consumption, urban consumption, government consumption, gross fixed capital formation, inventory change, and exports in 2007–2012. The results showed that the aggregate intensity of carbon emissions was mainly determined by the aggregate emissions intensity in investment, and the CEI effect generally contributed the most to the aggregate emissions intensity ratio changes at different levels. Using the world input-output database (WIOD), Meng et al. (2018) incorporated the two studies of value-added trade and carbon emissions embodied in trade into a unified framework, then through various routes in global value chains to systematically track both trade in value-added and CO_2 emission at the country, sector, and bilateral levels. However, the existing research rarely measures the embodied CEI of different trade patterns from the perspective of global value chain, which reflects the potential environmental cost of various trade patterns.

As for driving factors affecting carbon emissions and CEI, scholars often use decomposition analysis methods, including structural decomposition method (SDA), index decomposition analysis (IDA), logarithmic mean divisia index (LMDI), and Kaya equation (e.g., Xu and Ang 2013; Xu et al. 2014; Malik et al. 2016; Moutinho et al. 2018; Pu et al. 2018). Yao et al. (2015) analyzed the driving factors of carbon emissions in G20 countries and found that economic growth, population, and energy efficiency were important factors affecting carbon emissions in these countries. Wu et al. (2016) employed the Kaya equation to do Monte Carlo simulation and analyzed the influencing factors of China's carbon emissions. Mousavi et al. (2017) used the LMDI method to analyze the factors affecting Iran's industry carbon emissions and found that the increased energy consumption was the major factor. Tian et al. (2018) used the input-output table and SDA method to decompose driving factors of China's manufacturing carbon emissions into carbon emission intensity, input-output structure, and final demand. However, the decomposition analysis method is limited by the input-output table, and the decomposition factors need to have logical explanation and true meaning. Such method can only consider a few driving factors such as PGDP and energy consumption (Shuai et al. 2018).

A large amount of literature has been extensively studied on the driving factors of carbon emissions by regression method. Ehrlich and Holdren (1971) firstly proposed the IPAT model to analyze influencing factors of environment from the perspectives of population, wealth, and technology. Then, scholars have continued to expand the IPAT model in the following decades. Dietz and Rosa (1994) proposed an extended STIRPAT model, which still examined the relationship between environmental pressure and population, wealth, and technology. The STIRPAT model overcomes the unit elasticity hypothesis in the IPAT model and adds randomness to facilitate empirical analysis. It has been widely used in studies to identify factors affecting carbon emissions (e.g., Zhang and Cheng 2009; Wang et al. 2013; Xu and Lin 2015; Xie et al. 2017; Anser and Muhammad, 2019). Zhang and Zhou (2016) analyzed the impact of foreign direct investment (FDI), population, affluence, and technology on Chinese provincial carbon emissions with the STIRPAT model. They supported the pollution halo hypothesis and found that FDI could bring green innovation and reduced carbon emission. Xu and Lin (2017) analyzed the driving factors of Chinese provincial carbon emissions and found that economic growth, industrialization, urbanization, energy structure, and energy efficiency effected on carbon emissions, but there were regional differences. Shuai et al. (2018) used the STIRPAT model to perform partial-regression and stepwise regression analysis and found that China's industrial carbon emissions were mainly affected by PGDP, urbanization rate, tertiary industry ratio, and renewable energy ratio.

Since carbon reduction is a global problem, it is of significance to analyze the driving factors of carbon emissions and carbon emission intensity from the national level and guide countries to cope with climate change. Fan et al. (2006) analyzed the impact of population, affluence, and technology on carbon emissions among countries with different incomes. They found that economic growth had the greatest impact on carbon emissions, while the impact of population, affluence, and technology on carbon emissions varied due to different development level. Poumanyvong and Kaneko (2010) considered different income levels and used panel data from 99 countries to analyze the impact of urbanization on carbon emissions. Martínez-Zarzoso and Maruotti (2011) analyzed the impact of urbanization on carbon emissions in developing countries considering heterogeneity, and found that there was an inversed U-shaped relationship between urbanization and carbon emissions. Brizga et al. (2013) selected 15 countries of the former Soviet Union and analyzed the effects of energy intensity, industrialization, energy structure, carbon intensity, and population on their carbon emissions. Based on panel data from 25 African countries, Zoundi (2017) found that carbon emissions were increased by PGDP growth, while decreased by the growth of renewable energy consumption. Shuai et al. (2017) used data from 125 countries in 1990–2011 to analyze the impact of population, affluence, and technology on carbon emissions, and found that there were different effects among different income countries. However, these studies only analyze the driving factors of carbon emissions and CEI among countries. They do not examine the driving factors of CEI embodied in different trade patterns.

From the research theme, Su and Ang (2017) is the most relevant research to our study, but they only decompose China's overall carbon emission intensity into carbon emission intensity embodied in different final demand from the perspective of final demand. And they use the SDA structure decomposition method to analyze the driving factors of embodied CEI. It can only consider a few driving factors such as PGDP, intermediate input structure, and energy consumption due to the limitation of the input-output table. Therefore, we use the input-output method to calculate a country's actual economic benefits and the carbon emissions they undertake in various trades (domestic trade, final goods trade, traditional intermediate trade, and trade related to global value chain) from the perspective of global value chain. We construct the embodied CEI indicator, which is the ratio of value added of various trades to their carbon emissions. Then, based on the global multi-regional input-output table provided by the world input-output table database, we illustrate 37 countries' carbon emission intensity embodied in different trade patterns in 1995–2014. The results of the economic benefits obtained and carbon emissions undertaken from different trade patterns can provide reference for dividing global carbon reduction liabilities. Finally, the STIRPAT model is used to analyze the driving factors of carbon emission intensity embodied in different trade patterns.

In summary, our study contributes to the previous literature in three ways. (1) We firstly define the carbon emission intensity embodied in domestic trade and carbon emission intensity embodied in final goods trade, traditional intermediate trade, and trade related to global value chain. It provides reference for countries to better deal with climate changes and participates in international labor division. (2) Based on the global multi-regional input-output table, we use the input-output method to calculate the carbon emission intensity embodied in different trade patterns among countries. It can accurately reflect economic benefits obtained and carbon emissions undertaken from different trade patterns. (3) Different from the previous literature using structural decomposition method to analyze the driving factors, we use the STIRPAT model to analyze the driving factors of carbon emission intensity embodied in different trade patterns during 1995–2014. It provides deep analysis of the causes of embodied carbon emission intensity changes, especially in different trade patterns and different countries.

The remainder of this paper is organized as follows. The "Model and data" section introduces data and methodologies. The "Results of embodied carbon emission intensity" section presents results of embodied carbon emission intensity. The "Driving factors of embodied carbon emission intensity" section discusses the empirical results of driving factor analysis. The "Conclusions and discussions" section presents the conclusions and implications.

Model and data

Data

The data used in this paper mainly comes from three sources. One is the global multi-regional input-output (MRIO) table from 1995 to 2014. The MRIO table is derived from the World Input-Output Database (WIOD)[1] jointly prepared by 11 EU institutions. The database published in 2013 (Timmer et al. 2015) contains research subjects in the EU-27 and 13 major economies, including China, Russia, and the USA, as well as 35 industries[2] from 1995 to 2011 (this paper selects 1995 to 2011), and published in 2016 (Timmer et al. 2016) contains research subjects in the EU-28 and 15 major economies, including China, Russia, and the USA, as well as 56 industries[3] from 2000 to 2014 (this paper only selects the year of 2012, 2013, 2014). Other, the corresponding CO_2 emissions for 40 economies and 35 industries derived from the WIOD published in 2013 during 1995 to 2009, and the total

[1] http://www.wiod.org/

[2] Data for 35 sectors are classified according to the International Standard Industrial Classification revision 3 (ISIC Rev. 3).

[3] Data for 56 sectors are classified according to the International Standard Industrial Classification revision 4 (ISIC Rev. 4).

CO_2 emissions for 40 economies from International Energy Agency (IEA) during 1995 to 2014. The version released in 2016 does not provide the CO_2 emissions. Therefore, we take the following measures to expand the input-output table and the corresponding carbon emissions of each sector for various economies.

First, in order to make the MRIO table contain the same economies and industries, according to the documents of *WIOD SEA 2016: Sources and Methods* provided by WIOD, we will merge the MRIO tables from 2012 to 2014 provided in WIOD published in 2016 to be consistent with the MRIO tables from 1995 to 2011 provided in WIOD published in 2013, keeping all MRIO tables consistent with the industry and the country. Secondly, in order to make the data comparable, this study uses the 2010 USA GDP deflator provided by the World Bank database to subtract the original IO table data. Third, the initial CO_2 emissions for 40 economies and 35 industries derived from the WIOD published in 2013 during 1995 to 2009. According to Xu et al. (2017), we use the CO_2 emissions coefficient of 2009 as the initial CO_2 emission coefficient of each country by sector from 2010 to 2014. Then, we multiply the initial CO_2 emission coefficient during 2010 to 2014 by the total output of the MRIO table to obtain the initial CO_2 emissions of each country by sector from 2010 to 2014. Moreover, in order to keep the total CO_2 emissions of various countries consistent, we further use the total CO_2 emissions of various countries provided the IEA to adjust the CO_2 carbon emissions of each country by sector from 1995 to 2014, which according to the share of CO_2 emissions in each sector. Finally, a row is added at the bottom of the third quadrant to indicate the CO_2 emissions of sectors in each country, and then we construct a global multi-regional environmental-economic input-output table (see Table 1).

In Table 1, Z^{sr} is the intermediate product matrix exported from each sector of country s to the each sector of country r, and the dimension is $m \times m$; F^{sr} represents the final product vector of the country s export to country r, and the dimension is $m \times 1$; X^s is the output vector of the m sectors of country s, and the dimension is $m \times 1$; V^s and C^s are the added value and CO_2 emission vector of the m sectors of country s, respectively, and the dimension are $1 \times m$.

For the driving factors of CEI embodied in trade, we mainly examine the impact of PGDP, population, energy intensity, urbanization, industrial structure, and trade on embodied CEI. Among them, energy intensity is measured by the ratio of standard energy use to GDP; urbanization is measured by the proportion of urban population to total population; trade is measured by the ratio of trade to GDP; and the industrial structure is measured by the ratio of industrial sector value added to GDP. These data are derived from the World Bank database, and PGDP is adjusted by the dollar deflator in 2010. Descriptive statistics of the econometrics data are shown in Table 2.

Std. Dev., Min., and Max. indicate the standard deviation, minimum, and maximum values

The measurement model of embodied carbon emission intensity

According to Table 1, if the direct consumption coefficient matrix is defined as $A^{sr} = {}^{Z^{sr}}\big/_{\left(uX^{r'}\right)}$, u represents a $m \times 1$ one unit column vector, and A^{sr} represents the amount of intermediate use in the country r of the unit output produced in the country s. Then, the row balance relationship of the first quadrant and the second quadrant in Table 1 is:

Table 1 Global multi-regional environmental-economic input-output table

		Intermediate demand				Final demand				Total output
		G1	G2	$\cdots$	Gn	G1	G2	$\cdots$	Gn	
Intermediate input	G1	Z^{11}	Z^{12}	$\cdots$	Z^{1n}	F^{11}	F^{12}	$\cdots$	F^{1n}	X^1
	G2	Z^{21}	Z^{22}	$\cdots$	Z^{2n}	F^{21}	F^{22}	$\cdots$	F^{2n}	X^2
	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
	Gn	Z^{n1}	Z^{n2}	$\cdots$	Z^{nn}	F^{n1}	F^{n2}	$\cdots$	F^{nn}	X^n
Value added		V^1	V^2	$\cdots$	V^n					
Total input		$X^{1'}$	$X^{2'}$	$\cdots$	$X^{n'}$					
CO_2 emission		C^1	C^2	$\cdots$	C^n					

G indicates the country or region, superscript

' indicates the transpose of a vector or matrix, the same below

Table 2 Variable definition and statistical description

Variable	Definition	Mean	Std. Dev.	Min.	Max.
lnCEI	Carbon emission intensity embodied in trade (Tons-CO_2/Thousand of US\$), in logarithm	−1.021	0.811	−2.849	1.687
lnCEI _ Ev	Carbon emission intensity embodied in trade related to global value chain (Tons-CO_2/Thousand of US\$), in logarithm	−0.634	0.814	−2.349	2.238
lnCEI _ F	Carbon emission intensity embodied in domestic trade (Tons-CO2/Thousand of US\$), in logarithm	−1.183	0.873	−3.602	1.438
lnCEI _ Ef	Carbon emission intensity embodied in final goods trade (Tons-CO2/Thousand of US\$), in logarithm	−0.935	0.767	−2.649	1.682
lnCEI _ Ei	Carbon intensity embodied in traditional intermediate trade (Tons-CO2/Thousand of US\$), in logarithm	−0.616	0.784	−2.456	2.070
lnP	Population (people), in logarithm	16.863	1.907	12.841	21.034
lnPGDP	Gross domestic product per capita (US\$/people), in logarithm	9.846	1.015	6.433	11.626
lnEI	Total energy use divided by GDP (kg of oil equivalent per \$1000), in logarithm	4.826	0.353	4.025	5.840
lnUrban	The percentage of urban population in total population (%), in logarithm	4.239	0.245	3.281	4.583
lnTrade	The percentage of trade volume in GDP (%), in logarithm	4.309	0.595	2.750	5.946
lnIndustry	The percentage of industrial sector value added in GDP (%), in logarithm	3.369	0.235	2.370	3.862

$$X_{mn\times 1} = \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^n \end{bmatrix}_{mn\times 1}$$

$$= \begin{pmatrix} I-A^{11} & \cdots & -A^{1n} \\ -A^{21} & \ddots & -A^{2n} \\ \vdots & & \vdots \\ -A^{n1} & \cdots & I-A^{nn} \end{pmatrix}^{-1}_{mn\times mn} \begin{bmatrix} F^1 \\ F^2 \\ \vdots \\ F^n \end{bmatrix}_{mn\times 1}$$

$$= \begin{pmatrix} B^{11} & \cdots & B^{1n} \\ B^{21} & \ddots & B^{2n} \\ \vdots & & \vdots \\ B^{n1} & \cdots & B^{nn} \end{pmatrix}_{mn\times mn} \begin{bmatrix} F^1 \\ F^2 \\ \vdots \\ F^n \end{bmatrix}_{mn\times 1} \tag{1}$$

where F^s represents the final demand of the country s, which including the total final products demand in the country s and other countries, and satisfies $F^s = \sum_r^n F^{sr}$; the Leontief inverse B^{sr} represents the quantity of the output of country s for a one unit of final demand goods produced in country r. We can write Eq. (1) in matrix form: $X = (I-A)^{-1}F = BF$, where $B = (I-A)^{-1}$. From Eq. (1), we can obtain:

$$X^s = \sum_t^n B^{st}F^t = \sum_t^n \left(B^{st} \sum_u^n F^{tu} \right) \tag{2}$$

From Table 1, the volume of trade between countries is divided into two parts: trade in intermediate products (II quadrant) and trade in final products (I quadrant). Then, the exports from country r to country s are:

$$E^{rs} = A^{rs}X^s + F^{rs} \tag{3}$$

From the diagonal element of Eq. $(I-A)B = I$ and Wang et al. (2017) proves that:

$$B^{ss} = (I-A^{ss})^{-1} + (I-A^{ss})^{-1} \sum_{t\neq s}^{n} A^{st}B^{ts}$$

$$= L^{ss} + L^{ss} \sum_{t\neq s}^{n} A^{st}B^{ts} \tag{4}$$

where $L^{ss} = (I-A^{ss})^{-1}$ is the Leontief inverse matrix of region s. According to the classification of global trade patterns among countries developed by Wang et al. (2017) and Zhang et al. (2017), Eq. (3) can be expressed as:

$$E^{rs} = \underbrace{F^{rs}}_{E\_f^{rs}} + \underbrace{A^{rs}L^{ss}F^{ss}}_{E\_i^{rs}} + \underbrace{A^{rs}L^{ss}\sum_{t\neq s}^{n} A^{st}B^{ts}F^{ss} + A^{rs}\sum_{t\neq s}^{n} B^{st}F^{ts} + A^{rs}\sum_{t}^{n} B^{st}\sum_{u\neq s}^{n} F^{tu}}_{E\_v^{rs}} \tag{5}$$

where E_f^{rs} represents trade in final products. The exporter of the country r occupies the last stage of production and then directly exports final products. E_i^{rs} denotes intercountry "direct" trade in intermediate products based on the pattern of traditional trade in intermediate products. The intermediate product of country r exports is directly used in the last stage of production for the imported country s and is directly consumed by country s. E_v^{rs} is narrowly defined the global value chain-related trade.

According to Table 1, we can find that the total output of country r (X^r) is divided into two parts: intermediate demand (II quadrant) and final demand (I quadrant). Then, the total output of country r (X^r) is:

$$X^r = \underbrace{\sum_{s}^{n} Z^{rs}u}_{intermediate\ demand} + \underbrace{\sum_{s}^{n} F^{rs}}_{final\ demand} = \underbrace{\sum_{s}^{n} A^{rs}X^s}_{intermediate\ demand} + \underbrace{\sum_{s}^{n} F^{rs}}_{final\ demand}$$
$$= \underbrace{A^{rr}X^r + F^{rr}}_{domestic\ demand} + \underbrace{\sum_{s\neq r}^{n} A^{rs}X^s + \sum_{s\neq r}^{n} F^{rs}}_{exports\ demand} = \underbrace{A^{rr}X^r + F^{rr}}_{domestic\ demand} + \underbrace{\sum_{s\neq r}^{n} E^{rs}}_{exports\ demand} \tag{6}$$

Then, we can obtain:

$$X^r = (I - A^{rr})^{-1}\left(F^{rr} + \sum_{s\neq r}^{n} E^{rs}\right) = L^{rr}F^{rr} + L^{rr}\sum_{s\neq r}^{n} E^{rs} \tag{7}$$

And, according to Eq. (5), we can also obtain:

$$\begin{aligned} X^r &= L^{rr}F^{rr} + L^{rr}\sum_{s\neq r}^{n}\left(E\_f^{rs} + E\_i^{rs} + E\_v^{rs}\right) \\ &= L^{rr}F^{rr} + L^{rr}\sum_{s\neq r}^{n} E\_f^{rs} + L^{rr}\sum_{s\neq r}^{n} E\_i^{rs} + L^{rr}\sum_{s\neq r}^{n} E\_v^{rs} \end{aligned} \tag{8}$$

We further define the CO_2 intensity and the value added per unit output of the country r as $c^r = C^r/X^{r'}$ and $v^r = V^r/X^{r'}$, respectively, and their dimensions are set as $1 \times m$. Elements represent the CO_2 intensity and value added per unit output of each sector of the country r, respectively. It can be seen that the total CO_2 emissions and value added of the country r are:

$$TC^r = c^r X^r = \underbrace{c^r L^{rr} F^{rr}}_{①} + \underbrace{c^r L^{rr}\sum_{s\neq r}^{n} E\_f^{rs}}_{②} + \underbrace{c^r L^{rr}\sum_{s\neq r}^{n} E\_i^{rs}}_{③} + \underbrace{c^r L^{rr}\sum_{s\neq r}^{n} E\_v^{rs}}_{④} \tag{9}$$

$$GDP^r = v^r X^r = \underbrace{v^r L^{rr} F^{rr}}_{①} + \underbrace{v^r L^{rr}\sum_{s\neq r}^{n} E\_f^{rs}}_{②} + \underbrace{v^r L^{rr}\sum_{s\neq r}^{n} E\_i^{rs}}_{③} + \underbrace{v^r L^{rr}\sum_{s\neq r}^{n} E\_v^{rs}}_{④} \tag{10}$$

In Eqs. (9) and (10), ① indicates the amount of carbon emissions and value added caused by domestic demand, and has nothing to do with international trade; ② represents the amount of carbon emissions and value added induced by the final products trade between countries; ③ represents the amount of carbon emissions and value added caused by the traditional trade in intermediate products between countries; ④ represents the amount of carbon emissions and value added induced by the inter-country trade related to global value chains.

Therefore, the aggregate embodied CEI (carbon emission per unit of value added) CEI^r in country r is calculated as:

$$\begin{aligned} CEI^r &= \frac{TC^r}{GDP^r} = \frac{c^r L^{rr} F^{rr} + c^r L^{rr}\sum_{s\neq r}^{n} E\_f^{rs} + c^r L^{rr}\sum_{s\neq r}^{n} E\_i^{rs} + c^r L^{rr}\sum_{s\neq r}^{n} E\_v^{rs}}{v^r L^{rr} F^{rr} + v^r L^{rr}\sum_{s\neq r}^{n} E\_f^{rs} + v^r L^{rr}\sum_{s\neq r}^{n} E\_i^{rs} + v^r L^{rr}\sum_{s\neq r}^{n} E\_v^{rs}} \\ &= \frac{v^r L^{rr} F^{rr}}{GDP^r}\underbrace{\frac{c^r L^{rr} F^{rr}}{v^r L^{rr} F^{rr}}}_{CEI\_F^r} + \frac{v^r L^{rr}\sum_{s\neq r}^{n} E\_f^{rs}}{GDP^r}\underbrace{\frac{c^r L^{rr}\sum_{s\neq r}^{n} E\_f^{rs}}{v^r L^{rr}\sum_{s\neq r}^{n} E\_f^{rs}}}_{CEI\_Ef^r} + \frac{v^r L^{rr}\sum_{s\neq r}^{n} E\_i^{rs}}{GDP^r}\underbrace{\frac{c^r L^{rr}\sum_{s\neq r}^{n} E\_i^{rs}}{v^r L^{rr}\sum_{s\neq r}^{n} E\_i^{rs}}}_{CEI\_Ei^r} + \frac{v^r L^{rr}\sum_{s\neq r}^{n} E\_v^{rs}}{GDP^r}\underbrace{\frac{c^r L^{rr}\sum_{s\neq r}^{n} E\_v^{rs}}{v^r L^{rr}\sum_{s\neq r}^{n} E\_v^{rs}}}_{CEI\_Ev^r} \end{aligned} \tag{11}$$

where CEI_F^r indicates the CEI embodied in domestic trade for the country r; CEI_Ef^r, CEI_Ei^r, and CEI_Ev^r are the CEI embodied in international trade for the country r; CEI_Ef^r represents CEI embodied in final goods trade for the country r; CEI_Ei^r represents CEI embodied in traditional intermediate trade for the country r; CEI_Ev^r represents CEI embodied in trade related to global value chain for the country r.

The driving factor model of embodied carbon emission intensity

The STIRPAT model overcomes the unit elasticity hypothesis in the IPAT model and adds randomness to facilitate empirical analysis, we take the STIRPAT model to analyze the driving factors of CEI embodied in trade. The original form of the STIRPAT model is the IPAT model, which was first presented by Ehrlich and Holdren (1971), which assesses the impact of population (P), affluence (A), technology (T) on environmental pressure (I). The IPAT model is expressed as:

$$I = PAT \tag{12}$$

where I is the environmental pressure, P is the population scale, A is the affluence factor, and T represents technology. However, the IPAT model has some limitations such as it does not allow for non-monotonic and non-proportional changes in driving factors (York et al. 2003). To overcome these drawbacks, Dietz and Rosa (1994) proposed a stochastic model, which was the STIRPAT model. It can be expressed as:

$$I_i = aP_i^b A_i^c T_i^d \mu_i \tag{13}$$

After taking logarithms, the model can be represented as follows:

$$lnI_i = a + blnP_i + clnA_i + dlnT_i + \mu_i \tag{14}$$

where a is the constant term, b, c, and d are the coefficient of P, A, and T, respectively. μ denotes the disturbance term and i represents the analysis unit. Following Poumanyvong and Kaneko (2010) and Martínez-Zarzoso and Maruotti (2011), we measure P with population, A with PGDP, and T with energy intensity (EI). The regression model is as follows:

$$lnCEI\_Ev = \alpha_0 + \alpha_1 lnP + \alpha_2 lnA + \alpha_3 lnT + \varepsilon \tag{15}$$

Except variables in the STIRPAT model, we add three variables in our empirical model. First, we consider the impacts of urbanization on CEI. Martínez-Zarzoso and Maruotti (2011) proposed that urban economic activities may influence environmental quality in a distinct way as industrialization does. Second, we choose the ratio of total trade to GDP as the proxy variable of the openness level. Scholars indicate that trade openness can affect energy intensity through technology spillover, which has a great influence on carbon emissions (e.g., Wang and Zhao 2015; Huang 2018). Third, we use the ratio of the added value of secondary industry to GDP to reflect industrialization, and add it in the model. Xie et al. (2017) and Xie et al. (2018) indicated that the industrialization expands firms scale and increases energy consumption. It is an important influencing factor on carbon emissions. Therefore, we also add these variables into our model and the improved STIRPAT model is as follows:

$$\begin{aligned} & lnCEI, lnCEI\_Ev_{it}, lnCEI\_F_{it}, lnCEI\_Ef_{it}, lnCEI\_Ei_{it} \\ & \quad = \alpha_0 + \alpha_1 lnP_{it} + \alpha_2 lnPGDP_{it} + \alpha_3 lnEI_{it} \\ & + \alpha_4 lnUrban_{it} + \alpha_5 lnTrade_{it} + \alpha_6 lnIndustry_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{16}$$

where i is country, t is year, μ_i and γ_t captures individual and year fixed effects, respectively. ε_{it} is an error term. CEI is the aggregate embodied CEI. CEI_Ev represents CEI embodied in trade related to global value chain. CEI_F is CEI embodied in domestic trade. CEI_Ef is CEI embodied in final goods trade. CEI_Ei is CEI embodied in traditional intermediate trade. P is population size, $PGDP$ is affluence, we use GDP per capital to estimate, EI is technology, we use energy intensity to present technology level, $Urban$ is the urbanization level, $Trade$ is the trade volume, and $Industry$ is industrial structure.

Results of embodied carbon emission intensity

Overall

Figure 1 shows the embodied CEI of different trade patterns in the countries included in the WIOD[4] for 2014, as measured by Eq. (9). Horizontal comparisons show that, both developed countries and developing countries, the CEI embodied in domestic trade (CEI_F) is significantly lower than the CEI embodied in international trade in 2014 (also known as the CEI embodied in export trade, which includes the CEI embodied in final products trade CEI_Ef, CEI embodied in traditional intermediate trade CEI_Ei and CEI embodied in trade related to global value chain CEI_Ev). This result is consistent with the result of Su and Ang (2017). They found that, in 2007 and 2012, China's CEI embodied in domestic trade (0.22 and 0.17 kg CO_2/RMB) was lower than the CEI embodied in export trade (0.26 and 0.18 kg CO2/RMB). To a certain

[4] In order to compare the results and the reasonableness of the data, this article deletes Estonia (EST), Greece (GRC), Taiwan (TWN), and other countries (ROW) in WIOD. According to the national classification of World Economic Situation and Prospects 2018, we divided the remaining 37 countries into 8 developing countries and 29 developed countries. Among them, except for CHN, IND, IDN, RUS, BRA, KOR, MEX, and TUR, which belong to developing countries, the rest belong to developed countries.

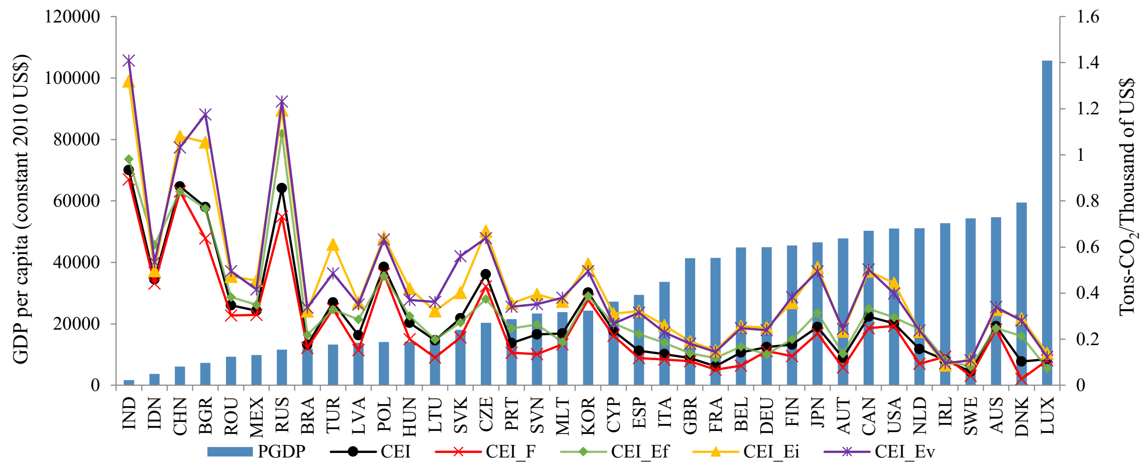

Fig. 1 Per capita GDP (Per capita GDP comes from the GDP of each country published in the World Bank database (2010 constant price US dollar)) and carbon emission intensity embodied in different trade patterns of various countries, in 2014

extent, this indicates that, for global economy, the amount of CO_2 emission by the unit value added in international trade is significantly higher than the amount of CO_2 emission by the unit value added in domestic trade. Therefore, the environmental cost of domestic trade is lower than the environmental cost of international trade.

Comparing the magnitude of CEI embodied in different international trade patterns, it is found that except for developed countries such as the Netherlands (NLD), Cyprus (CYP), and Ireland (IRL) and developing countries of Indonesia (IDN), the CEI embodied in final products trade (CEI_Ef) of the remaining research economies is significantly lower than the CEI embodied in other two export trade (CEI_Ei and CEI_Ev). It means that the environmental cost of the final goods trade is lower than that of the other two international trade patterns. Vertical comparisons show that, on the whole, the CEI of developing countries is significantly higher than that of developed countries. Figure 1 shows that in 2014, regardless of the aggregate embodied CEI or the CEI embodied in different trade patterns, developing countries are higher than developed countries, especially those with higher PGDP. This is mainly because countries with high PGDP and economic development usually have advanced production technology and emission reduction technology, and they are motivated to have less carbon emissions per unit of GDP, i.e., low carbon emission intensity.

The change trend of carbon emissions intensity

In order to accurately understand the trends of CEI embodied in different trade patterns, this section measures the average CEI embodied in different trade patterns of 8 developing countries and 29 developed countries. Then, this section selectively shows the trends of CEI embodied in different trade patterns for two representative developed countries (the United States, USA; the United Kingdom, GBR) and developing countries (China, CHN; Russia, RUS).

Figure 2 shows the trends of CEI embodied in different trade patterns in major economics from 1995 to 2014, which are calculated by Eq. (11). The results show that during 1995–2014, the aggregate embodied CEI and CEI embodied in different trade patterns (CEI_F, CEI_Ef, CEI_Ei, and CEI_Ev) of the average of developed countries, USA and GBR in developed countries, the average of developing countries, CHN and RUS in developing countries, all show a downward trend, but the decline in developing countries are significantly greater than that in developed countries. For example, during 1995–2014, the aggregate embodied carbon emission intensity of CHN, RUS, USA, and GBR decline by 66.86%, 72.61%, 39.47% and 55.24%, respectively. On the one hand, with technological progress and global economic growth, the global economy is achieving a low-carbon development path, which will reduce CEI; on the other hand, compared with developed countries, developing countries have larger space for emission reduction. This is because, initially, developing countries have low emission reduction technologies and high CEI, while developed countries have relatively high emission reduction technologies and significantly lower CEI. When the world is committed to reducing carbon emissions, developing countries will be technically and financially supported, which will significantly increase their emission reduction technologies and decrease CEI.

Although the decline of CEI in developing countries is greater than that in developed countries, but from the perspective of change trends, during the study period, the CEI of developing countries is still greater than 1 or be

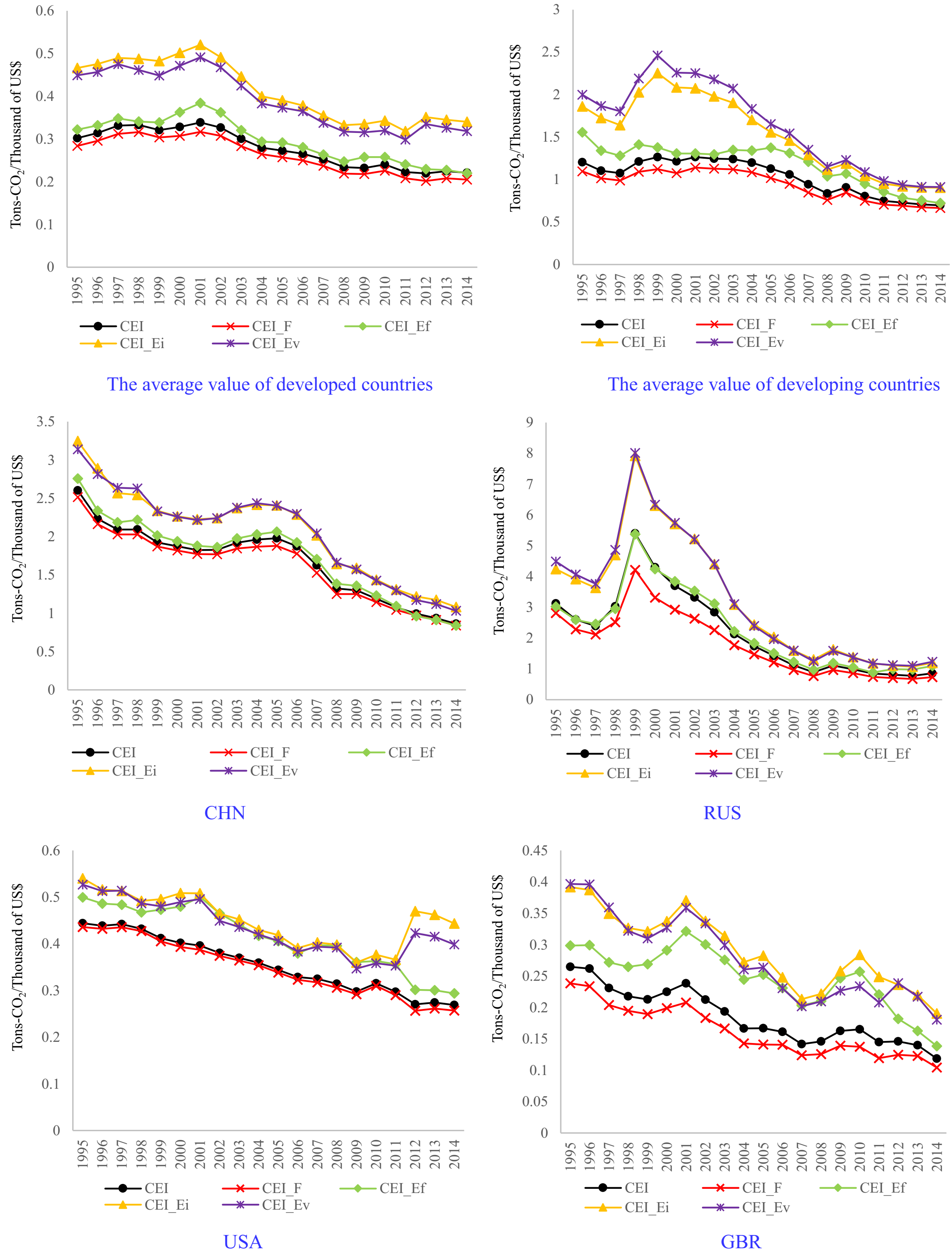

Fig. 2 The carbon emission intensity embodied in different trade patterns of major economics from 1995 to 2014

close to 1, while the carbon emission intensity of developed countries is less than 0.5. This means that the amount of CO_2 emitted by the unit value added of the developed countries is significantly lower than the amount of CO_2 emitted by the unit value added of the developing countries. It indicates that the environmental costs of developed countries are lower than those of developing countries, that is, the production technology level of enterprises in developed countries is higher than that of developing countries.

Table 3 Results of driving factors affecting overall embodied CEI

	Overall embodied CEI	Embodied CEI in developed countries	Embodied CEI in developing countries
lnP	0.572***	0.323**	− 0.400
	(4.92)	(2.27)	(− 1.01)
lnPGDP	− 0.460***	− 0.607***	− 0.713***
	(− 8.23)	(− 6.60)	(− 4.34)
lnEI	1.227***	1.134***	1.048***
	(16.74)	(12.73)	(5.56)
lnUrban	1.174***	1.096***	1.516***
	(8.70)	(4.87)	(5.18)
lnTrade	0.555***	0.348***	0.860***
	(15.71)	(7.09)	(12.84)
lnIndustry	− 0.033	− 0.016	− 2.227***
	(− 0.51)	(− 0.23)	(− 0.80)
Year FE	YES	YES	YES
Country FE	YES	YES	YES
R^2	0.91	0.92	0.91
Obs	740	580	160

Z statistics are in parentheses

***, **, and * denote significance at 1%, 5% and 10%, respectively

Driving factors of embodied carbon emission intensity

Considering the existence of omitted variables that do not change with time but vary with the country and do not change with the country but vary with time, we use the fixed effect method considering individual and time fixed effects to estimate the model (16). The results are shown in Table 3. The main driving factors of CEI embodied in overall trade, including domestic trade and international trade, are population, PGDP, energy intensity, urbanization, and trade. Overall, country's population scale has a positive effect on overall embodied carbon emission intensity at the 1% significance level. It indicates that the increase of population scale increases the carbon intensity embodied in trade. Furthermore, we compare the differences between the developed countries and developing countries. It shows that the population size of the developed countries has a significant positive impact on CEI, while it has no significant effect on CEI in developing countries. It may be due to the fact that the carbon emissions of developing countries such as China are not mainly derived from residential consumption, but emissions from production (Zhou and Liu 2016).

The degree of economic development (PGDP) has significant negative impact on the embodied CEI of the overall countries. One percent increase of PGDP can lead to 0.46% decrease of embodied CEI. This may be because the economic development improves living standards of residents, and accordingly increases residents' requirements for environmental quality. When the region participates in the global value chain, it will also reduce the participation of pollution-intensive production links, which causes reduction of the embodied CEI. Such effect exists in both developed and developing countries, and has a greater impact in developing countries. One percent increase in PGDP can promote 0.713% decline in the embodied CEI in developing countries. This may be related to the fact that developing countries are mostly involved in high-pollution trade process.

Energy intensity has a significant positive effect on the embodied CEI, and comparing the regression coefficients of other variables, it indicates that the impact of energy intensity on the embodied CEI is the largest. The higher energy intensity implies the lower energy efficiency and more consumption of energy for production. It leads the increase of the embodied CEI. This effect exists in both developed and developing countries. This is consistent with the conclusions of most studies. The energy intensity reflects the level of technical efficiency. Lower energy intensity means the higher technical efficiency, which can reduce the carbon emissions per unit of output, which leads to lower embodied CEI.

We find that urbanization has positive impact on the overall embodied CEI, 1% urbanization growth leads to 1.174% increase of the embodied CEI. It is similar to the results in Zhang and Lin (2012). As the urbanization process inevitably bring about the expansion of the construction industry, urbanization also leads to increased demand for automobiles and housing by residents. It inevitably increases energy consumption and brings heavy burden on the local environment, which causes urbanization to exacerbate the embodied CEI. Such effect is greater in developing countries, where urbanization increases by 1% and CEI increases by 1.516%. This may be because the energy consumption structure and technology of developing countries are inferior to those of the developed countries, which leads to increased carbon consumption and embodied CEI due to increased energy consumption during urbanization.

We also find that trade has a significant effect on CEI. Overall, the coefficient of trade is 0.555 and is significant at the 1% level. It indicates that a country's trade scale can effectively increase the overall embodied CEI. It is further found that the coefficient of trade in the developed countries and developing countries is 0.348 and 0.86, respectively. It is consistent with the study by Wang and Zhao (2015), who found that as China's trade expands, energy consumption and carbon emissions continue to increase. This also verifies the Pollution Heaven hypothesis (Walter and Ugelow 1979), indicating that trade of developing countries is mainly based on high pollution and low value-added products in. Developing countries should make more effort to improve the quality of international trade to deal with environmental issues.

Although the impact of industrialization on the CEI embodied in the overall trade is not significant, the industrialization has a significant negative impact on embodied CEI in developing countries. It indicates that the increase of the proportion of the secondary industry will lead to a decrease of the overall embodied CEI in developing countries. This may be due to the fact that the secondary industry still plays an important role in developing countries' economy. They make more effort to improve secondary industry quality and optimize intra-industry structure. Therefore, increase of the secondary industry value can help to reduce the carbon intensity in developing countries.

Table 4 Results of driving factors of CEI embodied in different trade patterns

	CEI_Ev	*CEI_F*	*CEI_Ef*	*CEI_Ei*
lnP	0.022	1.225***	0.004	− 0.153
	(0.13)	(8.28)	(0.03)	(− 1.05)
lnPGDP	− 0.475***	− 0.240***	− 0.634***	− 0.503***
	(− 6.03)	(− 3.36)	(− 8.14)	(− 7.15)
lnEI	1.441***	1.189***	1.293***	1.454***
	(13.96)	(12.73)	(12.67)	(15.78)
lnUrban	1.145***	1.113***	1.132***	1.193***
	(6.03)	(6.48)	(6.02)	(7.03)
lnTrade	0.544***	0.535***	0.250***	0.566***
	(10.93)	(11.88)	(5.08)	(12.72)
lnIndustry	− 0.595***	− 0.023	0.007	− 0.586***
	(− 6.58)	(− 0.28)	(0.08)	(− 7.25)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
R^2	0.84	0.88	0.83	0.87
Obs	740	740	740	740

Z statistics are in parentheses. ***, **, and * denotes significance at 1%, 5% and 10%, respectively

In order to analyze the different driving factors in various trade patterns, we employ the CEI embodied in trade related to global value chain, domestic trade, final goods trade, and traditional intermediate trade as the dependent variable, respectively. Then, we rerun the model (16), and results are shown in Table 4. We find that an increase in PGDP and industrialization can effectively reduce the CEI embodied in trade related to global value chains, while energy intensity, urbanization, and trade increase it. In addition, energy intensity and urbanization play the greatest effect. The main driving factors of the CEI embodied in domestic trade are population, PGDP, energy intensity, urbanization, and trade at the significance of 1% level. Among them, PGDP can effectively reduce the CEI embodied in domestic trade, while energy intensity, urbanization, and trade can increase the CEI embodied in domestic trade significantly. Moreover, energy intensity has the greatest effect on the CEI embodied in domestic trade.

The CEI embodied in final goods trade are mainly affected by the PGDP, energy intensity, and trade, which is significant at the level of 1%. With the development of economy, CEI embodied in final goods trade will be reduced. The expansion of economy can help to reduce environment pollution of the final goods trade. The CEI embodied in traditional intermediate trade is mainly driven by the PGDP, energy intensity, urbanization, trade, and industrialization. As the PGDP and industrialization increases 1%, the CEI embodied in traditional intermediate trade can be reduced by 1.445% and 0.586%, respectively. The expansion of PGDP and industrialization has emission mitigation impact.

We can find that there are significant differences in the driving factors of CEI embodied in different trade patterns. The expansion of the secondary industry has not reduced the embodied CEI of domestic trade and final goods trade but has helped reduce the embodied CEI of global value chains and traditional intermediate trade. PGDP has a significant effect on reducing carbon intensity of all trade patterns. In addition, the embodied carbon intensity of domestic trade is also affected by the population scale. Policymakers need to make different policies when dealing with environmental issues in different trade patterns.

Since developed countries and developing countries have large differences in economic development, resources, and policies, we classify our samples into developed countries and developing countries according to the division criteria in World Economic Situation and Prospects (United Nations 2018). The driving factors affecting the CEI embodied in different trade patterns in developed countries and developing countries are analyzed. The results are shown in Table 5.

The CEI embodied in trade related to global value chain of developed countries are mainly reduced by population, PGDP, and industrialization. The CEI embodied in trade

Table 5 Results of driving factors of embodied CEI in developed and developing countries

	CEI_Ev		*CEI_F*		*CEI_Ef*		*CEI_Ei*	
	Developed country	Developing country	Developed country	Developing country	Developed country	Developing country	Developed country	Developing country
lnP	− 0.601***	− 0.235	1.456***	− 0.323	− 0.354*	− 1.299***	− 0.498***	− 0.495
	(− 2.83)	(− 0.53)	(7.51)	(-0.85)	(-1.72)	(-2.97)	(-2.66)	(− 1.06)
lnPGDP	− 0.689***	− 0.851***	0.021	− 0.656***	− 0.869***	− 1.084***	− 0.704***	− 0.711***
	(− 5.02)	(− 4.62)	(0.17)	(− 4.17)	(− 6.54)	(− 5.98)	(− 5.82)	(− 3.66)
lnEI	1.388***	1.070***	1.252***	0.963***	1.184***	1.022***	1.362***	1.342***
	(10.43)	(5.05)	(10.32)	(5.34)	(9.20)	(4.92)	(11.61)	(6.02)
lnUrban	0.240	1.828***	2.272***	1.397***	0.602*	2.064***	0.520*	1.658***
	(0.71)	(5.56)	(7.42)	(4.99)	(1.85)	(6.39)	(1.76)	(4.79)
lnTrade	0.283***	0.827***	0.405***	0.824***	− 0.058	0.733***	0.422***	0.740***
	(3.86)	(10.99)	(6.06)	(12.85)	(− 0.81)	(9.92)	(6.54)	(9.33)
lnIndustry	− 0.679***	− 0.780**	0.017	− 0.112	0.079	− 0.666**	− 0.608***	− 0.881**
	(− 6.52)	(− 2.44)	(0.18)	(− 0.41)	(0.79)	(− 2.12)	(− 6.62)	(− 2.62)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
R2	0.84	0.90	0.89	0.91	0.83	0.89	0.87	0.89
Obs	580	160	580	160	580	160	580	160

Z statistics are in parentheses. ***, **, and * denotes significance at 1%, 5% and 10%, respectively

related to global value chain of developing countries are reduced by PGDP and industrialization. Among them, the energy intensity has the greatest impact on the CEI embodied in trade related to global value chain of developed countries, while the urbanization has the greatest impact on the CEI embodied in trade related to global value chain of developing countries.

For domestic trade, the embodied CEI of developed countries are mainly affected by population, energy intensity, urbanization, and trade, both of which can significantly increase the CEI embodied in domestic trade of developed countries. Besides, the embodied CEI of developing countries are also affected by PGDP, energy intensity, urbanization, and trade, while PGDP has a significant reduction impact on embodied CEI in domestic trade of developing countries.

For final goods trade, the embodied CEI of developed and developing countries are both driven by population, PGDP, energy intensity, and urbanization. The expansion of population and PGDP will inhibit the increase of CEI. Moreover, the embodied CEI of developing countries are also affected by trade and industrialization. The expansion of trade leads to the increase of the embodied CEI of developing countries, while the expansion of industrialization has negative impact on the embodied CEI. Furthermore, the negative effect of PGDP is the largest, while the population has the greatest inhibition effect.

For traditional intermediate trade, the embodied CEI of developed and developing countries are affected by PGDP, energy intensity, urbanization, trade and industrialization. Moreover, the embodied CEI of developed and developing countries are negatively affected by PGDP and industrialization. That of developing countries are also negatively affected by population.

Conclusions and discussions

As one of the global problems, climate change has attracted widespread attention. Many countries regard CEI indicator as emission reduction targets. With the development of trade and the deepening of labor division, there are large differences in the embodied CEI of different trade patterns, that is, the environmental costs and effects of different trades are different. Studying the embodied CEI of different trade patterns and their driving factors can provide implications for countries to formulate GHG reduction plans and participate in global labor division. To this end, we use the input-output method to calculate a country's actual economic benefits and the carbon emissions they undertake in various trades (domestic trade, final goods trade, traditional intermediate trade, and trade related to global value chain) from the perspective of global value chain. We construct the embodied CEI indicator, which is the ratio of value added of various trades to their carbon emissions. Then, we calculate 37 countries' CEI embodied in different trade patterns in 1995–2014. Also, the STIRPAT model is used to analyze the driving factors of carbon emission intensity embodied in different trade patterns.

The calculation results show that, both the developed countries and developing countries, the CEI embodied in domestic trade is significantly lower than the CEI embodied in international trade. It indicates that the environmental cost of domestic trade is lower than the environmental cost of international trade. Comparing different international trade patterns, the CEI embodied in final goods trade of most countries is significantly lower than that of the other two export trade patterns. Taking 2014 as an example, regardless of the aggregate embodied CEI or the CEI embodied in different trade patterns, embodied CEI in developing countries are higher than that in developed countries, especially countries with higher PGDP. From the perspective of change trends, during the sample period, the embodied CEI in developing countries is still greater than 1, while the CEI in developed countries is less than 1. It means that the environmental costs of developed countries are lower than that of developing countries.

The driving factors of the overall embodied CEI, including domestic trade and international trade, are population, PGDP, energy intensity and trade. The PGDP has significant negative impact on the embodied CEI for all countries trade, and such negative impact is greater in developing countries. Although the impact of industrialization is insignificant on the overall embodied CEI, it has significant negative impact in developing countries. Furthermore, the Pollution Heaven hypothesis exists, especially the trade has greater positive impact on the embodied CEI of developing countries. There are significant differences in the driving factors of embodied CEI under different trade patterns. The increase of PGDP and industrialization can effectively reduce the CEI embodied in trade related to global value chain and traditional intermediate trade, while only the increase of PGDP can effectively reduce the CEI embodied in domestic trade and final goods trade.

Identifying developed countries and developing countries, the reduction of the CEI embodied in trade related to global value chain in developing countries is mainly driven by PGDP and industrialization. Besides, the CEI embodied in trade related to global value chain in the developed countries is also driven by population. For domestic trade, the embodied CEI of the developed countries is mainly affected by population, energy intensity, urbanization and trade. The embodied CEI of developing countries is affected by the PGDP, energy intensity, urbanization and trade, but only the PGDP facilitates the reduction of the embodied CEI. For final goods trade, the embodied CEI of both developed and developing countries is reduced by increase of population and PGDP; industrialization has negative impact on the embodied CEI in the developing countries. For traditional intermediate trade, the embodied CEI of developed and developing countries is reduced by PGDP and industrialization. Meanwhile, the embodied CEI of developed countries is reduced by the expansion of population.

It provides implications for international organizations to assign carbon emission reduction responsibilities. The carbon reduction responsibility system guided by “producer responsibility” overestimates the efforts that developing countries undertake for global carbon reduction and global warming issue. By participating in the global value chain, the developed countries enjoy higher value-added benefits, while bear relatively less carbon reduction responsibility. International organizations should change the emission reduction responsibility system under the guidance of “producer responsibility” when formulating greenhouse gas reduction plans. They need to consider the transfer of carbon emissions in international trade, reasonably allocate reduction responsibilities between consumers and production, and establish fairness and feasibility reduction plan.

Meanwhile, it also provided implications for developing countries such as China to participate in international trade and assume carbon reduction responsibilities. The developing countries should pay attention to the level of economic development and the quality of industrialization, so as to promote the reduction in the embodied CEI in trade. As economic development and industrial output increase, they need to invest more in green technology research. China has clearly put forward a binding indicator for carbon intensity in the green development goals of the manufacturing industry, and carbon reduction in the industrial sector has been highly valued by China. Other developing countries can learn from it. The key to achieving the above-mentioned goals is to promote the upgrading of industrial production technology through the promotion of green production, thereby reducing the carbon intensity in trade. In addition, countries especially the developing countries must actively change its trade development pattern and promote low-carbon growth in exports. China and other developing countries mainly rely on the advantages of labor and natural resources to participate in the international division of labor. The trade pattern based on processing trade has intensified these countries’ carbon emissions growth. They need to change its trade development pattern, cultivate new advantages in trade competition, guide and support the export of low-carbon emissions industries, and thereby reduce the increase in carbon emissions caused by exports.

Funding information The authors are grateful for financial support from the General project of Hunan Social Science Achievement Review Committee (No. XSP20YBC083) and the Scientific Research Project of Hunan Provincial Education Department (No. 19B090).

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