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Drivers of global carbon emission changes: A heterogeneity perspective of decomposition and attribution analysis

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Due to the differences in economic development, resource endowment, and historical accumulation, different types of countries have significant technical heterogeneity in carbon emissions. Identifying the driving factors of carbon emission changes, under the premise of distinguishing national heterogeneity, can provide a basis for the formulation of the "Differentiated Responsibilities" emission reduction policies. Therefore, this study introduces the idea of Meta-frontier into the traditional production-theoretical decomposition analysis, and constructs a new influencing factor analysis framework. Based on the newly built method, the empirical study of 60 representative countries draws the following three meaningful conclusion: 1) Different types of countries have obvious heterogeneity in technology, efficiency and change trend of energy use. Specifically, countries with higher energy intensity values generally have a quicker decline rate than those with lower energy intensity values. There exists "catch-up" effects for the backward to the advanced countries. 2) Decomposition results show that potential energy intensity (PEI) is the dominant factor reducing carbon emissions, especially for those large economic output with large energy consumption (Group-L) countries (0.604). Economic activity effect (ECA) is the most significant driving force for countries with small economic output and small energy consumption (Group-S), reaching 1.806. Meanwhile, the attribution results showed different characteristics in different groups of countries. The impact of various factors that reflect the heterogeneity of production process on carbon emissions mainly comes from the contribution of Group-L. 3) We suggest that, in the process of carbon reduction, large energy consumption countries should pay more attention to the gap between the development and speed of the world's cutting-edge technologies.

KEYWORDS

carbon emissions, production-theoretical decomposition analysis, heterogeneity, meta-frontier, attribution analysis

Introduction

Global warming seriously restricts the sustainable development of social and economic and has become a serious challenge for the 21st century. In 2022, IPCC (2022): Mitigating Climate Change, stated that without immediate action, it is impossible to limit global warming to 1.5°C (IPCC, 2022). This will threaten human livelihood and health, such as accelerating sea level rise (Fuchs et al., 2020; IPCC, 2021). The main cause of greenhouse effect is the excessive carbon dioxide (CO_2) emission produced by the combustion of traditional fossil energy (Goh et al., 2018; Udemba and Tosun, 2022a). According to the scenario analysis by Huo et al. (2022), in 2030, global carbon emissions are most likely to increase by 30% above the 2010 level. Therefore, energy saving and CO_2 emission reduction have become the consensus of all countries in the world.

A growing number of countries are taking active steps to address the challenge of climate warming. For example, many responsible countries have signed legislations and treaties to reduce greenhouse gas (GHG) emissions, including the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol, the Copenhagen Accord, and the Paris Agreement. Under these emissions constraint frameworks, measures and policies to deal with global climate change have been effectively deployed (Chen, 2021).

In the process of economic development, the conflict between emission reduction and economic growth may be exacerbated by the specific development policies adopted by countries. This conflict poses a huge challenge to countries in addressing the trade-off between emissions reductions and economic growth. In addition, due to the diverse socioeconomic backgrounds, development pattern and resource endowments, there is huge production heterogeneity in different countries (Liu et al., 2022). For example, less developed Asia and Africa countries, such as the Philippines, Indonesia, Mongolia, Congo, and India, are characterized by a weaker economy and lower socioeconomic status, but with sufficient natural mineral resources and cheap labor (Huang et al., 2021). Compared with those technology-intensive and capital-intensive countries (suah as Japan, Germany, and America), these countries generally belong to a labor-intensive mode of production. According to Lin and Zhu (2021), the same Gross Domestic Production (GDP) output in different types of production modes should have different types of energy consumption and carbon emission process (i.e., the heterogeneity of energy intensity and carbon intensity). As such, in order to comprehensively formulate regional emission reduction policies, it is necessary to deeply understand the root causes of differences in carbon emission change in different types of countries.

However, regarding the global carbon emission changes, the production heterogeneity of carbon emissions in different countries have been barely discussed, especially in the heterogeneity related driving factors identification. Thus three questions are raised for the global carbon emission reduction, as follows: 1) is there any heterogeneity in carbon emissions of different types of countries, and what is the change trend of such heterogeneity? 2) What are the core driving factors influencing the change of global carbon emissions? And how do the factors related to heterogeneity affect the change of carbon emissions? 3) From the overall carbon emission control perspective, how to identify the source of emissions for a certain influencing factor, that is, how is the contribution heterogeneity of different countries?

To reply the above three questions, considering the production heterogeneity between different countries, this paper constructs a new decomposition framework to explore the drivers of the global carbon emission changes. As such, the contribution of this paper mainly lies in three aspects:

First, previous decomposition analysis methods generally cannot explore the heterogeneity related factors. To address this issue, this study constructed a new comprehensive decomposition model to investigate the driving factors of carbon emission changes. Specifically, a new pre-defined factors, i.e., the technology gap effect (TEG) has been further discussed. This is able to yield additional insights about the impact of production heterogeneity changes on carbon emissions. In addition, the proposed decomposition method can also be used to study changes of specific indicators in other different fields. Especially for those with significant heterogeneity characteristics, which needs further explore the "technology catch-up effect."

Second, in terms of driving factors of carbon emission changes, few studies have discussed them from the "process" perspective. In fact, the whole carbon emission process contains different stages, which played different roles in the change of carbon emissions. The identification of process contribution can make the responsibility of carbon emission reduction clearer. As such, this study constructs a new decomposition framework and systematically decomposes the influencing factors of carbon emission changes from three processes, i.e., the energy input process, the production process, and the economic output process.

Third, in existing studies, there has been an increasing focus on the internal relationship between energy consumption, economic output, and carbon emissions. However, few studies have accurately identified the transmission mechanism between them. Considering that the direct and indirect causes of carbon emissions are energy consumption and economic development respectively, this study all-around measures their internal relationships. This can help policymakers to formulate more balanced emission reduction policies from multiple dimensions of energy consumption and economic development.

Literature review

There are complex connections among energy consumption, carbon emissions, and economic development (Debone et al., 2021). In recent years, there has been an increasing focus on the field of environment protection and economic development, especially on the internal relationship between them (Ajmi et al., 2015; Acheampong and Boateng, 2019). Econometrics (Zhu et al., 2014; Dong et al., 2016) and decomposition analysis (Su and Ang, 2012; Wang et al., 2018) methods are the two mainstream tools to conduct the influencing factors analysis.

By comparison, the decomposition analysis method is to decompose the drivers according to the identical deformation, which can effectively avoid the subjective selection of influencing factors in the econometric method (Liu et al., 2022). And the decomposition results are conducive to the horizontal comparison of related research topics between different studies. As such, decomposition analysis method has been widely applied in the field of influencing factor analysis of carbon emission change (Shao et al., 2016; Wang et al., 2018; Long et al., 2022). Index decomposition analysis (IDA) and structural decomposition analysis (SDA) are the two popularly used decomposition methods, which are different but related (Debone et al., 2021). The detailed description and review of the two decomposition methods can refer to the literatures of Hoekstra and Bergh (2003), Wang et al. (2017a).

However, as a type of economic accounting method, existing SDA and IDA studies cannot capture the impact of technical factors on carbon emissions (energy consumption) change. To solve this problem, Pasurka (2006) introduced the decomposition idea into the production framework for the first time, which can identify the impact of technological progress and technical efficiency changes on carbon emissions. On this basis, Zhou and Ang (2008) further introduced Shepherd directional distance function and defined it as the production-theoretical decomposition analysis (PDA) method. Compared with the SDA and IDA methods, the main advantage of PDA is that it can separate the technical effect from other driving factors and accurately depict the impact of technical factors on carbon (energy) intensity (Kim and Kim, 2012). Nevertheless, the PDA method is only applicable to the multiplicative decomposition form. Lin and Du (2014) solved the this limitation by combining IDA and PDA methods. The combination of IDA and PDA methods is an important supplement to the existing research and application (Wang et al., 2017b; Hang et al., 2019). Representative studies including Liu et al. (2018), which proposed a joint approach combined PDA and IDA and further decomposed carbon emissions change into nine drivers.

Using the above research methods (IDA, SDA, and PDA), from the perspective of carbon emission change influencing factors, the driving factors can mainly be summarized into three aspects: the structure effect (Bulut and Muratoglu, 2018), the technology effect (Sueyoshi et al., 2019), and the scale effect (Xiao et al., 2020). But for the importance of the three, studies from different research perspectives give different answers.

Specifically, the structural effect is mainly reflected in the impact of changes in energy structure and economic structure on carbon emissions. Wang et al. (2020) pointed that gradually increasing the proportion of alternative fuels and reducing the proportion of high carbon emission industries in the economy are the keys to achieving the carbon peaking and carbon neutrality in China. From the perspective of energy structure, Wang et al. (2019) indicated that reducing energy consumption is not a wise manner for sustainable society development, especially for those developing countries. Meanwhile, for the industry structure, the results of Liu et al. (2018) showed that at the same rate of economic growth, the better the industrial structure is adjusted, the larger the carbon emission "decline range" becomes. As to the technology effect, most existing studies showed that technological advances can reduce carbon emission from the source and improve carbon efficiency in the process, thus reducing carbon emissions (Hang et al., 2019; Sueyoshi et al., 2019). Representative example by Ang (2015), which combined environmental theory and modern endogenous growth model to study the influencing factors of carbon emission (intensity) from 1953 to 2006. The results show that there is a negative correlation between carbon emissions and the ability to digest and absorb advanced technologies. Wang et al. (2018) also proves that technological progress plays an important role in reducing carbon emissions; the rebound effect of carbon emissions reduces these positive effects. Meanwhile, economic development, investment level, population size, and trade level will affect the carbon emission through their scale changes. The conclusions of mainstream studies unanimously indicated that scale growth is the most important factor to promote carbon emissions (Sarkodie et al., 2020; Xiao et al., 2020).

However, the above related existing research results few deeply analyze the impact mechanism of production process on carbon emissions; in other words, they ignored the influence of regional technology heterogeneity in the analysis of factors affecting carbon emissions. Due to the differences in market conditions, legal constraints, resource endowments and openness, production technologies related to carbon emissions are often heterogeneous in different countries or regions (Calvo-Sotomayor et al., 2019; Wei and Liu, 2022). And this in turn will inevitably generate different effect on energy consumption and hence carbon emissions in different countries (Oh, 2010; Lisenkova et al., 2013; Wongboonsin and Phiromswad, 2017). For example, typically the level of carbon emission rises with the consumption of fossil fuels; it is therefore a natural conjecture to link carbon emissions to energy endowment and energy consumption structure of a region (Wei et al., 2018). Under such conditions, it is insufficient to put countries or regions with large differences under the same production technology frontier to measure carbon emission performance, which is not conducive to the realization of the principle of "differentiated responsibility" (Shuai et al., 2017; Wang et al., 2019). Hayami (1969) first proposed the concept of a Meta-frontier to solve the problems that may arise from a single production frontier[1]. Subsequently, the meta-frontier thought has been widely used in many fields (Wang and Feng, 2021; Xia et al., 2022). Therefore, combined with the meta-frontier and the decomposition analysis method, the heterogeneity related factors in the carbon emissions change can be effectively identifed. However, the relevant research is still relatively rare. From a policy development perspective, highlighting what drives carbon emission with taking into consideration distribution heterogeneity will be more practical significant (Udemba and Tosun, 2022b).

Based on the above research context, considering the heterogeneity of carbon emission process, a new comprehensive decomposition framework by combining production theoretical decomposition analysis (PDA) and meta-frontier data envelopment analysis is constructed to identify the influencing factors among different types of countries. Additionally, in order to provide a reference for the differentiated designing of carbon emission reduction policy for different countries, we further apply attribution analysis method to measure how different type countries contribute to each factor. Finally, empirical analysises are carried out based on the panel data of global representative 60 countries from 2007 to 2014, and the results can help policymakers to formulate targeted emission reduction plans.

Methodology

Production technology considering heterogeneity

Assuming that there are N countries as decision making units (DMUs), and each country invests capital (K), labor (L), and energy (E) to produce desirable output—gross domestic production (GDP, denoted by Y). Meanwhile, undesirable output is inevitable in the production process, such as representative CO_2 emissions (C). According to Färe et al. (2007), the production technology set (T) of this production process can be expressed as Eq. 1.

$$T = \{(K, L, E, Y, C):\ (K, L, E)\ can\ produce\ (Y, C)\} \tag{1}$$

Based on production theory, T is generally a closed and bounded set, assumed to have three mathematical properties, i.e., 1) all the inputs and desirable outputs are strongly disposable; 2) undesirable outputs are weakly disposable; 3) T has null-jointness[2]. However, T lacks an explicit form and cannot be used directly for empirical analysis. A popular way to overcome this problem is to introduce non-parametric data envelopment analysis (DEA) method to model the production technology, T (Oh, 2010). Following Färe et al. (2007), the production technology (under the constant return scale assumption) can be expressed as Eq. 2.

$$\begin{aligned} T = \{(K, L, E, Y, C):\ & \sum_{n=1}^{N} \lambda_n K_n \le K,\ \sum_{n=1}^{N} \lambda_n L_n \le L,\ \sum_{n=1}^{N} \lambda_n E_n \le E, \\ & \sum_{n=1}^{N} \lambda_n Y_n \ge Y,\ \sum_{n=1}^{N} \lambda_n C_n = C, \\ & \lambda_n \ge 0, n = 1, 2, \cdots, N\}, \end{aligned} \tag{2}$$

Where λ_n is the weight coefficient, ensuring that the production frontier is a convex shape. The equality constraint of undesirable output ($\sum_{n=1}^{N} \lambda_n C_n = C$) reflects the weak disposability and zero connectivity.

The above production technology has been widely applied in the field of energy and environment research (Hang et al., 2019; Shironitta et al., 2019). However, constrained by the actual production process (such as differences in economy, geography, and market), it is not appropriate that all the DMUs share a common production technology (O'Donnell et al., 2008). Meta-frontier is generally used to describe the technical heterogeneity of different groups, and it has been widely used in the problem of regional production technology heterogeneity (Liu et al., 2022).

Following Liu et al. (2022), based on the differences in production technology, we first classify all the DMUs into H subgroups. The number of DMUs in the h-th group is N^h, and $\sum_{h=1}^{H} N^h = N$. As such, the h-th subgroup forms its own production technology frontier, corresponding to the production technology set T^h. The DMUs belonging to the same subgroup have a homogeneous technology level under the group frontier. Specifically, O'Donnell et al. (2008) pointed that if T^m denotes the set of production technology under the meta-frontier: 1) for any subgroup-h, if $(K, L, E, Y, C) \in T^h$, then $(K, L, E, Y, C) \in T^m$; 2) if $(K, L, E, Y, C) \in T^m$, then for some cases of $h \ge 1$, $(K, L, E, Y, C) \in T^h$; 3) the overall set of production

1 The basic idea of meta-frontier is that all the decision making units (DMUs) can be divided into different groups according to their inherent attributes, such as region, type, scale, etc. Each group forms a group production frontier. As such, a meta-frontier is obtained by enveloping all the group production frontier of different groups.

2 Details see the research by Liu et al. (2022).

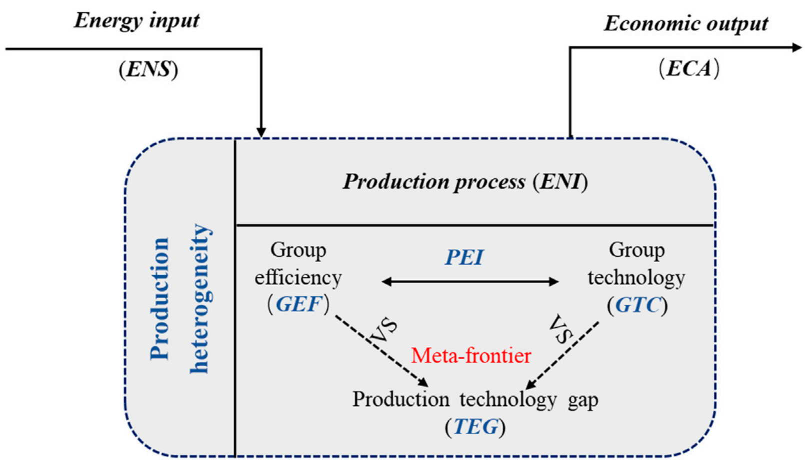

FIGURE 1
Process and influencing factors of carbon emissions.

technology can be expressed as $T^m = \{T^1 \cup T^2 \cdots T^H\}$, satisfying the over-arching requirement.

Production-theoretical decomposition analysis method considering heterogeneity

Based on the extended Kaya identify (Liu et al., 2022), global carbon emission changes can be decomposed as follows:

$$C^t = \sum_{i=1}^{I} \frac{C_i^t}{E_i^t} \times \frac{E_i^t}{Y_i^t} \times Y_i^t = \sum_{i=1}^{I} ENS_i^t \times ENI_i^t \times ECA_i^t, \tag{3}$$

where C denotes carbon emission; E denotes energy consumption; Y denotes GDP; i and t denotes the i-th country and time t, respectively. As such, on the right hand of Eq. 3, the first component (C_i^t/E_i^t) is defined as the i-th country's carbon emission factor in year t. In fact, a certain type energy is generally assumed to have an unchanged carbon emission factor, therefore C_i^t/E_i^t denotes energy consumption structure (*ENS*). E_i^t/Y_i^t is the i-th country's energy consumption per GDP in year t, which reflects energy intensity (*ENI*). The last component (Y_i^t) is the i-th country's GDP scale in year t, defined as economic activity (*ECA*).

According to Lin and Du (2014), changes in energy intensity are complicatedly influenced by the production process related factors, including the production heterogeneity between different countries. As such, this study introduced meta-frontier DEA technology into traditional PDA framework, the variation of carbon emissions in the i-th country in year t can be decomposed as follows:

$$\begin{aligned}
C^t &= \sum_{i=1}^{I} \frac{C_i^t}{E_i^t} \times \frac{E_i^t}{Y_i^t} \times Y_i^t = \sum_{i=1}^{I} ENS_i^t \times ENI_i^t \times ECA_i^t, = \sum_{i=1}^{I} \frac{C_i^t}{E_i^t}, \\
&\times \frac{E_i^t / \left[D_m^t\left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right) \times D_m^{t+1}\left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right)\right]^{1/2}}{Y_i^t}, \\
&\times \left[\frac{D_m^t\left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right)}{D_g^t\left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right)} \times \frac{D_m^{t+1}\left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right)}{D_g^{t+1}\left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right)}\right]^{1/2}, \\
&\times D_g^t\left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right) \times \left[\frac{D_g^{t+1}\left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right)}{D_g^t\left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right)}\right]^{1/2}, \\
&\times Y_i^t, \\
&\equiv ENS^t \times PEI^t \times TEG^t \times GEF^t \times GTC^t \times ECA^t.
\end{aligned} \tag{4}$$

Compared with Eq. 3, the *ENI* is further decomposed into four new factors in Eq. 4, i.e., the potential energy intensity (*PEI*), the production technology gap between group and meta-frontier (*TEG*), the group energy efficiency (*GEF*), and the group technology (*GTC*). As is shown in Figure 1, from the production heterogeneity perspective, the change of energy intensity not only reflects a country's own technology and efficiency level, but also synthesizes the gap between itself and the external optimal frontier in the actual production process.

Therefore, according to the research by Wang et al. (2018), changes in carbon emissions from time t to $t + 1$ can be expressed as follows:

TABLE 1 Connotations of carbon emissions change influencing factors.

Factors		Connotation (during the period of t to $t + 1$)
Energy input	$D_{ENS}^{t,t+1}$	The effect of energy structure on the carbon emission changes
Production process	$D_{PEI}^{t,t+1}$	The effect of potential energy intensity on the carbon emission changes
	$D_{TGE}^{t,t+1}$	The effect of technology gap on the carbon emission changes
	$D_{GEF}^{t,t+1}$	The effect of group energy efficiency on the carbon emission changes
Economic output	$D_{GTC}^{t,t+1}$	The effect of group technology progress on the carbon emission changes
	$D_{ECA}^{t,t+1}$	The effect of economic output on the carbon emission changes

$$D_{tot}^{t,t+1} = \frac{C^{t+1}}{C^t},$$
$$= \frac{\sum_{i=1}^{I} ENS_i^{t+1} \times PEI_i^{t+1} \times TEG_i^{t+1} \times GEF_i^{t+1} \times GTC_i^{t+1} \times ECA_i^{t+1}}{\sum_{i=1}^{I} ENS_i^{t} \times PEI_i^{t} \times TEG_i^{t} \times GEF_i^{t} \times GTC_i^{t} \times ECA_i^{t}},$$
$$\equiv \underbrace{D_{ENS}^{t,t+1}}_{Energy\,input} \times \underbrace{D_{PEI}^{t,t+1} \times D_{TEG}^{t,t+1} \times D_{GEF}^{t,t+1} \times D_{GTC}^{t,t+1}}_{Production\,process} \times \underbrace{D_{ECA}^{t,t+1}}_{Economic\,output}. \quad (5)$$

Combined with the Logarithmic Mean Divisia Index (LMDI) decomposition method, the contribution of each influencing factor in Eq. 5 can be accurately calculated. Supplementary Appendix S1A detailed expressed the entire calculation process. As such, the influencing factors of carbon emission changes during the period of t to $t + 1$ can be decomposed into six components and divided into three categories, summarized in Table 1.

Data description

Although the total global carbon emissions continued to grow, there were significant fluctuations between 2007 and 2014, so it is necessary to identify the key drivers of their anomalies. As such, the research period of this study spans from 2007 to 2014[3]. And this study sample included 60 countries (listed in Supplementary Appendix S1B). Both economic volume and carbon emissions of these 60 countries all account for more than 80% of the global total, especially in 2014, accounting for 82.4% and 88.7%, respectively. Therefore, these countries can represent the overall development trend of global economic development and carbon emissions.

Following Liu et al. (2022), we assume the production process uses labor (collected from the International Labor Organization, ILO), real capital formation (collected from the World Bank, WB), and energy consumption (collected from IEA) to product GDP (collected from WB) and undesirable output CO_2 emissions (collected from World Resource Institute, WRI). The variables for real capital formation and real GDP are subtracted from the 2000 consumer price index to eliminate price effects. The deflation is shown in Eqs 6, 7.

$$Y^{i,b} = dY^{i,n}, \quad (6)$$

$$d = \frac{1}{\prod_{m=b+1}^{n} (p^m/100)}, \quad (7)$$

where Y^i represents the value added in country i. The superscript b represents the value added in the base year price, and the superscript n refers to the value added at current prices. d represents the deflator derived from consumer price index p^m. p^m refers to the chained price index (previous year = 100) of the m-th year, ranging from the base year to the n-th year.

Following the idea of Liu et al. (2022), we choose energy intensity, a comprehensive index to measure energy and economy, to categorize the group boundaries. Specifically, 60 countries were divided into three types using K-Means cluster analysis (see Supplementary Appendix S1B)[4]. Group-L is composed of 14 countries, most of the countries in Group-L are large economic output countries with relatively large energy consumption (e.g., China and America); Group-M is composed of 20 countries, most of the countries in Group-M are middle scale economic countries with middle scale energy consumption (e.g., Sweden and Switzerland); Group-S is composed of 26 regions, most of the countries in Group-S are

3 Another reason is that, some representative studies have done the relevant studies and focused on this period (such as Liu et al., 2022; Duan et al., 2022), facilitating our comparative analysis.

4 Some articles use geography to divide countries into different groups (Oh, 2010). However, Lin and Du (2013) proved that a country's technological level has no direct relationship with its geography. As for the number of clusters, following the idea of Tibshirani et al. (2001), we adopted the Gap Statistic algorithm. And the results show that when K = 3, the value of Gap Statistic is the largest. Therefore, the 60 sample countries were divided into three categories in this study.

TABLE 2 The statistical characteristics of the key indicators in different groups.

Variables	Unit	Group	Min	Max	Std.D	Mean
Energy (E)	10^6 toe	Group-S	0.77	30.50	6.42	7.75
		Group-M	12.77	89.70	18.80	35.97
		Group-L	72.95	3051.50	780.80	576.96
CO_2 (C)	10^6 ton	Group-S	1.80	64.06	13.20	12.90
		Group-M	19.93	262.85	59.01	83.75
		Group-L	167.30	10291.93	2449.39	1535.27
GDP (Y)	Billion dollars	Group-S	3.72	101.73	20.19	27.37
		Group-M	77.89	709.18	143.17	280.05
		Group-L	432.22	17427.61	3869.03	3357.79
Energy intensity (EI)	Kg/dollar	Group-S	0.05	0.60	0.12	0.17
		Group-M	0.04	0.63	0.10	0.15
		Group-L	0.07	0.98	0.20	0.34

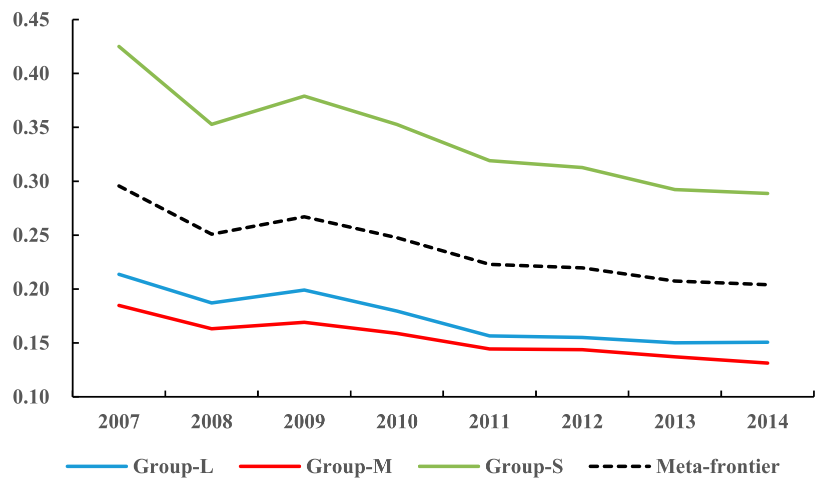

FIGURE 2
Evolution trend of energy intensity for each group, 2007–2014.

small scale economic countries with small scale energy consumption (e.g., Nepal and Uruguay).

Table 2 shows the statistical characteristics of the four key indicators in different groups. Obviously, the differences of these indicators between different groups are significant. Among them, Group-L had the highest average energy intensity value, followed by Group-S, and Group-M. This is mainly because Group-L includes developing economies with large levels of energy consumption, such as China, Russia, and Indonesia. Taking China as an example, China's energy structure is dominated by coal, which heat conversion rate is relatively lower compared with other type energies. In addition, due to the limited technical level, the comprehensive utilization rate of energy is poorer than those developed countries. As a result, the energy intensity is relatively higher in China. This further proves the rationality and effectiveness of the grouping.

Results and analysis

Production heterogeneity

As illustrated in Figure 1, the production heterogeneity of carbon emissions in various countries is mainly reflected in the production process, involved in the energy intensity (EI). Figure 2 shows the changes in energy intensity in different types of countries. During the study period, EI has experienced a downward trend, decreasing from 0.251 kg/dollar in 2007 to 0.204 kg/dollar in 2014. From 2008 to 2009, due to the impact of the financial crisis, economic development experienced a sharp decline, but energy consumption only slightly decreased. Therefore, EI has increased. As mentioned above, the 60 sample countries can be divided into three

TABLE 3 Test for β-convergence of energy intensity.

	All sample	Group-L	Group-M	Group-S
α	−0.0119	−0.0196*	−0.0043	−0.0152**
	(−1.4923)	(−1.8453)	(−0.2095)	(−1.8905)
β	−0.9230***	−0.9535***	−0.9628***	−1.7773***
	(−7.3495)	(−3.6022)	(−3.2186)	(−7.7739)
Adj-R^2	0.4733	0.4610	0.3300	0.7123

Note: 1)"***," "**," and "*" indicate that the levels of 1%, 5% and 10% are significant, respectively;
2)Values in brackets are t-statistics.

categories. From the group perspective, Group-S shows the highest EI, followed by Group-L and Group-M. This is mainly because the fact that Group-S is basically composed of developing countries. Compared with the other two groups, the modes of energy consumption and economic development of those countries in Group-S were relatively extensive. This is consistent with the study by Zhang and Wang (2015).

Further, to reveal the *EI* evolution process in the different group countries, the standard β-convergence theory is applied to conduct the test (Barro and Sala-i-Martin, 1992). The following regression model is used for β-convergence estimation:

$$\ln\left(\frac{y_{i,t}}{y_{i,0}}\right) = \alpha + \beta \ln\left(y_{i,0}\right) + \varepsilon_{i,t}, \tag{8}$$

where $y_{i,0}$ and $y_{i,t}$ denote the EI of i-th country in period 0 and period t, respectively; $\ln(y_{i,t}/y_{i,0})$ represents the average change rate of *EI* in the i-th country between time 0 and t; α is a constant value, reflecting the steady-state characteristic and the rate of technological progress; $\varepsilon_{i,t}$ is the error term at time t for the i-th country; β reflects whether *EI* converges to steady state or diverges. A statistically significant and negatively suggestive dataset shows β-convergence.

The β-convergence test of *EI* is analyzed by means of panel data regression analysis in Eviews 8.0. The Hausman test provides an indicator to determine which type of model should be used: a fixed effect model or a random effect model. The results show that the value of Chi-Sq. Statistic is 19.39 and the value of Prob. is 0.0029. Therefore, the original assumption is wrong, so the fixed effects model should be used here. The full results are shown in Table 3.

As shown in Table 3, within the three group countries, and the overall sample, the estimated coefficients of β are all negative and statistically significant at the level of 1%, which implies the existing of absolute β-convergence. In addition, the convergence speed can be determined according to the values. The values of β indicates that the convergence speed of Group-S is relatively faster, followed by the Group-M, and Group-L. This means that there existing a catch-up effect for the backward (large energy intensity) to the advanced countries (small energy intensity). Henceforth, in order to further improve this convergence rate and narrow EI difference, it is necessary to take certain measures to enhance the communication of energy use technology, management system arrangements, and other aspects between different types of countries.

According to the decomposition framework constructed above, differences in energy use technology and energy efficiency are the core factors that affect the production heterogeneity. Figure 3 illustrates the time series change of different type countries' energy use efficiency and energy use technologies.

As shown in Figure 3A, the energy efficiency of the sample countries has decreased in a fluctuation way, and rebounded after reaching the lowest value in 2013. This is mainly because since 2007, countries have paid more attention to economic output scale and neglected process optimization in order to get rid of the impact of the financial crisis as soon as possible (Wei et al., 2018). Taking Indonesia as an example, in addition to the relatively lower management level, the industrial structure of high energy consumption has not been reasonably optimized, resulting in a 29% decline in energy efficiency. For different types of countries, Group-M shows the best energy efficiency, followed by Group-L and Group-S. This is mainly due to the fact that Group-M is basically composed of developed countries that consume relatively less energy, having enough advantages (talent, management, and capital investment) to improve energy efficiency.

Compared with the trend of efficiency change, the heterogeneity of technology change is relatively greater (see Figure 3B). With the exception of Group-L, the other two groups have contributed positively to the overall technology improvement. From 2007 to 2012, the cumulative technology change rate of Group-M was relatively more significant. Compared with the other two groups of countries, the countries in Group-L, despite their large energy consumption, are in a leading position in terms of energy use technology and emission reduction technology, with little room for improvement. For example, many OECD countries have shifted from relying on energy intensive manufacturing industries to using less energy intensive service based economic activities. In contrast, most countries in Group-S are developing countries, technology promotion potential and space are relatively large, and the impact is more pronounced. Although Group-L countries are world leaders in energy use technology, a good sign is that the other countries are catching-up continuously.

Decomposition results and discussion

During the study period, the carbon emissions of the sample countries showed a significant increasing trend, with an average

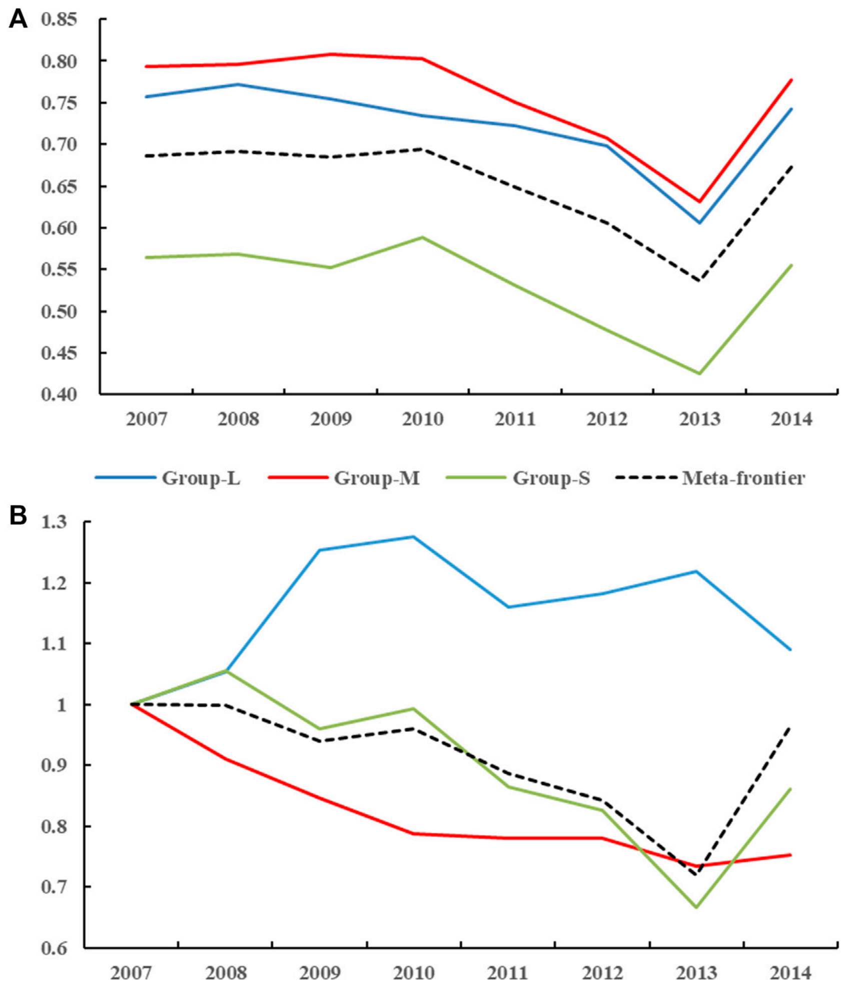

FIGURE 3
Time series changes of energy efficiency **(A)** and energy technology **(B)** of different groups in 2007–2014.

TABLE 4 Changes of sample countries' carbon emissions and its decomposition, 2007–2014.

	ENS	*ENI*				*ECA*	Total
		PEI	*TEG*	*GEF*	*GTC*		
2007–2008	1.0138	0.8982	0.8809	0.9837	1.1195	1.1558	1.0211
2008–2009	0.9873	1.0243	0.9876	0.9932	1.0011	0.9894	0.9825
2009–2010	0.9956	0.9096	1.0274	1.0038	1.0016	1.1343	1.0610
2010–2011	1.0241	0.8710	0.9728	1.0068	1.0388	1.1557	1.0488
2011–2012	0.9950	0.9492	0.9941	1.0069	1.0050	1.0635	1.0105
2012–2013	0.9886	0.9372	1.0334	0.9962	0.9943	1.0606	1.0060
2013–2014	0.9913	0.9481	1.1761	1.0063	0.8621	1.0397	0.9970
G-mean	0.9993	0.9329	1.0071	0.9994	1.0006	1.0839	1.0178
		0.9396					

annual growth rate of 1.78%. Using the decomposition analysis model constructed above, we can explore the driving factors of global carbon emissions changes from three aspects: energy input, production process and economic output. Table 4 presents the single-period decomposition results of the six influencing factors from 2007 to 2014. As is shown in Table 4, *ECA* has an enhanced effect on carbon emissions over the years, with an average annual growth rate of 1.084, which is the main obstacle for the decline of carbon emissions. Meanwhile, *ENS* and *ENI* both played positive roles in the carbon emission reduction (G-mean values are all less than 1). The findings are consistent with other studies on changes in global carbon emissions (e.g., Wang et al., 2020; Liu et al., 2022).

Energy intensity, an indicator reflecting changes in energy production technology, is the most important factor to curb the growth of carbon emissions, with an average annual contribution of 0.9396. Further decomposition of *ENI* showed that *PEI* and

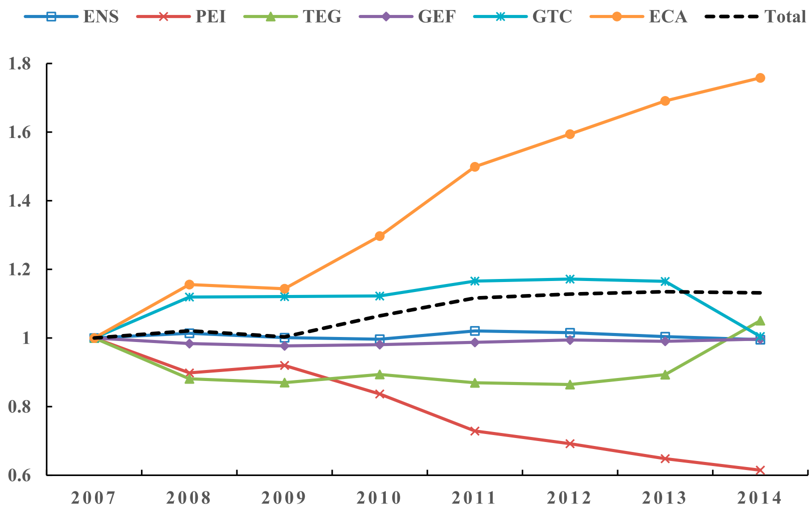

FIGURE 4
Cumulative changes of sample countries' carbon intensity and its decomposition, 2007–2014.

GEF were the key factors contributing to the reduction of carbon emissions, with the annual contribution rates of 0.933 and 0.999, respectively. However, during the period of 2008–2009, *PEI* not only failed to reduce carbon emissions, but also promoted the increase of carbon emissions (1.024). This phenomenon may be caused by the impact of the Asian financial crisis, which has greatly affected the investment in energy substitute (such as labor shortage and insufficient capital investment), thus consuming more energy at the same output level. This is consistent with the research conclusion by Zhang and Wang (2015). Since 2009, in order to get rid of the impact of energy shortage and economic crisis, major energy consuming countries around the world (such as the United States, China, and Russia) have taken more measures to conduct the energy saving and emission reductions. For example, China has invested more than 100 billion yuan in supporting the research, development, promotion and the application of low-carbon technologies in 2010. Thus, strengthening the role of *PEI* and *ENI* in reducing carbon emissions.

Figure 4 illustrates the multi-period decomposition results of the six influencing factors from 2007 to 2014. The average effects of *GEF* and *GTC* change on global carbon emission were 0.999 and 1.001, respectively. This reflects that neither production technology nor production efficiency can effectively curb the growth of carbon emissions. Especially for *GTC*, it was second only to *ECA* in its contribution to the growth of carbon emissions from 2007 to 2012 (see Figure 4). The good phenomenon is that, since 2012, *GTC* has continuously played an active role in reducing carbon emissions. This may be that global countries are gradually getting rid of the impact of the economic crisis, and energy-saving and emission reduction technologies have developed rapidly. For the *GEF*, except for 2007–2009 and 2012–2013, the emission reduction effect was not significant in other years. This indicates that there is still great potential in improving energy efficiency to achieve emission reduction.

As for *TEG*, reflecting the production heterogeneity, it has significantly promoted the carbon emission increasing. And its promoting effect is second only to *ECA*. From the perspective of evolutionary trend, Table 4 and Figure 4 show that the change trend of *TEG* is almost opposite to that of global carbon emissions. The greater the heterogeneity of production technology between different countries, the more uneven the production level, which will increase global carbon emissions. Therefore, countries should further emphasize exchange and learning from each other, thus narrowing the gap between countries with different energy use technology levels.

From the perspective of grouping, because different types of countries have obvious differences in resource endowment, production environment, technology level, management experience and other aspects, the impact degree and mechanism of carbon emission change factors on different types of countries should also be different (Wang et al., 2019). Single period decomposition results in different groups are summarized in Supplementary Appendix S1C. Figure 5 describes the cumulative decomposition results for sample countries' carbon emission change by different factors of different groups.

On the whole, countries in Group-S experienced the most obvious growth rate (1.288), followed by Group-L (1.136) and Group-M (1.046). As for the specific influencing factors, *ECA* is the dominant factor that promotes the increase of carbon emissions for all types of countries. Meanwhile, *PEI* has effectively helped all types of countries reduce their carbon emissions, and *PEI* is the most important emission reduction

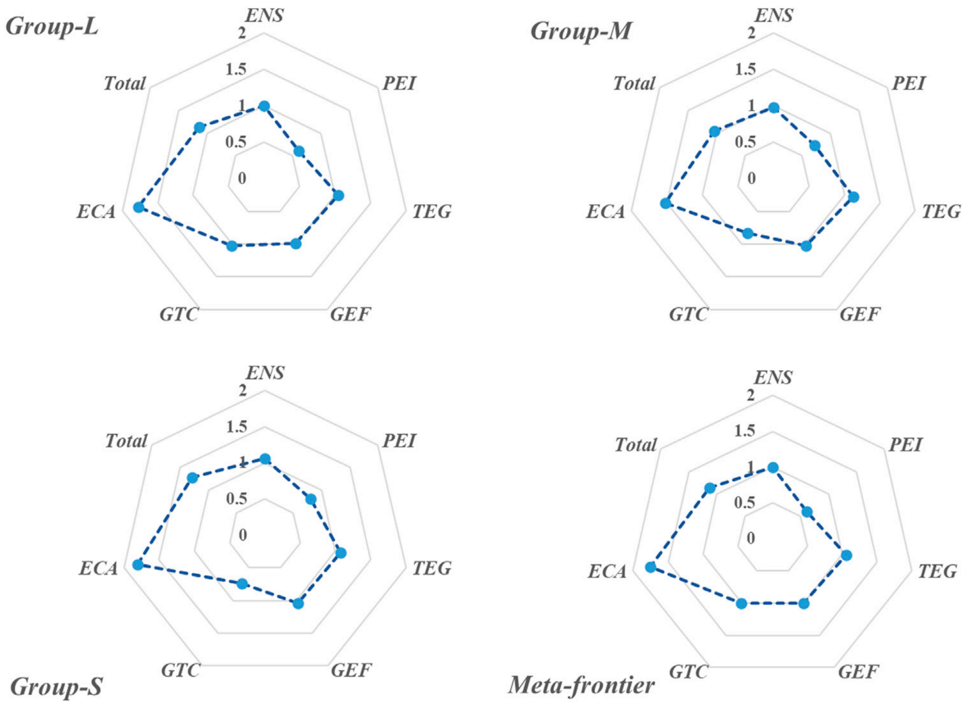

FIGURE 5
The cumulative decomposition results for sample countries' carbon emission change by different factors of different groups.

factor for Group-L and Group-M. For Group-S, the contribution of *GTC* (0.739) to carbon emission reduction is more obvious than *PEI* (0.812). This is due to the fact that Group-L and Group-M are mainly developed countries, and there are significant advantages in the application of low-carbon production technology. While Group-S is mainly composed of developing countries with relatively low energy consumption, which low carbon production technology has not been widely promoted and applied. As such, countries in Group-S generally have more room for technological progress, leading the more significant carbon emission reduction effect of *GTC*.

As one of the main factors contributing to the increase in carbon emissions, *TEG* contributed 12.6% to the growth of carbon emission in Group-M, followed by Group-S (7.64%) and Group-L (4.35%). The greater the gap, the more backward the energy-saving and emission reduction technology is, the greater the contribution to carbon emissions. The *TEG* effect has the least impact on the change of carbon emissions in developed countries with large energy consumption. This is mainly due to the fact that Group-L type countries generally have always been in the leading position in production technology and are the "promoters" of the global technological progress. Thus, compared with other type countries, the technology gap between Group-L and global technology frontier is relatively smaller, leading to the less impact on the change of carbon emissions in Group-L countries. This further indicates that different types of countries should strengthen cooperation and exchange on production technology to narrow the technological gap, thus decreasing the carbon emissions.

Meanwhile, the effects of energy efficiency (*GEF*) and energy structure (*ENS*) on the carbon emission of different groups were relatively small. Affected by resource endowment and energy price, there is no obvious difference in energy structure among countries at present, and the optimization of energy use structure is a long-term process. In addition, the improvement of energy efficiency involves a series of long-term reserves such as management level, experience accumulation and talent training. As such, in the short term, the impact of energy efficiency and energy structure change on carbon emission change is not significant.

Attribution results and discussion

After understanding how different factors drive the change of carbon emissions, how different type countries contribute to each factor should also be clarified. This can provide a reference for the differentiated designing of carbon emission reduction policy for different countries. Attribution analysis method, proposed by

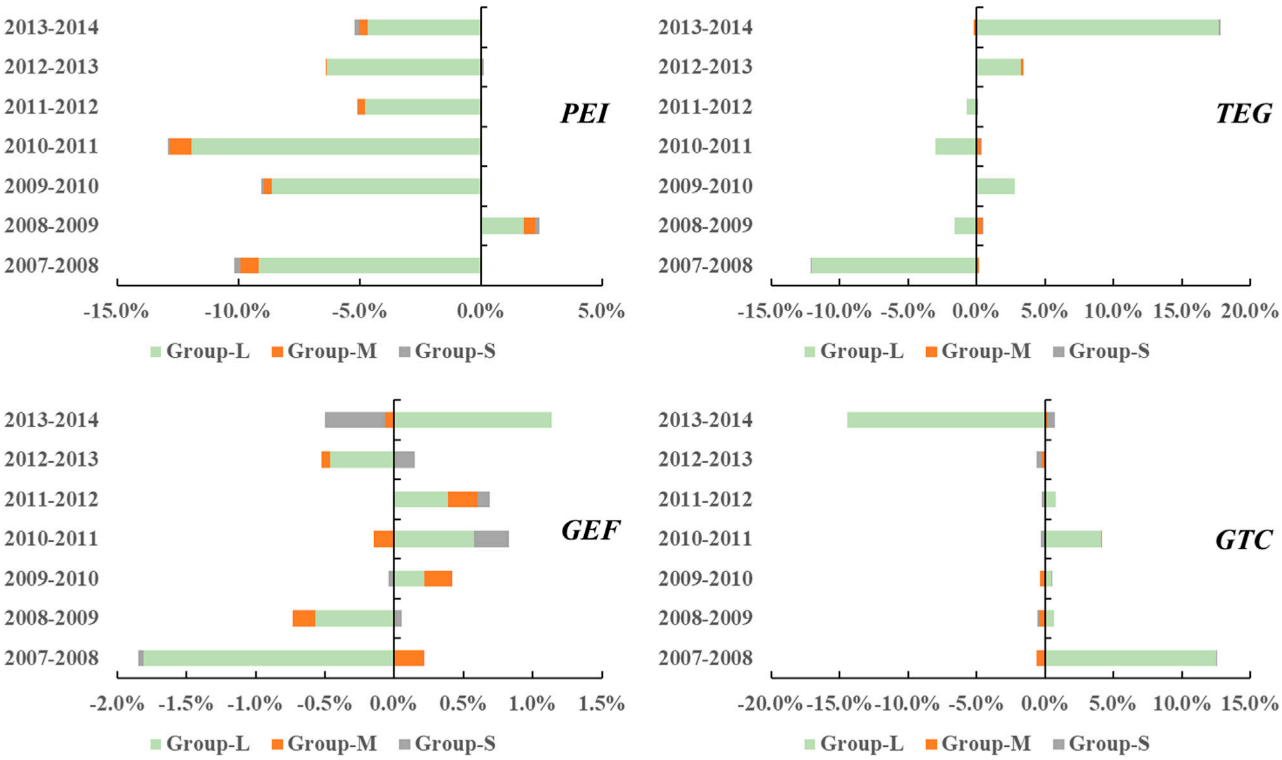

FIGURE 6
Percentage of the single-stage attribution results of the production process (*PEI, TEG, GEF*, and *GTC*) of each grouped country from 2007 to 2014 (Unit: %).

Choi and Ang (2012), can effectively realize this purpose. Taking "the potential energy intensity (*PEI*)" as an example, the contribution of each country to *PEI* can be calculated by using Eq. 9.

$$D_{pei}^{T-1,T} - 1 = \sum_{i=1}^{I} D_{pei}^{T-1,T} - 1 = \sum_{i=1}^{I} \frac{w_i^{S-V} F_i^{T-1} \big/ L\left(F_i^{T-1} \cdot D_{pei}^{T-1,T}, F_i^T\right)}{\sum_{i=1}^{I} w_{ij}^{S-V} F_{ij}^{T-1} \big/ L\left(F_i^{T-1} \cdot D_{pei}^{T-1,T}, F_i^T\right)} \cdot \left(\frac{F_i^T}{F_i^{T-1}} - 1\right), \tag{9}$$

where $F_i^s = E_i^s/[D_m^s(E_i^s, K_i^s, L_i^s, Y_i^s, C_i^s) \times D_m^t(E_i^s, K_i^s, L_i^s, Y_i^s, C_i^s)]^{1/2}/Y_i^s$. In this expression, $D_{pei}^{T-1,T} - 1$ represents the percentage change of potential energy intensity effect from time $T-1$ to time T. $w_i^{S-V} F_i^{T-1}/L(F_i^{T-1} \cdot D_{ens}^{T-1,T}, F_i^T)/\sum_{i=1}^{I} w_{ij}^{S-V} F_{ij}^{T-1}/L(F_i^{T-1} \cdot D_{ens}^{T-1,T}, F_i^T) \cdot F_i^T/F_i^{T-1}$ denotes the coefficient of contribution of the i-th group country to the percentage change in *PEI* during the period of $T-1$ to T. The contribution of each country to other five influencing factors can be calculated similarly. Supplementary Appendix S1D depicts the detail attribution results.

During the study period, different types of countries made different contributions to the change of carbon emissions in different years. The overall carbon emissions of the sample countries increased by 13.15% from 2007 to 2014, the carbon emission of Group-S increased by 28.81%, followed by Group-L (13.60%) and Group-M (4.63%). During 2008–2009 and 2013–2014, the overall carbon emissions decreased 1.75% and 0.30%, respectively. This is mostly because, during these two periods, most of the sample countries promoted the decline of carbon, especially for the leading role that Group-L played. In order to further explore the core driving force of the contribution of different types of countries to carbon emissions, Supplementary Appendix S1D depicts the cumulative contribution of different groups to the influencing factors of carbon emission change. Specifically, sample countries with different development modes and stages have different contributions to carbon emission across the four drivers (i.e., *PEI, TEG, GEF*, and *GTC*), as shown in Figure 6.

For *PEI*, from 2007 to 2014, except for 2008–2009, the cumulative contribution value of each country to *PEI* was promoting carbon emission reduction, of which Group-L was the most obvious, especially in 2010–2011 (−11.95%), 2007–2008 (−9.17%), and 2009–2010 (−8.64%). In particular, for 2012–2013 (0.12%), Group-S did not contribute to *PEI* reduction. This may be due to the fact that, in addition to the impact of economic environment, the energy consumption of Group-S countries is relatively small, and the decline of energy prices has a greater impact on the growth of total energy consumption. The attribution effect of each group to the *GEF* is almost the opposite to that of *PEI*. This is because the effect of *PEI* has a direct internal relationship with the effect of *GEF*. The economic connotation of *PEI* represents the energy intensity that peels off the ineffectiveness of energy use. When the overall energy intensity of a country changes little, the attribution effects of *PEI* and *GEF* thus have a reverse trend.

Meanwhile, for *GTC*, from 2007 to 2013, Group-L has always been the main body to increase the carbon emissions by *GTC*, with an average annual contribution rate of 3.09%. Of which, Group-L made the most significant contribution in 2007–2008 and 2010–2011. Different from Group-L, both Group-M and Group-S significantly reduce the carbon emissions of *GTC*. This is mainly due to the effective improvement of energy use technology in these two types of countries. Considering the fact that, with the continuous improvement of energy use technology, the technology gap will inevitably continue to narrow. As such, the attribution effect of each group to the *TEG* is almost the opposite to that of *GTC* (see Figure 6).

Conclusion

Identifying the key factors affecting the change of global carbon emissions can help targeted carbon emission reduction and curb global warming. Meanwhile, knowing the contribution degree of different countries to the influencing factors can help better share the emission reduction responsibility. Therefore, this study takes 60 representative countries as samples to decompose and attribute the changes of carbon emissions from 2007 to 2014. In particular, considering the obvious differences in resource endowment, production technology and management level among different countries, this study proposed a new decomposition analysis framework by combining PDA and Meta-frontier analysis. The newly built method can be used to further explore the impact of production technology heterogeneity on carbon emission reduction. In general, three important findings emerged from the empirical study.

First, the production process of different type countries has clear heterogeneity characteristics. The energy intensity level of different countries has a trend of β-convergence. There existing a catch-up effect for the backward to the advanced countries. In addition, differences in energy use technology and energy efficiency are the core factors that affect the production heterogeneity. For different types of countries, Group-M shows the best energy efficiency, followed by Group-L and Group-S. Compared with the trend of efficiency change, the heterogeneity of technology change is relatively greater. With the exception of Group-L, the other two groups have contributed positively to the global technology improvement, especially for the countries in Group-M. Henceforth, in order to further improve the convergence rate and narrow the technology gap, it is necessary to take certain measures to enhance the communication of energy use technology, management system arrangements, and other aspects between different types of countries.

Second, the decomposition analysis shows that potential energy intensity effect (*PEI*) is the most important reason for carbon emission reduction. Meanwhile, group energy efficiency effect (*TGE*), and energy structure effect (*ENS*) also played positive roles in carbon emission reduction. The other factors, including group technology change effect (*GTC*), technology gap effect (*TEG*), and economic activity effect (*ECA*) failed to inhibit carbon emissions. In particular, *ECA* has an enhanced effect on carbon emissions with an average annual increase rate of 1.084, which was the main driver to the increase of carbon emissions during the study period. From group perspective, *ECA* had the most significant pull effect on carbon emissions in Group-S, with a cumulative effect of 1.806, followed by Group-L (1.777) and Group-M (1.531). This suggests that developing countries and those with large energy consumption countries should pay more attention to the carbon reduction in the process of economic development. For example, these two types countries can reduce the impact of economic activity on carbon emissions through industrial structure adjustment, new energy application and other ways when making economic development policies.

Third, in the production process, the structure of the contribution coefficient shows different characteristics in different groups. The cumulative contribution value of each country to *PEI* was a promoting to carbon emission reduction, of which Group-L was the most obvious, especially in 2010–2011 (−11.95%), 2007–2008 (−9.17%) and 2009–2010 (−8.64%). Meanwhile, the attribution effect of each group to the *GEF* is almost the opposite to that of *PEI*. For *GTC*, from 2007 to 2013, Group-L has always been the main body to increase the carbon emissions by *GTC*, with an average annual contribution of 3.09%. Different from Group-L, Group-M and Group-S both played significant role in decreasing the carbon emissions by *GTC*. The attribution effect of each group to the *TEG* is almost the opposite to that of *GTC*. A country must be concerned not only with its own technological progress, but also with the development of global technology frontier and the pace of technological progress.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary Material.

Author contributions

XL contributed to the conception of the study and performed the data analyses and wrote the manuscript. YZ contributed significantly to analysis and manuscript preparation. QW helped perform the analysis with constructive discussions.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.1062500/full#supplementary-material

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Nomenclature

Abbreviations

CO_2 carbon dioxide

GDP gross domestic product

DEA data envelopment analysis

DMU decision making unit

ENS energy consumption structure

ENI energy intensity

ECA economic activity

PEI potential energy intensity

TEG production technology gap between group and meta-frontier

GTC group technology

PDA production-theoretical decomposition analysis

GEF group energy efficiency

Group-L large economic output countries with large energy consumption

Group-M medium economic output countries with medium energy consumption

Group-S small economic output countries with small energy consumption

LMDI logarithmic mean divisia index

SDA structural decomposition analysis

IDA index decomposition analysis

Variables

T production technology set

$\mathbf{E_i^t}$ energy consumption of country *i* in year *t*

$\mathbf{K_i^t}$ fixed asset investment of country *i* in year *t*

$\mathbf{L_i^t}$ amount of labor inputs of country *i* in year *t*

$\mathbf{Y_i^t}$ economic output of country *i* in year *t*

$\mathbf{C_i^t}$ carbon dioxide emissions of country *i* in year *t*

Parameters

N number of countries

$\boldsymbol{\lambda_i}$ weights assigned to each of N countries

$\boldsymbol{\theta_{i,g}}$ ($\boldsymbol{\theta_{i,m}}$) proportional contraction of energy input given outputs and technology under group (meta-) frontier

$\mathbf{w_i^{S-V}}$ weight of the country *i* in the whole sample