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Preventing carbon emission retaliatory rebound post-COVID-19 requires expanding free trade and improving energy efficiency

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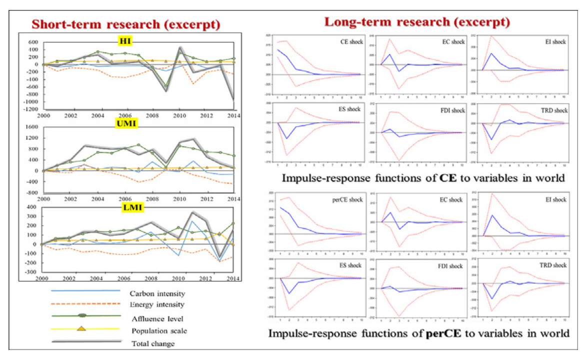
HIGHLIGHTS

- Global economy and three income level groups are selected as study objects.
- G7 group and BRICS countries are selected for specific countries study.
- Carbon reduction can take a lesson from 2008 global economic crisis.
- Energy intensity is critical for avoid retaliatory rebound after COVID-19 pandemic.
- Affluence level is still primary contributor to carbon emission increase.

GRAPHICAL ABSTRACT



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ABSTRACT

Existing studies have shown that the COVID-19 pandemic caused a sharp drop in carbon emissions in 2020. A recent example of the impact of sudden extreme events on carbon emissions occurred in the 2008 global financial crisis, in which carbon emissions droped in 2009, but jumped in 2010. This study is aimed to discuss how to prevent the retaliatory growth of carbon emissions post COVID-19 through learning the lessons from analysis of short-term and long-term drivers of carbon emissions. This study explored the short-term (annual) effects (population scale. affluence level, carbon intensity, energy intensity) of changes in carbon emissions by decomposing carbon emissions in the world, different income groups and selected countries before and after the 2008 financial crisis using LMDI technique. In addition, this study explored the long-term effects (energy consumption per capita, energy structure, energy intensity, foreign direct investment, and trade openness) of changes in carbon emissions by decomposing carbon emission in the world and different income groups from 1990 to 2014 using VAR technique. The decomposition results of short-term drivers of carbon emission uncovered that the deterioration in energy efficiency (increase in energy intensity) was the main reason for the retaliatory rebound in carbon emissions post-2008 financial crisis, especially in high-income countries. The decomposition results of long-term drivers of carbon emission uncovered that trade openness contributed to reduce carbon emission in the world and the incomes groups in the long term, although trade openness led to increase in carbon emission in developing countries in the short term. To prevent retaliatory rebound of carbon emissions, what we should learn two lessons from the decomposition of carbon emission: improving energy efficiency, and expanding trade openness. Unfortunately, energy efficiency has been neglected in the economic recovery plans to respond to COVID-19 of various countries, especially developed countries, and worse, trade protectionism is on the rise, especially in developed countries. Therefore, we are pessimistic about preventing a retaliatory rebound in carbon emissions post-COVID-19 for now.

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1. Introduction

The COVID-19 pandemic caused severe impact on public health and shocked global economy. In addition, the outbreak of COVID-19 had a serious impact on environment, more specifically on carbon emission. Le Quéré et al. (2020) found forced confinement has an important impact on global carbon emission changes. They estimated that the confinement is to decline global carbon emission by early April 2020 by 17% compared with 2019 mean level. As for carbon emission in the rest of the year, it depends on the duration and extent of the confinement. Jeff Tollefson analyzed several studies on carbon emission changes during the COVID-19 and he found carbon emission is bound to decline more than one billion tons in the first four months compared with the same period in 2019 (Tollefson, 2020). A report from Carbon Brief indicated that COVID-19 is likely to cause the largest annual fall in carbon emission as more countries enforcing lockdowns to stop this pandemic (Carbon Brief, 2020a). Then another report from Carbon Brief predicted that carbon emission probably see a decline up to 2729 million tons carbon emission in 2020 as a whole, which is the first one to quantify carbon emission changes on a daily basis (Carbon Brief, 2020b). Moreover, IEA (International Energy Agency, 2020) forecasted a decrease of 8% in 2020 carbon emission. Besides, Evans (2020) believed that as work resumption and economy stimulation, energy consumption will surge and carbon emission will rebound sharply. EIA estimated that carbon emission will decrease by 12.2% in 2020 and increase by 6.0% in 2021 in the United States (Energy Information Administration, 2020). Additionally, IMF predicted that carbon emission will rebound by 5.8% all over the world in 2021 (Le Quéré et al., 2020). How to prevent possible carbon emission rebound after COVID-19 is quite a matter of importance.

Recently, people have gone through several huge hit, for instance, oil crisis, the Asian financial crisis, 2008 global financial crisis. People may take a lesson from these events and get to a better position when confronting global hit again. Hence, learning from the recent 2008 global financial crisis, we are determined to figure out carbon emission changes and its driving factors by applying LMDI decomposition method. However, this single decomposition analysis in short-term may fail to depict carbon emission after COVID-19. Besides, as the pandemic rapidly spread globally, trade protectionism has gradually risen, which will definitely seriously influence the world economic landscape and carbon emission. Taking trade into consideration will be conducive to prevent possible retaliatory rebound after COVID-19. Consequently, we exert effort to study long-term effects of free trade on carbon emission and per capita carbon emission, expecting to provide practical reference for post-COVID-19 carbon emission control.

The rest parts of paper are organized as follow. Section 2 reviews relevant and informative literatures. Section 3 describes both short-term and long-term research methods, which roughly contains LMDI decomposition method and econometric method. Section 4 analyzes carbon emission and per capita carbon emission changes from the perspective of short-term and long-term. Section 5 comes to conclusions and proposes some policy implications.

2. Literature review

Recently, as global warming alleviating, people have paid much more attention on carbon emission and made efforts to decrease it. For instance, in accordance with Intended Nationally Determined Contributions (INDCs), the Paris Agreement encouraged every country to tackle climate change after 2020 according to its own situation (Rogelj et al., 2016). The United Nations Framework Convention on Climate Change (UNFCCC) promoted a "quantified emissions limitation and reduction objective" (Rogelj et al., 2019; Schleussner et al., 2016). However, in late 2019, a new pandemic emerged and rapidly spread out, which will definitely threaten human security, and have a serious impact on economic growth and carbon emission. What the post-epidemic carbon emission like? How to achieve established carbon emission target?

People have gotten through several crises and accumulated some practical experience. When dealing with carbon emission change after COVID-19 pandemic, it may be helpful to take a lesson from 2008 global economic crisis. In addition, in order to promote carbon emission, it is necessary to monitor carbon emission changes and even go a step forward to figure out factors driving carbon emission changes. Decomposition analysis is usually available to investigate carbon emission driving factors. Generally speaking, the structural decomposition analysis (SDA); the production-theoretical decomposition analysis (PDA); and the index decomposition analysis (IDA) are three frequently applied methods (Zhang et al., 2019; Wang and Su, 2020). These three decomposition methods all have advantages and disadvantages and applications (Chang et al., 2019; Wang and Wang, 2020). In accordance with the purpose of this study, IDA is properly applied. Among various IDA methods, LMDI is the preferred one because it can perfectly handle zero value and conduct without residuals (Ang, 2004; Ang and Choi, 1997). Scholars have done enormous researches on carbon emission decomposition analysis, which covers a wide area from province (Wang and Jiang, 2020), country (Jiang et al., 2019; Ma et al., 2019; Yasmeen et al., 2020), region (Li et al., 2019; Li et al., 2020), to even globe (Chang et al., 2019). Li and Qin (2019) examined challenges for China to peak carbon emission in 2030 from both historical and future perspective. The results turned out that achieving China's carbon emission peak in 2030 is quite a challenge. Wang and Jiang (2020) selected BRICS countries as object to investigate the impact of labor and investment on carbon emission by combining LMDI and C-D function. Besides, a lot of scholars put an eye on industrial carbon emission decomposition analysis, from manufacture (Chontanawat et al., 2020), power sector (Liao et al., 2019; Xie et al., 2019), agriculture (Wen et al., 2019), logistics sector (Quan et al., 2020), residential building sector (Liang et al., 2019), transport sector (Kim, 2019) and so on.

Since COVID-19 has been declared as a global pandemic by WHO on 11 March 2020. It shall be proper to consider carbon emission changes influenced by COVID-19 in global background. To our extent, there exists great gap on economic growth and carbon emission among regions. Hence, in order to uncover specific carbon emission changes and make targeted measurements, we attempt to explore carbon emission changes and its behind driving factors in three income level groups (high-income, upper-middle income, lower-middle income) before and after 2008 global economic crisis (with a time series from 2000 to 2014). Then for more specific results, we further explore carbon emission changes and influencing factors of G7 group and BRICS countries, including main developed and developing countries. Through the above investigation, we can understand carbon emission globally and deep into specific country, which is conducive to understand carbon emission changes before and after COVID-19, and formulate and implement practical measurements to control carbon emission.

In addition, the outbreak of pandemic will hinder global economy, and this impact is more severe than 2008 global economic crisis and even the Great Depression (Abodunrin et al., 2020). As economy go wrong, trade protectionism will worsen. Ahmed et al. (2015) argued that the implementation of measures to cut down carbon emissions worldwide can only be achieved through the form of international trade. Trade openness helped more underdeveloped economies to improve the national economic level and get rid of poverty. But the environmental pollution associated with this economic boom cannot be ignored (Ahmed and Long, 2013). Consequently, more scholars invested in investigating the correlation between trade and environmental degradation. In essence, the contradiction between trade and environmental pressure is indirect, based on the fundamental theory that free trade stimulates economic growth and thus accelerates environmental degradation. However, the impact of trade development on the environment has various performances in different countries, which may depend on the actual national conditions of each country, including economic development level, relevant economic policies, industrial structure and other aspects (Forslid and Okubo, 2015). Given that, this chapter provides a brief review of existing literature on trade–carbon emissions.

From the perspective of single country, Andersson (2018) combined input-output frameworks and nonlinear models to explore the impact of trade liberalization on the rapid growth of CO2 emissions in China. Their results supported the fact that trade liberalization is the key determinant of the increment of carbon emissions embodied in import of China during the period 1995–2008. Based on the multi-regional output-output tables, Ren et al. (2014) showed that the continued expansion of trade openness and the continuous inflow of foreign investment are important reasons for the soaring carbon emissions in China's industrial sector. It is worth mentioning that trade openness is seen as a pivotal indicator of inward direct investment, which is usually used to verify the authenticity of the PHH hypothesis. Actually, the PHH hypothesis depicts the long-term linkage between carbon emissions, trade, and foreign direct investment. For instance, Farhani and Ozturk investigated the drivers of total carbon emissions in Tunisia from 1971 to 2012. The results were found to be against the PHH hypothesis, but the increase in trade openness would sacrifice environmental quality (Farhani and Ozturk, 2015). Shahbaz et al. (2017) found that Pakistan's trade openness and financial development led to an increase in carbon emissions during the period 1971–2011, illustrating that trade liberalization adversely affected the environment.

From the perspective of multi-region, some important economic organizations and emerging economies have aroused the interest of scholars, such as OECD, South Africa, BRICS and so on due to the increasing impact of unilateral trade on the free trade system. Managi et al. (2009) investigated the impact of trade openness on carbon emissions in OECD countries and non-OECD countries and concluded that trade benefited the environmental improvement of OECD countries but accelerated GHG emissions in non-OECD countries. In order to verify the existence of the PHH hypothesis, Kearsley and Riddel (2010) focused on the impact of international trade on seven common environmental pollutants in 27 OECD countries. They concluded that a higher degree of trade openness was good for improving the environment and boost economic prosperity. When studying whether the ecological footprints of 93 countries conform to the EKC curve, Al-Mulali and Ozturk (2015) found that trade openness had a positive impact on environmental degradation in countries with different income levels. Using a panel of 102 countries, Liddle (2018) analyzed the impact of import volume and export volume on carbon emissions in 1990–2013. The results implied that, when the total carbon emissions were accounted for using the principle of consumer responsibility, most countries were net importers, especially China and India. In other words, trade was bad for reducing carbon emissions.

This study has made contributions to the relevant research of carbon emission changes in major two aspects. Firstly, in short-term research, this paper took 2008 global financial crisis as a lesson, tried to figure out possible carbon emission changes after COVID-19. Then, learning from previous experience, this paper exerted efforts to investigate factors driving carbon emission by applying LMDI decomposition analysis. Secondly, different from previous researches, this paper took trade into consideration and tried to uncover the impact of trade on carbon emission changes in a long-term research. On the whole, this paper examined carbon emission changes and influencing factors in both short-term and long-term, expecting to provide helpful references for carbon emission control after COVID-19.

3. Methods and data sources

3.1. LMDI decomposition model

According to Kaya identity, carbon emission (indicated by C) can be decomposed as follow:

$$C = \frac{C}{E} \times \frac{E}{GDP} \times \frac{GDP}{P} \times P \tag{1}$$

E represents energy consumption; gross domestic product (GDP) represents economic output; P represents population scale. Furthermore, indicator CE indicates carbon emission per unit energy consumption, which is called carbon intensity; indicator EI indicates energy consumption per unit economic output, namely, energy intensity; indicator AL indicates per capita GDP, which can be named as affluence level; indicator P indicates population scale.

Subsequently, Eq. (1) is further simplified as the following Eq. (2)

$$C = CE \times EI \times AL \times P \tag{2}$$

In accordance with LMDI decomposition model, the changes of carbon emission from base year to target year can be described as follows:

$$\Delta C = C^t - C^0 = \Delta C_{CE} + \Delta C_{EI} + \Delta C_{AL} + \Delta C_P \tag{3}$$

In Eq. (3), ΔC_{CE}, ΔC_{EI}, ΔC_{AL}, ΔC_P demonstrate carbon intensity effect, energy intensity effect, affluence level effect and population scale effect. The calculation process is shown in Eqs. (4)–(8).

$$\Delta C_{CE} = \sum L\left(C^t, C^0\right) \times \ \ln \frac{CE^t}{CE^0} \tag{4}$$

$$\Delta C_{EI} = \sum L\left(C^t, C^0\right) \times \ \ln \frac{EP^t}{EP^0} \tag{5}$$

$$\Delta C_{AL} = \sum L\left(C^t, C^0\right) \times \ \ln \frac{AL^t}{AL^0} \tag{6}$$

$$\Delta C_P = \sum L\left(C^t, C^0\right) \times \ \ln \frac{P^t}{P^0} \tag{7}$$

$$L\left(C^t, C^0\right) = \begin{cases} \dfrac{C^t - C^0}{\ln C^t - \ln C^0} \ \left(C^t C^0 \neq 0\right) \\ C^t / C^0 \ \left(C^t = C^0\right) \\ 0 \ \left(C^t C^0 = 0\right) \end{cases} \tag{8}$$

3.2. Estimating equation

In order to investigate the impact of trade activities on total carbon emissions and per capita carbon emissions, two indicators related to free trade: trade output and foreign direct investment are introduced. Additionally, per capita energy consumption, energy intensity and energy structure[1] are considered. Consequently, On the basis of the specifications of Shahzad et al. (2017) and Zoundi (2017), the long-term estimation equations of this paper are as follows:

$$\ln C_t = \beta_1 \ \ln EC_t + \beta_2 \ \ln EI_t + \beta_3 \ \ln ES_t + \beta_4 \ \ln FDI_t + \beta_5 \ \ln TRD_t + \varepsilon_1 \tag{9}$$

$$\mathrm{lnper}C_t = \beta_1 \ \ln EC_t + \beta_2 \ \ln EI_t + \beta_3 \ \ln ES_t + \beta_4 \ \ln FDI_t + \beta_5 \ \ln TRD_t + \varepsilon_2 \tag{10}$$

In the above formula, $t = 1, 2, 3, \cdots$ represents the time span; *ln* represents the natural logarithmic form of the variables. C represents carbon emissions at time t; perC represents the per capita carbon emissions at time t; EC is the per capita energy consumption, ES is the

[1] There is a trend that using renewable energy and clean energy to replace the use of fossil energy, which will definitely play an important role in the structure of primary energy consumption. Hence, in this article, energy structure refers to the share of non-fossil energy consumption in total energy consumption.

energy structure, represented by the proportion of renewable energy in the primary energy consumption structure. *FDI* denotes foreign direct investment, *TRD* denotes trade output, calculated by the ratio of total import and export trade to GDP. βi is the long-time elastic coefficient between the influencing factors and the interpreted variable, and ε is the error term.

3.3. Co-integration testing technique

The stability of time series is the basic condition for conducting time series related research, and it is also a necessary prerequisite for ensuring the validity and reliability of empirical results. This paper uses the ADF unit root test method, which is widely used for examining the stability of raw time series, the regression model can be rearranged into the following form (Zhang et al., 2017):

$$\Delta y_t = c + \phi y_{t-1} + \sum_{i=2}^{p} \varphi_i \Delta y_{t-(i-1)} + \varepsilon_t \tag{11}$$

where $\phi = \left(\sum_{i=1}^{p} a_i\right) - 1;\ \varphi_i = -\sum_{j=i+1}^{p} \alpha_j$, c is a constant term. The Null hypothesis of the ADF test is $H_0 : \phi = 0$; that is, the time series contains a unit root and is unstable; the alternative hypothesis is $H_0 : \phi < 0$, indicating that the original sequence is stationary. Only when the null hypothesis is rejected can the time series be proved to be stable and suitable for modeling.

Johansen co-integration procedure is applied to detect the existence of a long-term co-integration relationship between variables. Compared with the traditional E-G co-integration approach, the Johansen test method has better adaptability and accuracy. It can not only detect long-term relationships between multiple variables, but also obtain the number of co-integration relationships. The main principle of the Johansen test program is the loop test, which verifies whether the variables are integrated for a long time from the null hypothesis. The principle of Johansen co-integration program can be expressed in the following form:

$$\begin{aligned}\Delta \ln C_t = \Big\{ & \alpha_0 + \sum_{k=1}^{p} \alpha_{1k} \Delta \ln C_{t-k} + \sum_{k=0}^{p} \alpha_{2k} \Delta \ln EC_{t-k} + \sum_{k=0}^{p} \alpha_{3k} \Delta \ln EI_{t-k} \\ & + \sum_{k=0}^{p} \alpha_{4k} \Delta \ln ES_{t-k} + \sum_{k=0}^{p} \alpha_{5k} \Delta \ln FDI_{t-k} \\ & + \sum_{k=0}^{p} \alpha_{6k} \Delta \ln TRD_{t-k} + \varphi_0 \ln C_{t-1} + \varphi_1 \ln EC_{t-1} + \varphi_2 \ln EI_{t-1} \\ & + \varphi_3 \ln ES_{t-1} + \varphi_4 \ln FDI_{t-1} + \varphi_5 \ln TRD_{t-1} + V_t \Big\}\end{aligned} \tag{12}$$

In the above Eq. (12), Δ represents the first-order difference form of variables, α_0 represents the intercept term and the parameter of the equation; p is the number of lag periods. The null hypothesis of co-integration test ($H_0 : \varphi_0 = \varphi_1 = \varphi_2 = 0$) considers that there is no cointegration between study variables, and the alternative hypothesis ($H_1 : \varphi_0 \neq \varphi_1 \neq \varphi_2 \neq 0$) indicates that the study variables are long-term integrated. It is only when the null hypothesis is rejected that the variables are long-term correlated.

3.4. Model specification

The vector autoregressive (VAR) model is generally employed to detect or predict long-term and short-term dynamic correlations between economic variables (Xu and Lin, 2016). It treats all variables as endogenous variables and overcomes the shortcomings of errors due to subjective settings in the simultaneous equation model (Cheng et al., 2019; Dolatabadi et al., 2018). The general form of the VAR model can be expressed as follows:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \delta_t \ t = 0, 1, 2, \cdots \tag{13}$$

where Y denotes an $K \times 1$ endogenous vector, A represents the corresponding $K \times K$ coefficient matrix. p is the number of lag periods of economic model, and δ_t is a random error term.

3.4.1. Impulse response function

IR analysis is one of the most important analytical procedures in the VAR system. It can comprehensively capture the impact of the impact variable on the response variable during the study period, reflecting the complex dynamic relationship between variables. The model can be rearranged as follows to perform an impulse response analysis:

$$Y_t = \alpha + \sum_{i=0}^{\infty} \varepsilon_i \mu_{t-i} \tag{14}$$

In the Eq. (14), ε_i is a coefficient matrix, α is a constant term, and μ_{t-i} is an error vector. The definition of the impulse response function can be expressed as (Ding et al., 2017):

$$F = d_{ij}^{q} = \frac{\partial Y_{t+q}}{\partial \varphi_{jt}} \tag{15}$$

In the Eq. (15), d_{ij}^{q} denotes the interference of variable j at time t; Y_{t+q} represents the response of variable φ_{jt} to the structural impact of other endogenous variables.

3.4.2. Variance decomposition

VD refers to decomposing the variance of an endogenous variable to other explanatory variables. VD can clearly demonstrate the contributions of each impact factor to the dependent variable, and then estimate their relative importance (Ahmad et al., 2017; Jadidzadeh and Serletis, 2017). The dynamic VD technique proposed by Sims (1980) is defined as:

$$y_{it} = \sum_{j=1}^{k} \left(c_{ij}^{(0)} \beta_{jt} + c_{ij}^{(1)} \beta_{jt-1} + c_{ij}^{(2)} \beta_{jt-2} + c_{ij}^{(3)} \beta_{jt-3} + \cdots \right) \tag{16}$$

In the Eq. (16), each term represents the total effects of the j-th perturbation term β_j on y_{it} from the past to the present. Based on the above Eq. (16), this study assumes that β_j does not have sequence correlation, then the variance of the variable can be expressed as:

$$\mathrm{E}\left[\left(c_{ij}^{(0)} \beta_{jt} + c_{ij}^{(1)} \beta_{jt-1} + c_{ij}^{(2)} \beta_{jt-2} + c_{ij}^{(3)} \beta_{jt-3} + \cdots \right)^2 \right] = \sum_{q=0}^{\infty} \left(c_{ij}^{(q)} \right)^2 \eta_{jj} \tag{17}$$

As shown in the Eq. (17), this model uses the variance to estimate the total effects of the perturbation term j on the variable i from the past to the present. In this case, the variance of the variable y_i can be decomposed into K different and unrelated effects.

3.5. Data source

As for short-term research, this study selects global economy and three income level groups (high-income, upper-middle income, lower-middle income) as objects to investigate the changes of carbon emission. The low-income countries are excluded because the energy consumption data is not available. Besides, data of carbon emission, energy consumption, GDP and population all come from the World Development Indicators released online by the World Bank (The World Bank, 2020). In order to eliminate the impact of inflation, the GDP is constant in 2010 US$.

As for long-term research, this paper focuses on the multi-faceted effects of trade on carbon emissions. Five economic variables are used to explore the long-term effects of free trade on total carbon emissions (*CE*) and per capita carbon emissions (***perCE***), namely energy consumption (*EC*), energy intensity (*EI*), energy structure (*ES*), foreign direct investment (*FDI*) and trade output (*TRD*). *EC* refers to per capita energy consumption, which can more clearly exhibit the energy use of residents. *EI* is calculated by using energy consumed per 1000 US dollars, which can reflect the degree of energy technology development of the country. *ES* refers to the proportion of non-fossil energy in the energy mix. *FDI* refers to the direct investment equity flows in the economy. *TRD* is expressed as the ratio of the sum of imports and exports to GDP. To eliminate the interference caused by the heteroscedasticity of the raw data, this paper uses the natural logarithmic form of the annual data for calculation. All above data are collected from the World Bank (The World Bank, 2020).

4. Results and discussion

4.1. Short-term decomposition analysis

4.1.1. Carbon emission decomposition analysis of world economy

As shown in Fig. 1, carbon emission of world economy only appeared negative increase in 2008–2009, decreasing by 289.7 million tons totally. In addition, world economy maintained a drastic increase in respect of carbon emission from 2002 to 2006, with an average increase rate of 4.49%. Regarding to factors influencing carbon emission changes, affluence level effect was primary contributor to world's carbon emission increase. In 2008–2009, the impact of affluence level effect on carbon emission sharply decreased by −2.97%, but it bounced to 3.13% in 2009–2010, which was demonstrated in the red frame in Fig. 1. Population scale effect, the second largest carbon emission contributor, was quite stable, promoting carbon emission increase. Carbon intensity effect was rather unstable, having both positive and negative effect on carbon emission. While as to energy intensity effect, it remarkably drove carbon emission decrease, except for 2002–2003, 2008–2010. Actually, the carbon emission changes in 2008–2010 quite attracted our attention.

4.1.2. Carbon emission decomposition analysis of three income level groups

As shown in Fig. 2, carbon emission changes of high-income level group were fairly stable in 2000–2008, and violently fluctuated in 2008–2014. Specifically, high-income countries rapidly decreased by 721.5 million tons, with an increase rate of −5.24% in 2008–2009, and increased by 458 million tons, with an increase rate of 3.51% in 2009–2010. As for factors influencing carbon emission, affluence level effect was also the main contributor to carbon emission increase all the time (except for 2007–2009). What deserved to mention was that

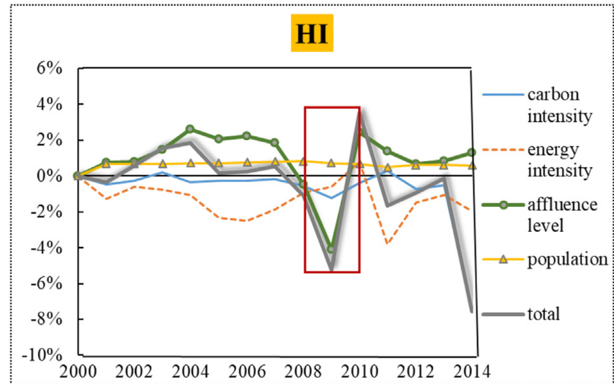

Fig. 2. Carbon emission changes of high-income countries.

it decreased carbon emission by 4.12% compared with last year, with an outstanding contribution of 79% to carbon emission decrease in this period. Just like world economy, population scale effect stably drove carbon emission increase, and its impact on carbon emission decreased slightly with time going by. Both carbon intensity effect and energy intensity effect had negative impact on carbon emission increase, while the impact of energy intensity effect was a little stronger than carbon intensity effect. In addition, energy intensity effect caused carbon emission to increase in 2009–2010, and to decrease in the remaining years.

Carbon emission changes of upper-middle income level group were demonstrated in Fig. 3, carbon emission of upper-middle income countries maintained a rapid increasing trend from 2000 to 2014. Actually, total carbon emission possessed the rapidest increase rate (10.6%) in 2002–2003, which caused carbon emission to increase by 911.1 million tons totally. Moreover, carbon emission presented an obvious inverted-V shape in 2008–2010. Regarding to factors influencing factors, they were completely different. Affluence level effect significantly caused carbon emission to increase. However, due to global economic crisis, the impact of affluence level effect on carbon emission drastically diminished, with a slight growth rate of 0.97%, far smaller than the remaining years. Overall, the impact of population scale effect and carbon intensity effect were evenly matched, though there was fluctuation in the respect of carbon intensity effect. Furthermore, energy intensity effect had positive impact on carbon emission decrease, but its impact lagged far behind compared with the other three factors. Therefore, upper-middle income countries still confronted heavy pressure to curb carbon emission increase.

As for lower-middle income level group, its carbon emission nearly maintained an increasing trend in 2000–2008 and fluctuated drastically in 2008–2014 (see Fig. 4). It only achieved carbon decease in 2012–2013, which decreased carbon emission by 138.9 million tons. Though impacted by global economic crisis, its carbon emission still

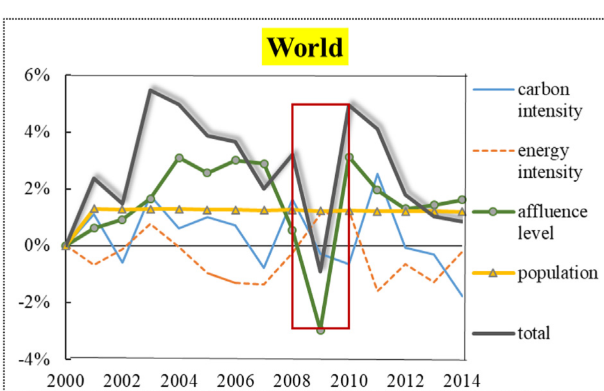

Fig. 1. Carbon emission changes of world economy.

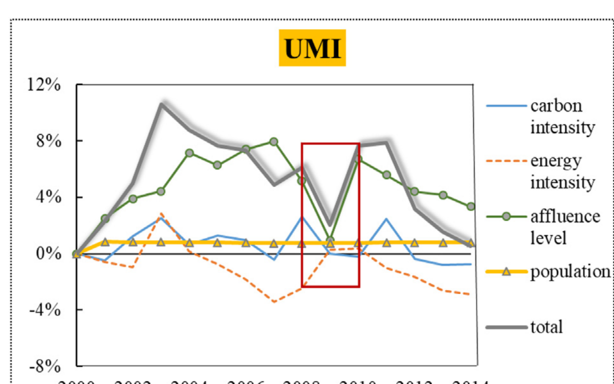

Fig. 3. Carbon emission changes of upper-middle income countries.

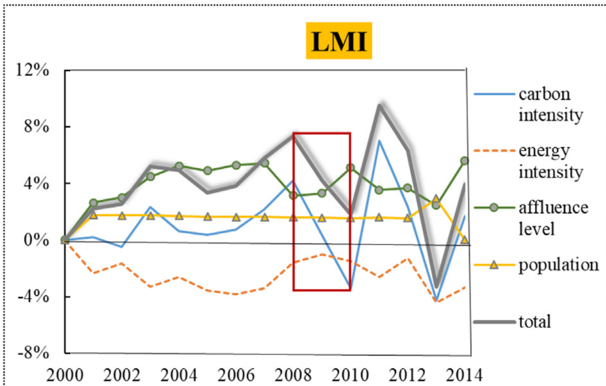

Fig. 4. Carbon emission changes of lower-middle income countries.

continued to increase, and just slightly slower growth rate (4.22% in 2008–2009, 1.79% in 2009–2010). With respect to factors influencing carbon emission, both affluence level effect and population scale effect promoted carbon emission increase during the whole period, which increased by 1827.4 million tons and 713.2 million tons respectively. Besides, affluence level effect appeared an inversed-V shape in 2008–2010; population scale effect appeared an inversed-V shape in 2012–2014 surprisingly. There was no doubt that energy intensity was major contributor to carbon emission decrease, which decreased carbon emission by 1162.2 million tons. However, due to global economic crisis, energy intensity deteriorated in 2008–2010, which caused less carbon emission decrease. Carbon intensity effect ranked the third place in promoting carbon emission increase. However, it significantly drove carbon emission decrease in 2008–2010.

4.1.3. Carbon emission decomposition analysis of G7 group

G7 group consists of seven main developed industrialized countries. Their carbon emission changes and the impact of all decomposed factors were demonstrated in Fig. 5. Generally speaking, all countries have

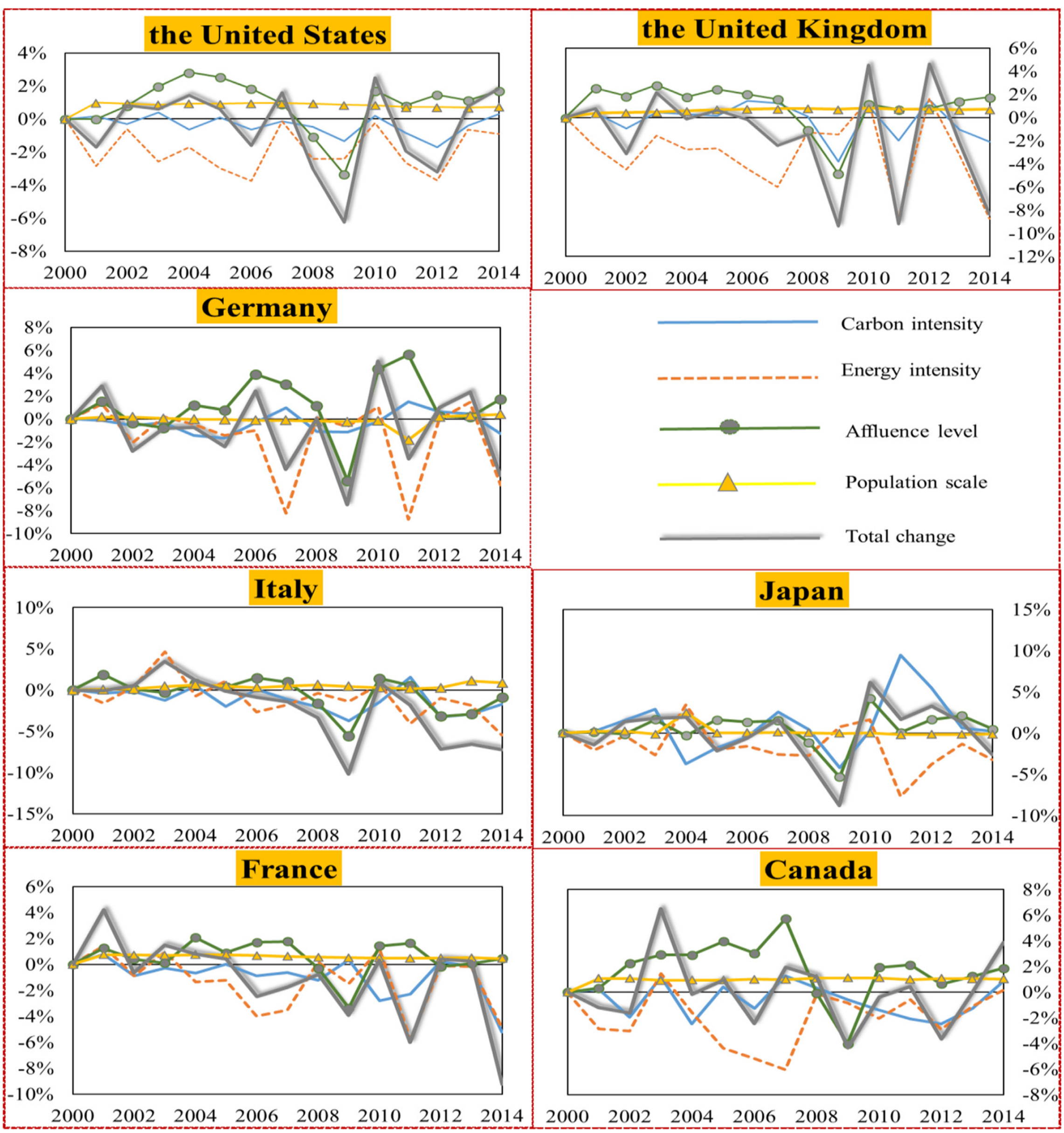

Fig. 5. Carbon emission changes of G7 group.

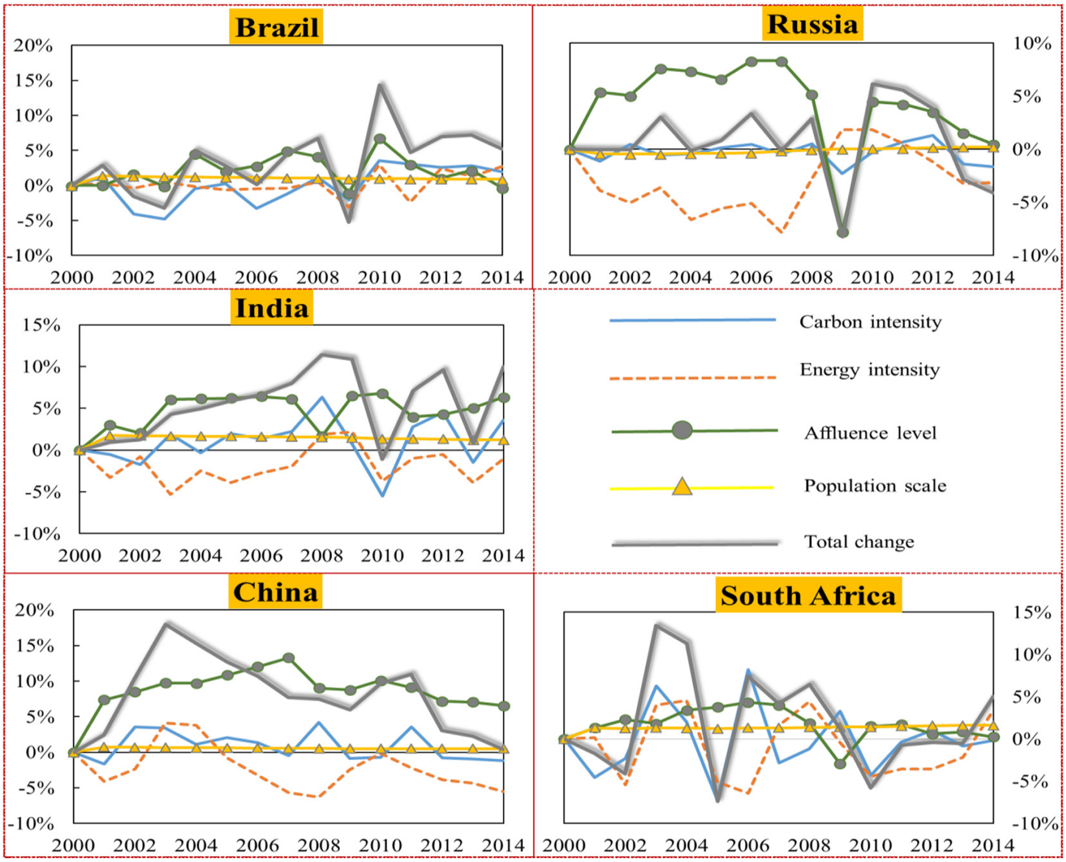

Fig. 6. Carbon emission changes of BRICS countries.

achieved carbon reduction during the whole period, except for Canada, which increased carbon emission by 2.81million tons. For those six countries, the United States ranked in the first place in reducing carbon emission, with a reduction of 439.41 million tons. As for carbon emission growth rate, an upward trend only emerged in the United States and Canada, which signifying that the carbon emission of the United States gradually deteriorated and converted to increase. On the whole, G7 group have done great effort to reduce carbon emission and got brilliant achievement. Besides, in G7 group, more special attention shall be put to the United States and Canada, for the former converted to increase carbon emission, the latter still promoted carbon emission increase in the whole period.

Table 1
Stationarity test results.

Groups	Series	At level		At 1st difference		At 2nd difference		Order of integration
		t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.	
World	lnCE	1.0536	0.9958	−3.2862	0.0276	–	–	I(1)
	lnperCE	0.5703	0.9856	−3.1509	0.0366	–	–	I(1)
	lnTRD	−1.2539	0.6334	−6.1589	0.0000	–	–	I(1)
	lnFDI	−1.4974	0.5177	−3.7939	0.0091	–	–	I(1)
	lnEC	0.8330	0.9925	−4.0289	0.0054	–	–	I(1)
	lnEI	−0.0967	0.9372	−3.5141	0.0185	–	–	I(1)
	lnES	−0.9469	0.7549	−3.6449	0.0127	–	–	I(1)
HI	lnCE	−2.3230	0.1732	−4.9820	0.0006	–	–	I(1)
	lnperCE	−0.5883	0.8557	−4.9721	0.0006	–	–	I(1)
	lnTRD	−0.6986	0.8288	−5.7642	0.0001	–	–	I(1)
	lnFDI	−1.4170	0.5570	−3.8226	0.0086	–	–	I(1)
	lnEC	−1.7820	0.3798	−4.9654	0.0006	–	–	I(1)
	lnEI	1.3796	0.9983	−4.5404	0.0017	–	–	I(1)
	lnES	−0.7538	0.8141	−4.3947	0.0025	–	–	I(1)
MI[a]	lnCE	0.0079	0.9501	−2.1688	0.2220	−5.1066	0.0006	I(2)
	lnperCE	−0.3087	0.9093	−2.0967	0.2476	−5.0830	0.0006	I(2)
	lnTRD	−2.3574	0.1636	−5.1978	0.0004	–	–	I(1)
	lnFDI	−4.6042	0.0013	–	–	–	–	I(0)
	lnEC	−0.2000	0.9255	−2.1156	0.2407	−6.3001	0.0000	I(2)
	lnEI	−0.3271	0.9068	−2.9136	0.0598	−6.0552	0.0001	I(2)
	lnES	−0.8779	0.7767	−2.3269	0.1725	−6.6335	0.0000	I(2)

[a] MI (which is also written as MIG) refers to middle-income level group, which consists of upper-middle income level group and lower-middle income level group.

Focusing on factors driving carbon emission, for all counties in G7 group, energy intensity effect made the largest contribution to carbon reduction, which decreased by 1542.19 million tons in the United States, 230.29 million tons in the United Kingdom, 192.44 million tons in Germany, 71.22 million tons in France, 264.96 million tons in Japan, 54.47 million tons in Italy, and 157.96 million tons in Canada respectively. On the contrary, affluence level effect was regarded as primary inhibitor to carbon emission, except for Italy, where affluence level effect gradually changed to reduce carbon emission and made positive impact to carbon reduction overall. Through comparing the impact of energy intensity effect and affluence level effect on carbon emission, the former was always stronger than the latter. Carbon intensity effect always made a positive impact to carbon reduction (except for Japan) and population scale effect made a negative impact to carbon reduction (except for Germany).

Regarding to carbon emission growth rate, all seven countries presented an obvious inversed -V shape in 2008–2010 because of global economic crisis. Generally, all for factors tries to decreased carbon emission in 2008–2009, while increasing carbon emission in 2009–2010. Furthermore, carbon emission growth rate of all countries fluctuated drastically after global economic crisis, particularly the United Kingdom, Germany, France.

4.1.4. Carbon emission decomposition analysis of BRICS countries

All five countries in BRICS belong to developing countries, and their carbon emission changes were presented in Fig. 6. Different from G7 group, all countries in BRICS failed to reduce carbon emission. Especially China, the largest developing countries, its carbon emission increased from 3405.18 million tons in 2000 to 10,291.93 million tons in 2014, increasing by 6886.75 million tons totally. Only China's carbon emission always maintained an increasing trend in 2000–2014, the other four countries decreased carbon emission in several years, for instance, Brazil and Russia in 2008–2009, South Africa in 2009–2013 and so on.

Regarding to factors driving carbon emission, energy intensity effect drove carbon emission to decrease (except for Brazil), while affluence level effect drove carbon emission to increase overall. In addition, the impact of affluence level effect was always stronger than energy intensity effect on carbon emission in these five developing countries. Population scale effect was interesting in Russia, which decreased carbon emission in 2000–2008 and increasing carbon emission in 2008–2014. For the remaining four countries, population scale effect consistently drove carbon emission to increase in the whole period. Carbon intensity effect had both positive and negative impact on carbon emission in BRICS countries, which indicated that there existed great difference in energy utility efficiency.

From the above discussion, it can be said that global economic crisis has obvious impact on carbon emission whether on world economy or three income level groups. The difference is that world economy, high-income level group, and upper-middle income level group all presented an inversed-V shape in 2008–2010, while lower-middle not. Energy intensity effect deteriorated, particularly in upper-middle income level countries, for it decreasing carbon emission in 2008–2010.

G7 group achieve better achievement in the respect of carbon reduction and energy intensity made a great contribution. On the contrary, BRICS countries still had a long way to curb carbon emission increase, especially the largest developing county, China. Besides, energy intensity effect also deteriorated in 2008–2010 both in G7 group and BRICS countries, no matter it slowed down carbon reduction speed or converted carbon emission to increase.

In fact, as the globalization deepening, subprime crisis, which originated in the United States, dragged the remaining countries, whether developed country or developing country in this crisis. Subsequently, it evolved into a global economic crisis in 2007–2009, especially serious in 2008. Even countries with sound monetary policies and regulatory frameworks have been affected by this economic downturn. A significant sign of this economic downturn was unemployment. For example, Spain had reached its historical highest unemployment of 13.3% in January 2009; while the United States had continued to increase its unemployment rate, which broke a history of 26 years, and reached a new peak of 9.4% in May 2009. Many large companies confronted bankruptcy or were broken. Subsequently, in order to recover economy, a lot of monetary and fiscal policies have been formulated and implemented. For example, for the purpose of against drastic diminish of electronic goods export, and expanding domestic market, Chines government decided to promoted the "Home Appliances to the Countryside" program, which aimed to stimulate consumption by providing subsidy. In this period, countries made economic recovery a top priority, while loosed environmental regulatory. Hence, energy intensity reversely deteriorated and caused carbon emission increase when recovering economy.

In addition, in late 2008, oil price was decreasing due to the declining demand. As the crisis deepening, the oil price continued to go down. However, when economy tried to recover, more energy consumption will be needed. Low price oil will be a better choice out of economic reason. But as oil demand increase and economic recovery, oil price will also recover.

4.2. Long-term econometric analysis

4.2.1. Stationarity test

Table 1 exhibits the unit root tests results. The results show that at the 5% confidence level, all variables passed the unit root test, and can be used for the next quantitative analysis.

Table 2
Johansen co-integration tests results.

Income groups	Model	Hypothesized no. of CE(s)	Eigenvalue	Trace statistic	0.05 critical value	Prob. **
World	M1	None *	0.9346	164.2729	95.7537	0.0000
		At most 1 *	0.8543	104.2657	69.8189	0.0000
		At most 2 *	0.7921	61.8824	47.8561	00014
		At most 3	0.5883	27.3292	29.7971	0.0938
		At most 4	0.2937	7.8067	15.4947	0.4863
		At most 5	0.0072	0.1591	3.8415	0.6900
	M2	None *	0.9333	162.4598	95.7537	0.0000
		At most 1 *	0.8332	102.9077	69.8189	0.0000
		At most 2 *	0.7872	63.5091	47.8561	0.0009
		At most 3	0.6271	29.4664	29.7971	0.0546
		At most 4	0.2921	7.7656	15.4947	0.4908
		At most 5	0.0076	0.1667	38.415	0.6830
HI	M1	None *	0.8125	116.7948	95.7537	0.0008
		At most 1 *	0.7606	79.9627	69.8189	0.0062
		At most 2 *	0.6275	48.5081	47.8561	0.0434
		At most 3	0.4925	26.7822	29.7971	0.1071
		At most 4	0.3538	11.8605	15.4947	0.1637
	M2	At most 5	0.0974	2.2545	3.8415	3.8415
		None *	0.8248	111.2023	95.7537	0.0028
		At most 1 *	0.7024	72.8831	69.8189	0.0279
		At most 2 *	0.6150	46.2143	47.8561	0.0707
		At most 3	0.4943	25.2125	29.7971	0.1540
		At most 4	0.2997	10.2128	15.4947	0.2647
		At most 5	0.1024	2.3762	3.8415	0.1232
MI	M1	None *	0.7696	136.2271	95.7537	0.0000
		At most 1 *	0.7696	76.3940	69.8189	0.0136
		At most 2 *	0.6686	45.5704	47.8561	0.0807
		At most 3	0.3888	22.3753	29.7971	0.2781
		At most 4	0.3240	12.0358	15.4947	0.1552
		At most 5	0.1660	3.8132	3.8415	0.0508
	M2	None *	0.9410	135.4986	95.7537	0.0000
		At most 1 *	0.7693	76.0767	69.8189	0.0145
		At most 2 *	0.6627	45.2791	47.8561	0.0856
		At most 3	0.3942	22.4594	29.7971	0.2736
		At most 4	0.3215	11.9355	15.4947	0.1601
		At most 5	0.1651	3.7900	3.8415	0.0516

* Denotes rejection of the hypothesis at the 0.05 level.
** Denotes MacKinnon-Haug-Michelis (1999) p-values.

4.2.2. Long-term estimation

Table 2 provides the results of the Johansen co-integration test. Noted that each income group consists of two models, namely model (1) (CE, EC, EI, ES, FDI, TRD) and model (2) (perCE, EC, EI, ES, FDI, TRD). From Table 2, at a 5% confidence level, the variables of each group are integrated in the long run. In WDG group, there are at least three long-term nexuses between CE, perCE and other explanatory variables. In HIG group, at least two nexuses of CE, perCE and influencing factors are found. In the countries of MIG, there exist at least two long-term relationships between CE, perCE and influencing factors.

Subsequently, the study estimates the relevant elastic coefficients between these variables, shown in the following Eqs. (18)–(23).

$$\ln CE_{WDG} = 0.6163 \ \ln EC_t - 0.0042 \ \ln EI_t - 0.5434 \ \ln ES_t - 0.0190 \ \ln FDI_t + 0.1216 \ \ln TRD_t + 0.0151 \tag{18}$$

$$lnperCE_{WDG} = 0.6961 \ \ln EC_t - 0.0854 \ \ln EI_t - 0.5669 \ \ln ES_t - 0.0205 \ \ln FDI_t + 0.1077 \ \ln TRD_t + 0.0004 \tag{19}$$

$$\ln CE_{HIG} = 1.1029 \ \ln EC_t - 0.1398 \ \ln EI_t - 0.0730 \ \ln ES_t - 0.0025 \ \ln FDI_t + 0.0096 \ \ln TRD_t + 0.0021 \tag{20}$$

$$nperCE_{HIG} = 1.1105 \ \ln EC_t - 0.1767 \ \ln EI_t - 0.0883 \ \ln ES_t - 0.0026 \ \ln FDI_{\mathrm{t}} + 0.0066 \ \ln TRD_t - 0.0052 \tag{21}$$

$$\ln CE_{MIG} = 0.5363 \ \ln EC_t + 0.2984 \ \ln EI_t - 0.3250 \ \ln ES_t + 0.0278 FDI_t + 0.1841 \ \ln TRD_t + 0.0976 \tag{22}$$

$$lnperCE_{MIG} = 0.5356 \ \ln EC_t + 0.2991 \ \ln EI_t - 0.3267 \ \ln ES_t + 0.0274 \ \ln FDI_t + 0.1849 \ \ln TRD_{\mathrm{t}} + 0.0962 \tag{23}$$

In world group, EC and TRD exert a positive impact on CE and perCE; EI, ES and FDI slow down the accumulation of carbon emissions. The results reveal that FDI may not lead to accelerated growth of domestic carbon emissions, while trade openness is the driving factor for stimulating carbon emissions. This finding provides policy implications for countries that aim to achieve carbon reduction targets through the INDCs approach. For example, reducing energy consumption per capita by improving energy efficiency can suppress excessive carbon emissions. Besides, vigorously promote renewable energy to further reduce the share of fossil energy in the energy consumption structure can help curb carbon emissions from the source. Furthermore, the government can appropriately relax restrictions on domestic investment in order to attract more foreign investment and boost economic growth.

In HI group, EC and TRD cause the carbon emissions increment, and the remaining factors are beneficial to control carbon emissions. In MI group, ES is an offset factor for CE, while EC, EI, FDI and TRD accelerate CE. The results reflect the actual situation in most developing countries. Developed countries invest their money in developing countries, using the labor and environmental resources of developing countries to produce, thus meeting the actual needs of the country (Wang et al., 2017). In this process, along with the transfer of funds, developed countries have transferred part of the environmental pressure to developing countries. FDI is not conducive to developing countries to implement carbon emission reduction measures.

To sum up, EI has a positive impact on CE in MI group, while its impact in other two groups is negative. This result shows that EI of developing countries is still at a higher level, which may hinder their carbon emissions reduction. Compared with the other two groups, the countries in MI group should pay more attention to improving energy efficiency and accelerating the research and development and innovation of energy-saving technologies, thereby achieving the goal of reducing energy intensity. ES negatively affected CE in all three groups. This indicates that the higher the proportion of renewable energy in the energy mix, the better the reduction of carbon emissions (Wang and Zhang,

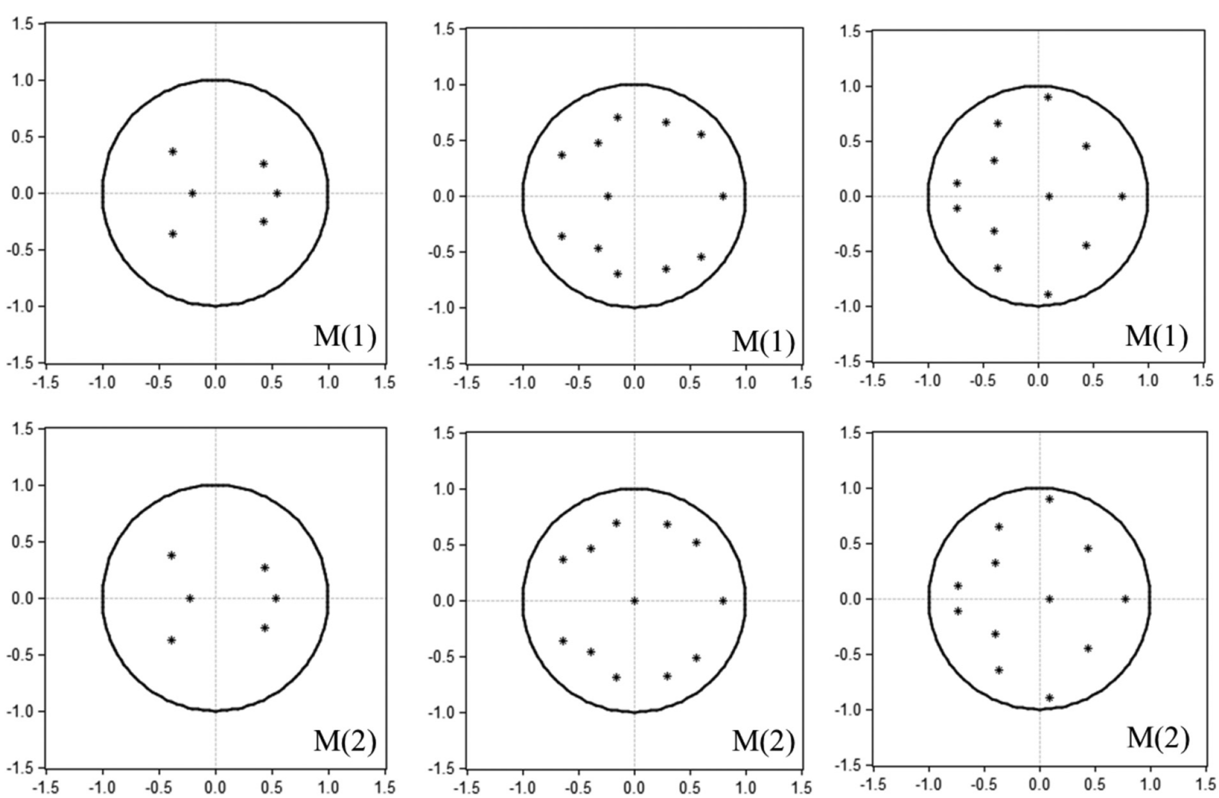

Fig. 7. Model robustness test.

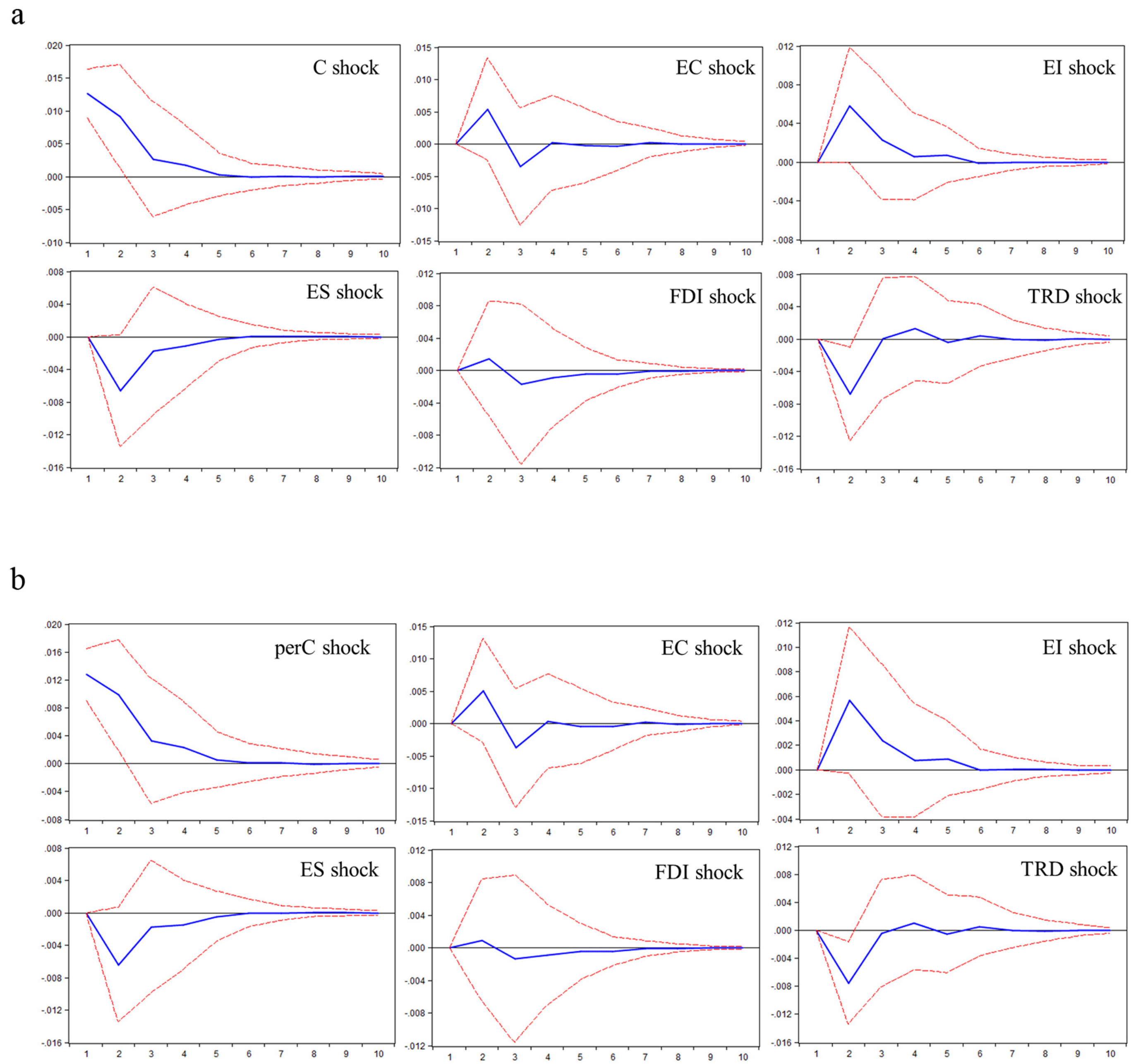

Fig. 8. a. Impulse-response functions of CE to variables in world. b. Impulse-response functions of perCE to variables in world.

2020). In view of this, strengthening the development and utilization of renewable energy, such as wind energy and solar energy, can accelerate the realization of carbon emission reduction targets.

As for FDI, there is not enough evidence to confirm the existence of PHH hypothesis. However, in MI countries, the inflow of FDI indeed brings a lot of energy consumption, resulting in stimulating carbon emissions. This is because the production costs (including labor and raw materials) in developing countries are relatively low, and their environmental regulatory system needs to be improved. According to long-term estimates, TRD accelerates carbon emissions growth. Above results can be explained by the "Jevons Paradox" in energy economics (Yoo et al., 2019). With the deepening of economic globalization, the international division of labor and the global production network become more complete, leading to closer trade links between countries. In this system, countries share talents, technologies and knowledge, expand trade openness, thus greatly reducing production costs and further promoting international trade. Under these circumstances, higher trade openness would promote carbon emissions rather than the reduction.

4.2.3. Impulse response analysis

The model should be tested for stability before building, since the robustness of the model directly determines the accuracy and effectiveness of the experimental results. This paper uses the AR eigenvalue to detect the robustness of the model. It is verified that the AR roots of the variables are all within the unit circle, as shown in Fig. 7, indicating that the six economic models established are stable.

Figs. 8–10 show the dynamic effects of EC, EI, ES, FDI and TRD on CE and perCE in three income groups. The horizontal axis denotes the lag period in which the impact variable affects the response variable, and the vertical axis denotes the response degree of the explained variable. The solid line is the impulse response function, reflecting the response

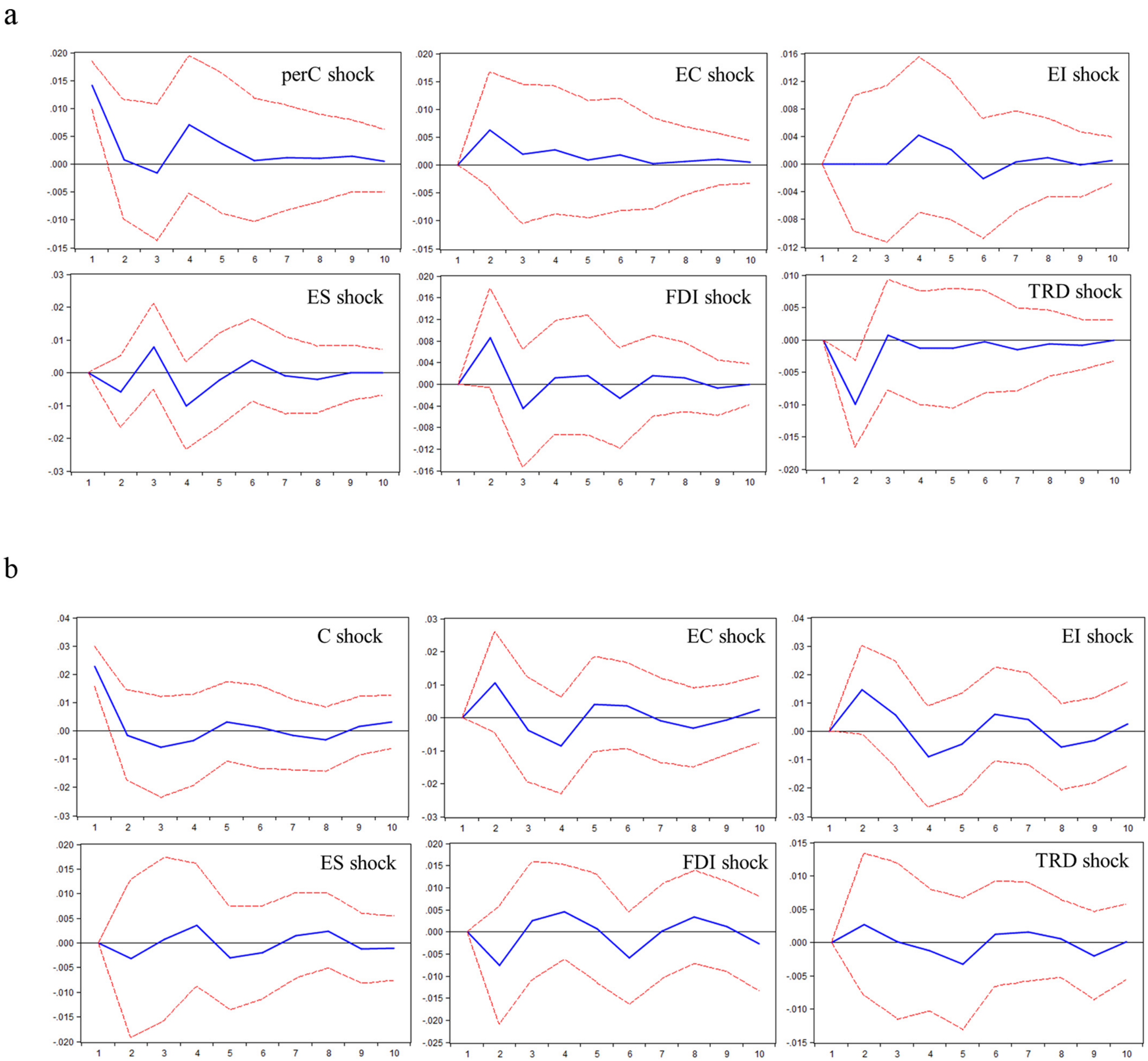

Fig. 9. a. Impulse-response functions of CE to variables in HI. b. Impulse-response functions of perCE to variables in HI.

of each variable to the corresponding impact, and the dotted line represents the standard deviation area.

Fig. 8 is the IR images of world. Overall, the impact of EC, EI, ES, FDI and TRD on CE is basically consistent with the impact on perCE. More precisely, EC imposes a positive impact on CE in early stages, and this effect has diminished over time. In the medium term, EC declined, and CE correspondingly showed a downward trend. Finally, as the growth rate of EC slows down, its contribution to CE continues to decrease, and the image eventually stabilizes around zero (greater than zero). In a nutshell, EC is positively correlated with changes in CE because the release of GHG (Behera and Dash, 2017). Consequently, reducing EC levels is helpful in controlling carbon emissions. From a long-term perspective, EI has a positive impact on CE, and this impact is more pronounced in the short term. Countries are trying to explore effective ways to cut energy intensity because of the widespread concern caused by climate change issues. Improving energy efficiency is considered effective in reducing energy consumption. It minimizes energy waste by improving and innovating energy technologies, thereby mitigating energy consumption in the production process.

ES negatively affected CE, indicating that the improvement in energy mix help cut down carbon emissions. In recent decades, countries are actively developing new energy and clean energy to replace traditional energy for production activities (Hansen et al., 2019; Liu, 2019). As a result, these measures brought about an increasing share of renewable energy in the energy mix and slowed the accumulation of CE. FDI plays a negative role in promoting carbon emissions, although this hindrance is less significant. From a long-term perspective, FDI is conducive to improving the environmental quality of the country. Governments should encourage enterprises to introduce foreign capital and expand production scale, which can not only promote economic prosperity, but also prevent environmental degradation. TRD initially exerted a negative impact on CE, but since the third period, as trade share

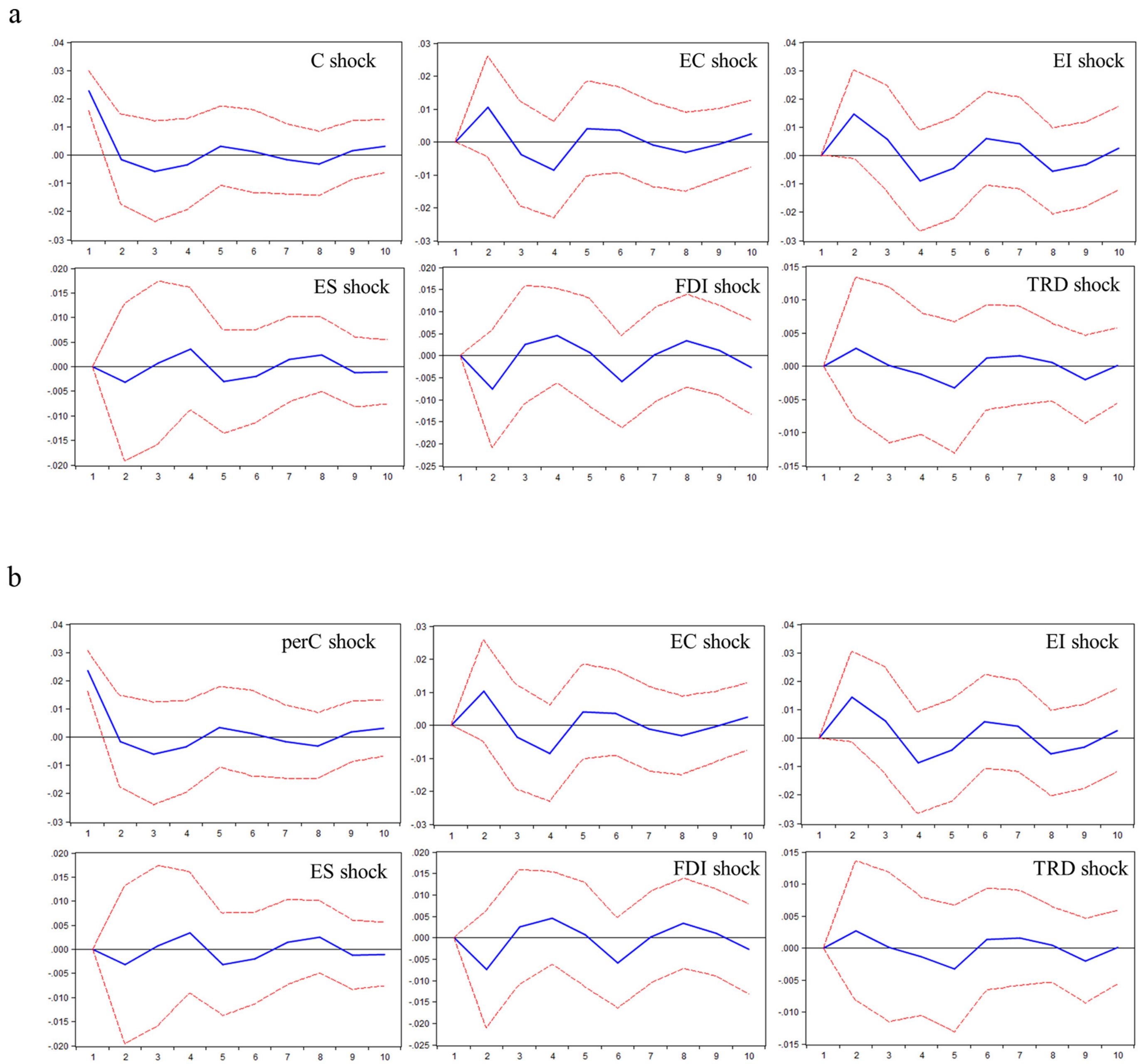

Fig. 10. a. Impulse-response functions of CE to variables in MI. b. Impulse-response functions of perCE to variables in MI.

increased in GDP, it has a gradual weakening effect on CE. Although TRD has a positive impact on CE, this promotion is minimal and does not cause a significant increase in CE.

Fig. 9 illustrates the IR images of HI. EC has a positive influence on CE throughout the study interval. It can be inferred that the EI of HI countries will cause carbon emissions growth in the future. Therefore, it is necessary for developed countries to take measures to continuously reduce EI to suppress CE. Compared with other factors, the impact of ES on CE is more obvious. Throughout the research cycle, ES had a negative impact on CE for most of the time, and occasionally positively affected CE. The impact of FDI on CE is uncertain, with positive and negative impacts alternating. At last, the IR image of CE to FDI is stable below the horizontal line, implying that in the long run, FDI has a negative impact on CE and will not cause serious environmental pollution. As for TRD, both in the short-term and long-term, the increase in trade volume exerts a negative impact on CE, indicating that free trade decreases domestic carbon emissions in HI countries.

Fig. 10 exhibits the IR images of MI group. EC initially exerted a positive impact on CE, and after the third period, the impact turned negative. In the 10th period, the IR curve showed an upward trend implying that EC will promote CE in MI countries in the future. Similarly, the impact of EI on CE also shows obvious phase characteristics, with positive and negative effects alternating. These results indicate that EI in developing countries is still at a high level, which is a barrier to carbon reduction.

ES has a relatively small impact on CE, causing a small change in CE, no more than 5%. But from a long-term perspective, ES negatively affects CE, suggesting that increasing the share of renewable energy in the energy mix help reduce CE in MIG countries. In the long run, FDI and TRD are conducive to improving environmental quality and curbing excessive CE. The difference is that FDI can reduce carbon emissions in a short period of time, while TRD may promote CE in the short run. Therefore, although free trade is beneficial for developing countries to achieve CE reduction targets in the long run, and it causes rapid accumulation of CE in a short time. This finding supports trade liberalization.

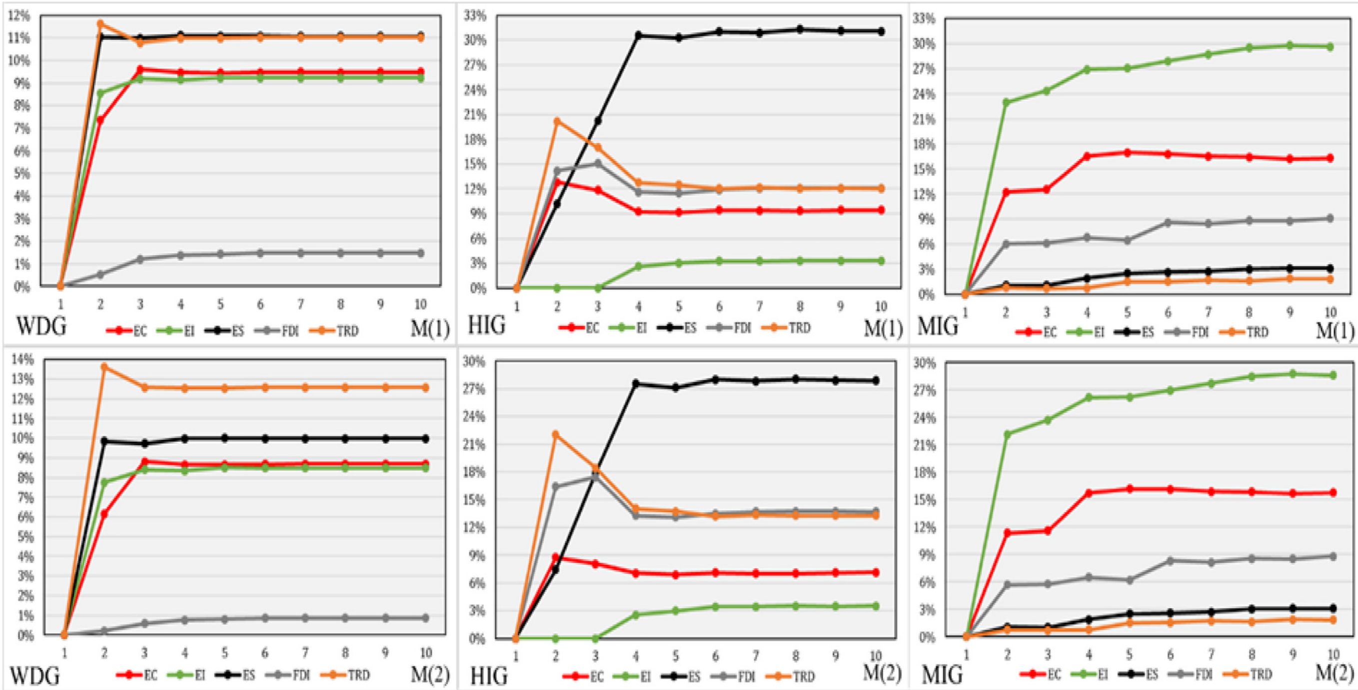

Fig. 11. Variance decomposition results.

In summary, in three groups, EC is positively correlated with CE. The impact of EI on CE varies among three groups. This mainly because HI countries have advanced energy technologies, which can ensure that the energy intensity is basically stable at a relatively low level and will not promote excessive growth of carbon emissions. But for MI economies, there is still much room for energy intensity reduction, so the promotion of carbon emissions is relatively significant. ES negatively affects CE, as renewable energy plays an increasingly important role in the energy mix. However, the impact of ES on CE is not significant, meaning that non-renewable energy still dominates. It is an effective way to solve this problem by vigorously promoting and popularizing clean energy. FDI has a negative impact on CE in the long run, although it causes CE to increase in the short term. This finding suggests that the establishment of the PHH hypothesis is conditional, that is, the large inflow of foreign investment in a short period will indeed damage the country's environment and bring about an increase in pollutant emissions; but in the long run, FDI will not lead to a sharp increase on CE.

The impact of TRD on CE is uncertain and depends on the country's income level. For developed countries, trade is conducive to carbon emission reduction, while for MI countries, trade negatively affects CE in the long run, but may accelerate it in the short term. There is not sufficient evidence in this paper that free trade is conducive to global carbon reduction.

4.2.4. Variance decomposition analysis

As shown in the Fig. 11, the image in the upper row decomposes the variance of CE into various variables; the image in the lower row is the decomposition results of the variance of perCE. In world group, TRD is the biggest impact factor, while FDI makes the smallest contribution. On a global scale, the impact of free trade on CE cannot be underestimated and ignored. Accordingly, protecting the free trade system and opposing trade protection policies are of great significance for effectively controlling global GHG emissions. In HI group, ES is the largest contributor, followed by TRD, FDI, EC and EI. This result indicates that TRD and FDI in developed countries are not the cause of significant changes in CE but improving ES result in significant changes in CE. The impact of EC on CE is relatively small, indicating that energy use efficiency is high in countries with high-income level, and the growth of EC will not lead to excessive growth of CE. In MI group, EI is the biggest contributor, followed by EC and FDI. In contrast, the contribution of ES and TRD is the smallest, no more than 3%.

In general, the drivers of carbon emissions are different at various stages of economic development. This result reveals that developed countries should focus on improving energy mix, while developing countries should fully consider the impact of EI when implementing measures to reduce CE.

5. Conclusions and policy implications

This paper aims to explore carbon emission changes and factors influencing this change after this COVID-19 pandemic from both short-term research and long-term research. We have come to the following conclusions and proposed scientific and practical policy implications:

For short-term research, high-income level group initially achieved carbon reduction. As for middle-income level group, which significantly increased carbon emission, upper-middle income level group was deemed as the largest contributor. Moreover, from the perspective of specific countries, it may come to a conclusion that developed countries were likely to curb carbon increase, while developing countries may still struggle with carbon emission control. In addition, since the impact of global economic crisis, most countries tended to slower or even reduce carbon emission in 2008–2009 and present a retaliatory rebound of carbon emission in 2009–2010, which may teach a lesson for carbon emission changes after COVID-19 pandemic.

Affluence level effect was prominent inhibitor to carbon reduction in all studies objects, particularly the upper-middle income level group and lower-middle income level group, which almost located in the process of rising economy. Energy intensity effect prominently drove carbon reduction, especially in high-income level group and G7 group. In these countries, the positive impact of energy intensity was stronger than passive impact of affluence level on carbon reduction. Consequently, improving energy intensity may also help to reduce carbon emission after COVID-19 pandemic. More investment shall be put to promote energy-saving technologies and strengthen research and development in related technologies; more clean and renewable energy shall be used in present energy system; encourage more monetary and fiscal polies implicated to improve energy intensity.

For long-term research, the estimation equations indicate that EI has a positive impact on CE in middle-income level group, while negative impact on the other groups. It is essential to strengthen the research and development (R&D) and innovation of energy technology to reduce the energy intensity. Trade is shown to accelerate carbon emissions, but this promotion effect is minimal in the long-run. In comparison, international trade is more likely to contribute to the carbon emissions of middle-income countries.

According to the results of IR analysis, ES has a negative impact on CE, as renewable energy plays an increasingly important role in the energy mix, inhibiting the accelerated growth of CE. In all income groups, FDI is negatively correlated with CE in the long run but cause an increase in CE in the short term. This finding supports the PHH hypothesis under certain conditions. For developed countries, TRD is conducive to carbon emission reduction; for middle-income countries, TRD exerts a negative impact on CE in the long term but accelerates CE growth in the short term. Consequently, government shall de devoted themselves to promote trade openness in long-term, since adhering to free trade is good for achieving global emissions reduction targets.

CRediT authorship contribution statement

Qiang Wang: Conceptualization, Methodology, Software, Data curation, Writing - original draft, Supervision, Writing - review & editing. **Shasha Wang:** Methodology, Software, Data curation, Investigation, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Abodunrin, Oyinlola, Oloye, G., Adesola, Bola, 2020. Coronavirus pandemic and its implication on global economy. International Journal of Arts, Languages and Business Stuates 4.

Ahmad, N., Du, L., Lu, J., Wang, J., Li, H.-Z., Hashmi, M.Z., 2017. Modelling the CO2 emissions and economic growth in Croatia: is there any environmental Kuznets curve? Energy 123, 164–172.

Ahmed, K., Long, W., 2013. Climate change and trade policy: from legal complications to time factor. Journal of International Trade Law and Policy 12, 258–271.

Ahmed, K., Shahbaz, M., Qasim, A., Long, W., 2015. The linkages between deforestation, energy and growth for environmental degradation in Pakistan. Ecol. Indic. 49, 95–103.

Al-Mulali, U., Ozturk, I., 2015. The effect of energy consumption, urbanization, trade openness, industrial output, and the political stability on the environmental degradation in the MENA (Middle East and North African) region. Energy 84, 382–389.

Andersson, F.N.G., 2018. International trade and carbon emissions: the role of Chinese institutional and policy reforms. J. Environ. Manag. 205, 29–39.

Ang, B.W., 2004. Decomposition analysis for policymaking in energy: which is the preferred method? Energy Policy 32, 1131–1139.

Ang, B.W., Choi, K.-H., 1997. Decomposition of aggregate energy and gas emission intensities for industry: a refined Divisia index method. Energy J. 18, 59–73.

Behera, S.R., Dash, D.P., 2017. The effect of urbanization, energy consumption, and foreign direct investment on the carbon dioxide emission in the SSEA (South and Southeast Asian) region. Renew. Sust. Energ. Rev. 70, 96–106.

Carbon Brief, 2020a. Analysis: coronavirus set to cause largest ever annual fall in CO2 emissions. https://www.carbonbrief.org/analysis-coronavirus-set-to-cause-largest-ever-annual-fall-in-co2-emissions.

Carbon Brief, 2020b. Daily global CO2 emissions 'cut to 2006 levels' during height of coronavirus crisis. https://www.carbonbrief.org/daily-global-co2-emissions-cut-to-2006-levels-during-height-of-coronavirus-crisis.

Chang, C.-P., Dong, M., Sui, B., Chu, Y., 2019. Driving forces of global carbon emissions: from time- and spatial-dynamic perspectives. Econ. Model. 77, 70–80.

Cheng, F., Li, T., Y-m, Wei, Fan, T., 2019. The VEC-NAR model for short-term forecasting of oil prices. Energy Econ. 78, 656–667.

Chontanawat, J., Wiboonchutikula, P., Buddhivanich, A., 2020. An LMDI decomposition analysis of carbon emissions in the Thai manufacturing sector. Energy Rep. 6, 705–710.

Ding, Z., Liu, Z., Zhang, Y., Long, R., 2017. The contagion effect of international crude oil price fluctuations on Chinese stock market investor sentiment. Appl. Energy 187, 27–36.

Dolatabadi, S., Narayan, P.K., Nielsen, M.Ø., Xu, K., 2018. Economic significance of commodity return forecasts from the fractionally cointegrated VAR model. J. Futur. Mark. 38, 219–242.

Energy Information Administration, 2020. Short-term energy outlook. https://www.eia.gov/outlooks/steo/.

Evans, S., 2020. Analysis: coronavirus set to cause largest ever annual fall in CO2 emissions. https://www.carbonbrief.org/analysis-coronavirus-set-to-cause-largest-ever-annual-fall-in-co2-emissions.

Farhani, S., Ozturk, I., 2015. Causal relationship between CO2 emissions, real GDP, energy consumption, financial development, trade openness, and urbanization in Tunisia. Environ. Sci. Pollut. Res. 22, 15663–15676.

Forslid, R., Okubo, T., 2015. Which firms are left in the periphery? Spatial sorting of heterogeneous firms with scale economies in transportation. J. Reg. Sci. 55, 51–65.

Hansen, K., Mathiesen, B.V., Skov, I.R., 2019. Full energy system transition towards 100% renewable energy in Germany in 2050. Renew. Sust. Energ. Rev. 102, 1–13.

International Energy Agency. Global Energy Review 2020: the impacts of the Covid-19 crisis on global energy demand and CO 2 emissions. https://www.iea.org/reports/global-energy-review-2020, (Paris), 2020.

Jadidzadeh, A., Serletis, A., 2017. How does the U.S. natural gas market react to demand and supply shocks in the crude oil market? Energy Econ. 63, 66–74.

Jiang, R., Li, R., Wu, Q., 2019. Investigation for the decomposition of carbon emissions in the USA with C-D function and LMDI methods. Sustainability 11.

Kearsley, A., Riddel, M., 2010. A further inquiry into the pollution haven hypothesis and the Environmental Kuznets Curve. Ecol. Econ. 69, 905–919.

Kim, S., 2019. Decomposition analysis of greenhouse gas emissions in Korea's transportation sector. Sustainability 11.

Le Quéré, C., Jackson, R.B., Jones, M.W., Smith, A.J.P., Abernethy, S., Andrew, R.M., et al., 2020. Temporary reduction in daily global CO2 emissions during the COVID-19 forced confinement. Nat. Clim. Chang. 10, 647–653.

Li, H., Qin, Q., 2019. Challenges for China's carbon emissions peaking in 2030: a decomposition and decoupling analysis. J. Clean. Prod. 207, 857–865.

Li, J., Chen, Y., Li, Z., Huang, X., 2019. Low-carbon economic development in Central Asia based on LMDI decomposition and comparative decoupling analyses. Journal of Arid Land 11, 513–524.

Li, X., Wang, J., Zhang, M., Ouyang, J., Shi, W., 2020. Regional differences in carbon emission of China's industries and its decomposition effects. J. Clean. Prod. 270, 122528.

Liang, Y., Cai, W., Ma, M., 2019. Carbon dioxide intensity and income level in the Chinese megacities' residential building sector: decomposition and decoupling analyses. Sci. Total Environ. 677, 315–327.

Liao, C., Wang, S., Fang, J., Zheng, H., Liu, J., Zhang, Y., 2019. Driving forces of provincial-level CO2 emissions in China's power sector based on LMDI method. Energy Procedia 158, 3859–3864.

Liddle, B., 2018. Consumption-based accounting and the trade-carbon emissions nexus. Energy Econ. 69, 71–78.

Liu, J., 2019. China's renewable energy law and policy: a critical review. Renew. Sust. Energ. Rev. 99, 212–219.

Ma, X., Wang, C., Dong, B., Gu, G., Chen, R., Li, Y., et al., 2019. Carbon emissions from energy consumption in China: its measurement and driving factors. Sci. Total Environ. 648, 1411–1420.

Managi, S., Hibiki, A., Tsurumi, T., 2009. Does trade openness improve environmental quality? J. Environ. Econ. Manag. 58, 346–363.

Quan, C., Cheng, X., Yu, S., Ye, X., 2020. Analysis on the influencing factors of carbon emission in China's logistics industry based on LMDI method. Sci. Total Environ. 734, 138473.

Ren, S., Yuan, B., Ma, X., Chen, X., 2014. International trade, FDI (foreign direct investment) and embodied CO2 emissions: a case study of Chinas industrial sectors. China Econ. Rev. 28, 123–134.

Rogelj, J., den Elzen, M., Höhne, N., Fransen, T., Fekete, H., Winkler, H., et al., 2016. Paris Agreement climate proposals need a boost to keep warming well below 2 °C. Nature 534, 631–639.

Rogelj, J., Huppmann, D., Krey, V., Riahi, K., Clarke, L., Gidden, M., et al., 2019. A new scenario logic for the Paris Agreement long-term temperature goal. Nature 573, 357–363.

Schleussner, C.-F., Rogelj, J., Schaeffer, M., Lissner, T., Licker, R., Fischer, E.M., et al., 2016. Science and policy characteristics of the Paris Agreement temperature goal. Nat. Clim. Chang. 6, 827–835.

Shahbaz, M., Nasreen, S., Ahmed, K., Hammoudeh, S., 2017. Trade openness–carbon emissions nexus: the importance of turning points of trade openness for country panels. Energy Econ. 61, 221–232.
Shahzad, S.J.H., Kumar, R.R., Zakaria, M., Hurr, M., 2017. Carbon emission, energy consumption, trade openness and financial development in Pakistan: a revisit. Renew. Sust. Energ. Rev. 70, 185–192.
Sims, C.A., 1980. Macroeconomics and reality. Econometrica 1–48.
The World Bank, 2020. https://data.worldbank.org.cn/.
Tollefson, J., 2020. How the coronavirus pandemic slashed carbon emissions—in five graphs. Nature https://www.nature.com/articles/d41586-020-01497-0.
Wang, Q., Jiang, X-t., et al., 2020. Comparative analysis of drivers of energy consumption in China, the USA and India – A perspective from stratified heterogeneity. Sci. Total Environ. 698, 134117.
Wang, Q., Jiang, R., 2020. Is carbon emission growth decoupled from economic growth in emerging countries? New insights from labor and investment effects. J. Clean. Prod. 248, 119188.
Wang, Q., Su, M., 2020. Drivers of decoupling economic growth from carbon emission – an empirical analysis of 192 countries using decoupling model and decomposition method. Environ. Impact Assess. Rev. 81, 106356.
Wang, Q., Wang, S., 2020. Is energy transition promoting the decoupling economic growth from emission growth? Evidence from the 186 countries. J. Clean. Prod. 260, 120768.
Wang, F., Liu, B., Zhang, B., 2017. Embodied environmental damage in interregional trade: a MRIO-based assessment within China. J. Clean. Prod. 140, 1236–1246.
Wang, Q., Zhang, F., 2020. Does increasing investment in research and development promote economic growth decoupling from carbon emission growth? An empirical analysis of BRICS countries. J. Clean. Prod. 252, 119853.
Wen, Y., Ceng, K., Lei, B., Zhou, Y., 2019. Study on the influencing factors of agricultural carbon emission in Sichuan based on LMDI decomposition technology. IOP Conference Series: Materials Science and Engineering 592, 012179.
Xie, P., Gao, S., Sun, F., 2019. An analysis of the decoupling relationship between CO2 emission in power industry and GDP in China based on LMDI method. J. Clean. Prod. 211, 598–606.
Xu, B., Lin, B., 2016. Reducing carbon dioxide emissions in China's manufacturing industry: a dynamic vector autoregression approach. J. Clean. Prod. 131, 594–606.
Yasmeen, H., Wang, Y., Zameer, H., Solangi, Y.A., 2020. Decomposing factors affecting CO2 emissions in Pakistan: insights from LMDI decomposition approach. Environ. Sci. Pollut. Res. 27, 3113–3123.
Yoo, S., Koh, K.W., Yoshida, Y., Wakamori, N., 2019. Revisiting Jevons's paradox of energy rebound: policy implications and empirical evidence in consumer-oriented financial incentives from the Japanese automobile market, 2006–2016. Energy Policy 133, 110923.
Zhang, C., Zhou, K., Yang, S., Shao, Z., 2017. Exploring the transformation and upgrading of China's economy using electricity consumption data: a VAR–VEC based model. Physica A: Statistical Mechanics and its Applications 473, 144–155.
Zhang, C., Su, B., Zhou, K., Yang, S., 2019. Decomposition analysis of China's CO2 emissions (2000–2016) and scenario analysis of its carbon intensity targets in 2020 and 2030. Sci. Total Environ. 668, 432–442.
Zoundi, Z., 2017. CO2 emissions, renewable energy and the Environmental Kuznets Curve, a panel cointegration approach. Renew. Sust. Energ. Rev. 72, 1067–1075.