The Effect of China's Regional Economic Competitiveness on CO2 Emissions-Based on Economic Factors

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The effect of China's regional economic competitiveness on CO\textsubscript{2} emissions-based on economic factors

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Abstract
Under the pressure of emission-reduction, China's regional economy needs to eliminate the mode of high energy consumption, high pollution, and high emission. However, the economic development of each region has its own characteristics. Therefore, to analyze the differences in the effect of regional economic development on CO\textsubscript{2} emissions, this work made an investigation from the perspective of regional economic competitiveness. First, using the panel data of thirteen economic factors from 2003-2017, this work evaluated the economic competitiveness of 30 provinces from the four aspects: competitiveness of residents' wealth (WC), competitiveness of opening-up (OC), competitiveness of technology (TC), and competitiveness of industrial structure (IC). Furthermore, the panel principal component regression model (PPCR) was established for the eastern region, the central region, and the western region according to the score of competitiveness in four aspects. The results suggested that the promoting effect of WC on CO\textsubscript{2} emissions presented the rule opposite to WC. In other words, the stronger the competitive advantage of WC, the weaker its effect on promoting CO\textsubscript{2} emissions. The "pollution refuge" hypothesis was verified in all three regions of China. And the promotion of CO\textsubscript{2} emissions by OC was the strongest in the central region, followed by the eastern region, and the weakest in the western region. TC promoted CO\textsubscript{2} emissions in the central region, but inhibited CO\textsubscript{2} emissions in the eastern and western regions. Finally, the inhibiting effect of IC on CO\textsubscript{2} emissions showed the same law as IC. Based on the conclusions, some recommendations were put forward.

Keywords: CO\textsubscript{2} emissions; China; regional; economic competitiveness; economic factors
1. Introduction

Human economic activities consume much fossil energy and play a vital role in CO$_2$ emissions (Fang et al., 2018). Furthermore, as China is concerned, its economic development has made remarkable achievements. Nevertheless, at the same time, China's energy consumption and pollution emissions have expanded sharply. In 2010, China surpassed the United States as the largest energy consumer, accounting for 20.3 percent of global energy consumption (Wang, 2010). As early as 2007, China was the world's largest emitter, with more than 6 billion tons of CO$_2$ emissions, accounting for 21 percent of global CO$_2$ emissions (IEA, 2007). In 2017, China's total energy consumption and CO$_2$ emissions from fossil fuel combustion were 4.49 billion tons of standard coal and 10.4 billion tons (Quéré et al., 2018). Therefore, China is facing tremendous pressure on energy-conservation and emission-reduction, which requires China's economic development to get rid of the old norm of high energy consumption, high pollution, and high emissions, and attain low-carbon economy.

The low-carbon economy should focus on many aspects. First of all, technological progress is the key to the low-carbon economy (Kang et al., 2018). Production-based technological advances, which can increase output while reducing factor inputs, are conducive to reducing pollution emissions (Santra, 2017). In addition, the advances of environmentally friendly technological such as clean energy technologies, energy-saving technologies, and carbon sequestration technologies can effectively reduce CO$_2$ emissions (Y. Chen et al., 2020). Secondly, industrial structure adjustment and optimization are the main ways to develop a low-carbon economy. Industrial restructuring and optimization can led to the flow of productive factors to high-productivity sectors (Laan et al., 2021). Moreover, the ultimate goal of economic development is to satisfy consumption. Therefore, the development of a low-carbon economy promotes the gradual upgrading of the consumption from high-carbon material consumption to low-carbon service consumption (Schanes et al., 2016). So, on the basis of technological progress, the development of a low-carbon economy not only requires the industrial structure adjustment and optimization, but also requires the upgrading of consumption structure. In addition, in the context of economic globalization and opening-up, China's economic development should avoid the phenomenon of "pollution refuge".

However, the adjustment and optimization of industrial structure, technological progress, upgrading of consumption structure, and opening-up undoubtedly affect the region's economic development (Arndt, 1990; Fagerberg, 1996), and then affect the economic competitiveness of China's three regions (Fig. 1). Therefore, this work summarized the economic factors into four major parts: residents' wealth, opening-up, technological progress, and industrial structure. First of all, as far as residents' wealth is concerned, the GDP per capita and the level of residents' consumption reflect the ability of residents to create wealth and consume wealth. Then the regional differences in the effect of residents' ability to create wealth and consume wealth on CO$_2$ emissions reflect the regional differences of residents' wealth on CO$_2$ emissions. One concern, then, is how residents' ability to create wealth and consume wealth impacts CO$_2$ emissions. Secondly, as far as opening-up is concerned, foreign trade and foreign direct investment reflect the degree of economic dependence on foreign countries. Nevertheless, the external dependence on economic development may lead to the hypothesis of "pollution refuge". Another concern, then, is whether there are "pollution refuge" in the three regions (Baumol et al., 1888). Moreover, technological progress is the core driving force of economic development, and the primary way of technological progress is independent R&D and technology diffusion (Chen et al., 2019). Therefore, we are concerned about whether there are differences in how technology advances in the three regions and how they affect CO$_2$ emissions. Finally, the adjustment and optimization of the industrial structure are conducive to promoting the rationalization of the industrial structure (Yu et al., 2018), which in turn is conducive to the allocation of resources and energy-saving and emissions-reduction. Therefore, measuring the rationalization of industrial structure in the three regions and the effect on CO$_2$ emissions is critical. In short, it is necessary to solve two crucial issues. One is how to measure the difference in the economic competitiveness of the three regions. The second is to explore the different effects of the economic competitiveness of the three regions on CO$_2$ emissions.

To this end, this work introduced the economic competitiveness. The main contribution of this work is two parts. First, the economic competitiveness of the three regions was evaluated using the principal component factor analysis (PCFA) method. Then, the evaluation results showed that the economic competitiveness consists of four parts: the competitiveness of residents'
wealth, the competitiveness of opening-up, the competitiveness of technology, and the competitiveness of industrial structure. Furthermore, based on the score of four parts of economic competitiveness, the principal component panel regression model (PCPR) was set to investigate the distinct effects of economic competitiveness on CO$_2$ emissions for the three regions. The remainder of this work is organized as follows. Section 2 shows the overview of the literature. Section 3 describes the data and methodology used in this work. Section 4 provides the empirical results. Section 5 shows the further discussion. Finally, the conclusion and policy implications are given in Section 6.

2. Literature review

2.1. Researches on the effect of economic factors on CO$_2$ emissions

On the effect of economic factors on CO$_2$ emissions, much research has been done in the past literature. For example, some scholars measured the impact of economic development on CO$_2$ emissions with GDP per capita. Chen et al. (2018) analyzed the data of the OECD countries on CO$_2$ emissions from 2001 to 2015, which showed that GDP per capita was the primary reason for the enlargement of emissions. For BRICS countries, Cheng et al. (2019) argued that GDP per capita has increased CO$_2$ emissions per capita. Qiang et al. (2021) used panel threshold regression to study the impact of GDP per capita on CO$_2$ in 154 countries. It is believed that the contribution effect of GDP per capita to CO$_2$ decreases with the increase of GDP per capita. For China, scholars have determined the inverted U-shaped association between GDP per capita and CO$_2$ emissions (Dong et al., 2018; Riti et al., 2017; Wang et al., 2019; Zhao et al., 2014). In addition, Wang et al. (2020) used the vector self-regression model to compare China's eastern, central and western provinces. It was found that GDP per capita in all three regions of China was the cause of the increase in CO$_2$ emissions. In China, Guan et al. (2008) identified CO$_2$ emissions from household consumption as 40 to 50 percent of China's total emissions and said the contribution of household consumption to CO$_2$ emissions is higher in more developed regions. Wang et al. (2014) and Cao et al. (2019) believed that as China's economy grows, rising incomes and consumption levels are the main driving forces of CO$_2$ emissions. From the perspective of China's consumption patterns, Dai et al. (2012) found that when household consumption shifts from material goods consumption to service consumption, it has a dampening effect on CO$_2$ emissions.

Some literature focused on whether opening-up produces "pollution refuge hypotheses" or "pollution haven hypotheses" in China. For instance, Wang (2016) confirmed that FDI's "pollution haven hypothesis" effect is greater than the "pollution refuge hypothesis" effect from the perspective of all-element energy efficiency. Instead, Zheng et al. (2017) confirmed that the "pollution haven hypotheses" is basically established in China, where FDI has improved the quality of the environment to some extent. In addition, Jun et al. (2020) verified that foreign trade has harmed China's environment and that this harmful effect has become more and more evident since China acceded to the WTO. Jin et al. (2016) discussed the role of China's foreign trade in CO$_2$ emissions and found a "pollution refuge hypothesis" in the western region, while a "pollution haven hypothesis" in the eastern region. Moreover, they believed that the "pollution refuge hypothesis" has been transmitted from the eastern region to the western region. Using panel data of 30 provinces, Zhang et al. (2020) empirically analyzed the influence of FDI on CO$_2$ emissions from the regional perspective for China. They found that FDI curbed CO$_2$ emissions in the eastern and central regions, while it is opposite in the western regions.

For technological progress, most scholars support the inhibitory effect of technological progress on CO$_2$ emissions in China. Zhang et al. (2017) believed that most of China's environmental innovations have effectively reduced CO$_2$ emissions, especially energy efficiency technologies, R&D, and patented technologies took a prominent effect in curbing CO$_2$ emissions. Based on linear and nonlinear analysis, Luan et al. (2019) discovered that domestic R&D activities and technology introduction can help reduce China's emissions and suggested that improving R&D activities is an effective means to reduce emissions. At the regional level for China, Wei et al. (2010) found significant differences in the association between technological progress and CO$_2$ emissions. Independent innovation has a powerfully negative effect on CO$_2$ emissions in the eastern region, but no significant effect in the central and western regions. The introduction of technology has a significant negative effect on CO$_2$ emissions in the eastern and central regions, but no significant effect in the western region. In addition, Li et al. (2012) found that technological progress has a significant role in reducing emissions in the eastern and western regions, while increasing emissions in the central region. In contrast, Y. Chen et al. (2020) confirmed that technological advances have reduced CO$_2$ emissions in central and
western China and increased carbon emissions in eastern China.
China's secondary industry is a significant contributor to CO₂ emissions (Cole et al., 2008). Similarly, Sun et al. (2016) showed that the secondary industry accounts for most of China's total CO₂ emissions. Thus, Zhang et al. (2014) supported that the enlargement of the proportion of the tertiary industry has a crucial role in curbing China's CO₂ emissions. With the adjustment and upgrading of industrial structure in China, the proportion of the secondary industry is gradually decreasing, while the proportion of the tertiary industry is gradually increasing. Numerous studies have shown that the adjustment of industrial structure is beneficial to reduce CO₂ emissions (Tian et al., 2019; Zhang et al., 2019; Zhu et al., 2020). Mi et al. (2015) concluded that industrial structure adjustment could elevate the rationalization of industrial structure and reduce pollution emissions without affecting economic growth. Further, Zheng et al. (2020) employed the panel threshold regression model to empirically investigate the influence mechanism of China's industrial structure change on air pollution, and found that industrial structure adjustment can reduce the contribution of secondary industry and economic development to environmental pollution.

2.2. Researches on the effect of economic competitiveness on CO₂ emissions

Based on cross-border panel data of 66 countries worldwide, Zhang et al. (2016) used spatial measurement methods to explore the effect of trade competitiveness on CO₂ emissions and found a significant nonlinear inverse "U" relationship between trade competitiveness and CO₂ emissions. For the corporate perspective, Rokhmawati (2021) has proven in Indonesia that reducing greenhouse gas emissions can drive competitiveness. For China, Gao (2010) confirmed that the increase in China's export trade competitiveness has led to a large amount of carbon dioxide emissions. At the same time, China's increased carbon emissions have also contributed to improving trade competitiveness. Similarly, Zhang et al. (2014) also found that the increase in China's trade competitiveness does depend on excessive carbon dioxide emissions. From the perspective of Chinese manufacturing enterprises, Niu et al. (2012) believed that emission reduction is not contradictory to enterprises' competitiveness. They confirmed that enterprises rely on advanced technology and effective management to support the realization of economic and environmental benefits win-win situation. Further, An et al. (2019) constructed a panel vector self-regression estimation model using panel data from western China, and empirically analyzed the dynamic association between pollution and economic competitiveness. The results showed that there is an interactive association between pollution and economic competitiveness in the western region: economic competitiveness contributes more to the change of environmental pollution, and environmental pollution has less impact on economic competitiveness.

However, we found that the existing literature on the effect of the economic factors on CO₂ emissions focused on specific aspects of the economy, such as GDP per capita, consumption level, trade, FDI, industrial structure, technology, etc. Few pieces of literature simultaneously considered the effect of these economic factors on CO₂ emissions. In addition, concerning the effect of economic competitiveness on CO₂ emissions, the existing literature mainly researched from the perspective of corporate competitiveness and trade competitiveness. To fill the above gaps, this work comprehensively measured thirty economic factors with economic competitiveness, and analyzes the differences in the economic competitiveness of China's three regions. Furthermore, the effect of the competitiveness of residents' wealth, the competitiveness of opening-up, the competitiveness of technology, and the competitiveness of industrial structure on CO₂ emissions was analyzed.

3. Data and methodology

3.1. Data sources

Based on the completeness and availability of data, this work employed panel data of thirty provinces in China from 2003 to 2017. Thirty provinces were classified into the eastern, central, and western regions (Fig. 1). Then, the energy consumption data came from China's energy statistics yearbook (Department of Energy Statistics, 2002-2018). Thirteen economic factors (Table 1) came from the National Bureau of Statistics (China, 2020). The CO₂ emissions data were calculated by Eq. (1) based on the carbon emissions coefficient (Appendix Table A.1) published by IPCC, 2006.

\[
CE_{it} = \sum_{j=1}^{8} E_{itj} \times \delta_j \quad (i = 1 \ldots 30; t = 2003 \ldots 2017)
\]

Where, \(i = 1 \ldots 30\) denotes 30 provinces of China, \(t = 2003, \ldots, 2017\) denotes the study period, \(j = 1 \ldots 8\) denotes the eight fossil fuels; \(CE_{it}\) denotes the CO₂ emissions; \(E_{itj}\) denotes the \(j\)th fuel consumption of \(i\)th province in the \(t\)th year, \(\delta_j\) denotes the CO₂ emissions coefficient (Appendix Table A.1) published by IPCC, 2006.
denotes CO₂ emissions coefficients of fossil fuels.

Table 1

| Variables                  | Definition                                                                 | Unit         |
|----------------------------|---------------------------------------------------------------------------|--------------|
| CO₂ emission (CE)          | Total CO₂-emissions                                                     | Ten thousand tons |
| GDP per capita (PGDP)      | GDP divided by population at the end of the year                           | CNY 1        |
| Residents’ consumption level (RC) | Total residents’ consumption divided by population                        | CNY 1        |
| Urban residents’ consumption level (URC) | Total urban residents’ consumption divided by urban population         | CNY 1        |
| Rural residents’ consumption level (RRC) | Total rural residents’ consumption divided by rural population    | CNY 1        |
| Foreign trade dependence (FTD) | Total imports and exports divided by GDP                                 | %            |
| Export dependence (ED)     | Total exports divided by GDP                                              | %            |
| Import dependence (ID)     | Total imports divided by GDP                                              | %            |
| Foreign direct investment dependence (FDI) | Total foreign direct investment divided by GDP                           | %            |
| Technical output amount (TOA) | Contract amount of technical output in technology market                  | CNY 100 million |
| Technical introduction amount (TIA) | Contract amount of technical input in technology market                  | CNY 100 million |
| R&D intensity (R&D)        | Total R&D investment divided by GDP                                       | %            |
| Secondary industry (SI)    | The added value of the secondary industry divided by GDP                 | %            |
| Tertiary industry (TI)     | The added value of the tertiary industry divided by GDP                  | %            |

3.2. Principal component factor analysis

Principal component factor analysis (PCFA) is employed to evaluate economic competitiveness. Factor analysis has a vital role in using a few common factors to explain many variables with solid correlations: dimensionality reduction (Ivosev et al., 2008).

The common factor analysis model is as Eq. (2).

\[
\begin{align*}
X_1 &= a_{11}F_1 + a_{12}F_2 + \cdots + a_{1m}F_m + \varepsilon_1 \\
X_2 &= a_{21}F_1 + a_{22}F_2 + \cdots + a_{2m}F_m + \varepsilon_2 \\
& \vdots \\
X_p &= a_{p1}F_1 + a_{p2}F_2 + \cdots + a_{pm}F_m + \varepsilon_p
\end{align*}
\]

Where, \(X_1, X_2, \ldots, X_p\) are twelve economic factors. \(F_1, F_2, \ldots, F_m\) are independent of each other and are common factors, and \(COV(F_i, F_j, \ldots, F_m) = 1\). \(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_p\) are so-called special factors. The \(a_{ij}(i = 1, \ldots, p; j = 1, \ldots, m)\) are the factor loading, which indicates the degree of correlation between \(X_i\) and \(F_j\). What needs to be explained is that this work uses the principal component method to solve \(a_{ij}(i = 1, \ldots, p; j = 1, \ldots, m)\). The Factor scores of \(F_1, F_2, \ldots, F_m\) can be obtained by the least squares regression method proposed by Thurstone (1934). The comprehensive score \(\bar{F}\) is derived from Eq. (3).

\[
\bar{F} = (\gamma_1 \times F_1 + \gamma_2 \times F_2 + \cdots + \gamma_m \times F_m) / \gamma
\]

Where, \(\gamma(j = 1, 2, \ldots, m)\) represents the variance contribution rate of factor \(F_j\). \(\gamma\) represents the total variance contribution rate of all common factors and \(\gamma = \gamma_1 + \gamma_2 + \cdots + \gamma_m\).

3.3. Panel Principal Component Regression

This work performed the Panel Principal Component Regression (PPCR) model to simulate the association between CO₂ emissions and economic competitiveness. Statistically speaking, different data units and different data magnitudes tend to cause two significant problems: One is the error in measuring variable; the other is the error in measuring the relationship between variables (Mosteller et al., 1977). Furthermore, it could be affecting the final estimation result of the model. Therefore, the
original data of CE should be standardized before establishing the PPCR model. It is important to note here that the common factors $F_1, F_2, \cdots, F_m$ obtained by the PCFA method have met the standardized conditions. This work established the PPCR model to explain the effect of economic competitiveness CO$_2$ emissions, as follows:

$$ZCE_{it} = \alpha + \beta_1WC_{it} + \beta_2OC_{it} + \beta_3TC_{it} + \beta_4IC_{it} + \varepsilon_{it} \quad (4)$$

Where, $i = 1, \cdots, 30$ denotes 30 provinces of China, $t = 2003, \cdots, 2017$ marks the study period. $\alpha$ denotes constant term, $\beta_j (j = 1, \cdots, A)$ are the parameters, $\varepsilon_{it}$ is random error. $ZCE_{it}$ denotes standardized data of the CO$_2$ emissions, which represents environmental pollution. $WC_{it}, OC_{it}, TC_{it}$, and $IC_{it}$ are the four common factors obtained by the PCFA method. In addition, $WC_{it}, OC_{it}, TC_{it}$, and $IC_{it}$ are the competitiveness of residents’ wealth, the competitiveness of opening-up, the competitiveness of technology, and the competitiveness of industrial structure, respectively.

4. Empirical Results

4.1. Economic competitiveness

4.1.1. Evaluation of economic competitiveness

The PCFA method (Principal component factor analysis) has been widely used for the evaluation of competitiveness (Duleba et al., 2019; Lu, 2019; Stanickova, 2015). The PCFA method has advantages in evaluating competitiveness. First, the common factors obtained by the PCFA method can fuse the information of numerous indicators and eliminate the collinear relationship of multiple indicators (Lafi et al., 1992). Second, the common factors obtained by PCFA can be given practical significance by the methods of factor rotation (Jolliffe, 2014). Third, the common factors are new variables, which lay the foundation for the Principal Component Regression model. Given this, the PCFA method was employed to evaluate the economic competitiveness. In addition, this work employed KMO and Bartlett’s test to test the correlation between economic factors. The test outcomes of KMO and Bartlett fully illustrated the high degree of correlation between economic factors (Appendix Table a.2).

The results of PCFA are shown in tables 2 and 3. The first four common factors ($F_1, F_2, F_3, F_4$) explained the variance of 90.783 percent of the thirteen original economic factors. The factor loadings of the first common factor $F_1$ on urban residents’ consumption level, rural residents’ consumption level, residents’ consumption level, and GDP per capita were 0.905, 0.902, 0.870, and 0.851, respectively. Therefore, we called the first common factor $F_1$ competitiveness of residents’ wealth, which reflected the ability of regional residents to create and consume wealth. The factor loadings of the second common factor $F_2$ on foreign trade dependence, export dependence, import dependence, and foreign direct investment dependence were 0.916, 0.909, 0.799, and 0.717, respectively. We named the second common factor $F_2$ as the competitiveness of opening-up, reflecting regional economies’ degree of external dependence. The factor loadings of the third common factor $F_3$ on technical output amount, technical introduction amount, and R&D intensity were 0.882, 0.769, and 0.662, respectively. We defined the third common factor $F_3$ as the competitiveness of technology, demonstrating the power of regional technology R&D and technology diffusion. Finally, the factor loadings of the fourth common factor $F_4$ on secondary industry and tertiary industry were -0.956 and 0.784. We defined the fourth common factor $F_4$ as the competitiveness of industrial structure, which reflected the reasonable degree of regional industrial structure. It should be noted that of the thirteen economic factors, only the factor loading of the secondary industry was negative. In other words, the increase of the proportion of secondary industry will reduce the competitiveness of the regional industrial structure. On the contrary, the improvement of the remaining economic factors will enhance the corresponding regional economic competitive advantage. Then, we got the economic competitiveness index system (Appendix Table a.3).

Furthermore, the competitiveness scores of WC, OC, TC, and IC were obtained by least squares regression method (Thurstone, 1934). They are shown in the Appendix (Table b.1, b.2, b.3, and b.4). In addition, the comprehensive economic competitiveness score was derived from Eq. (5), and shown in the Appendix Table b.5.

$$CEC_{it} = \left(29.265 \times WC_{it} + 24.926 \times OC_{it} + 20.439 \times TC_{it} + 16.153 \times IC_{it}\right)/90.783 \quad (i = 1, \cdots, 30; t = 2003, \cdots, 2017) \quad (5)$$

| Component | Eigenvalues | % of Variance | Cumulative % |
|-----------|-------------|---------------|--------------|
| $F_1$     | 2.720       | 29.265        | 29.265        |
| $F_2$     | 2.589       | 24.926        | 54.190        |
| $F_3$     | 2.267       | 20.439        | 74.630        |
| $F_4$     | 2.082       | 16.153        | 90.783        |

Table 2

Total variance explained
4.1.2. Characteristics of three regions

Figures 2 and 3 clearly show the characteristics of the three regions. First of all, from a regional perspective, the CO₂ emissions gradually reduce according to the eastern, central, and western order. From the perspective of time, the CO₂ emissions in all three regions expanded in 2003-2011 and were relatively stable in 2011-2017. Secondly, in terms of comprehensive economic competitiveness, the eastern region is significantly better than the central and western regions. In contrast, the central region and the western region have no noticeable differences. Moreover, the three regions have shown differences in the competitiveness of residents' wealth, opening-up, technology, and industrial structure.

Regarding the competitiveness of residents' wealth, the eastern region is potent than the central and western regions. This is because the four factors contained in the competitiveness of residents' wealth in the eastern region are remarkably higher than in the central and western regions. In addition, although there is no apparent difference in the competitiveness of the residents' wealth in the central and western regions in the first half of the research time, the western region showed a slight advantage over the central region in the second half of the study period. Therefore, we believed that the competitiveness of residents' wealth of the eastern region was the most competitive advantage, the west region was second, the central region was the weakest. In other words, the eastern region is the strongest, the western region second, and the central region the weakest for the ability of residents to create and consume wealth.

In terms of the competitiveness of opening-up, the eastern region is most potent, the central region is second, and the western region is the weakest. Moreover, the competitiveness of opening-up for the three regions showed a downward trend, of which the decline was most evident in the eastern region. However, the competitiveness of opening-up for the eastern region still has apparent advantages. As a result, the degree of external dependence of the economies of the three regions has decreased year by year, especially in the eastern regions. It is also important to note that FDI in the central region continues to increase, while there...
has been a clear downward trend in the western region since 2012.

Fig. 3. The average values of CO$_2$ emissions (CE) and thirteen economic factors in regions (Eastern, central, and western regions).

For the competitiveness of technology, the eastern region has significant advantages. The intensity of independent R&D in the eastern region is much higher than that in other regions, indicating that the technological progress in the eastern region depends mainly on independent R&D. At the same time, the contract amount of technology export is higher than the technology introduction in the eastern region, indicating that the eastern region is the net output region of the technology. In addition, compared with the eastern region, the competitiveness of technology of the central and western regions is at a significant disadvantage. First, the R&D efforts in the central and western regions are weaker than those in the eastern region. Furthermore, the technology introduction turnover in the central and western regions is higher than the technology output turnover, indicating that both regions are net technology introduction areas. Moreover, the central region's independent technology R&D are more potent than that of the western region. So, the western region's technological progress depends more on technology diffusion than the central region.

As far as the competitiveness of industrial structure is concerned, it is arranged from highest to lowest according to western
region, eastern region and central region. The nodes of the secondary industry's decline and the tertiary industry's increase in the western region are about 45 percent and 40 percent, respectively. However, the decline of the secondary industries in the eastern and central regions was higher than 50 percent. Moreover, the rising of the tertiary industry in the central region is significantly lower than that in the western region. Therefore, the nodes of industrial structure adjustment in the western region are better than those in the eastern and central regions, which makes the industrial structure of the western region more reasonable.

4.2. Estimation results of the PPCR model

4.2.1. Unit root and cointegration tests

The stationary of panel data should be tested before estimating the PPCR model (Hadri, 2000). To avoid the phenomenon of "pseudo-regression", this work employed the LLC test (Levin et al., 2002), IPS test (Im et al., 2003), the Fisher-ADF and the Fisher-PP (Choi, 2001) tests to check the stationary of the variables used in the PPCR model. Table 4 showed the unit root test results for the three regions. It can be found that all variables accepted the null hypothesis at their levels, that was, the unit root process. Moreover, all variables rejected the null hypothesis that was unit root process in the first-order difference. Therefore, the first-order difference stationarity can be determined. Furthermore, this work employed Kao test (Kao, 1999), Pedroni test (Pedroni, 2004), and Westerlund test (Westerlund, 2005) to check the long-term cointegration relationship among variables. As shown in Table 5, almost all statistics rejected the null hypothesis that there was no cointegration relationship. Thus, we have determined the cointegration of the panel data used in the PPCR model.

Table 4

Panel unit root test results for three regions.

| Variable | Eastern region | Central region | Western region |
|----------|----------------|----------------|----------------|
| ZCE      |                |                |                |
| WC       | 2.87           | 2.17           | -1.20          |
| OC       | 4.54           | 4.53           | 4.61           |
| IC       | 2.11           | 1.04           | 1.05           |
| Fisher ADF | 8.46          | 8.78          | 10.67          |
| Fisher PP | 24.31         | 15.19         | 16.41          |
| Levels   |                |                |                |
| 2001     | 98.76          | 97.82          | 97.94          |
| 2002     | 97.31          | 96.96          | 96.98          |
| 2003     | 95.90          | 95.76          | 95.82          |
| First difference |                |                |                |
| Levels   |                |                |                |
| 2001     | 84.59          | 86.71          | 94.46          |
| 2002     | 72.13          | 100.02         | 93.10          |
| 2003     | 64.99          | 66.11          | 69.18          |

Table 5

Cointegration tests for three regions.

| Tests     | Hypothesis | Eastern region | Central region | Western region |
|-----------|------------|----------------|----------------|----------------|
| Kao test  | H0: No cointegration | -1.1170*** | -1.6673** | 1.4335** |
|           | H1: All panels are cointegrated | -3.6250*** | -1.7142** | 1.2914* |
|           | Dickey-Fuller t | -2.2000*** | -2.5000*** | -0.7000* |
|           | Augmented Dickey-Fuller t | -2.2563*** | -1.6965** | 1.4886** |
|           | Unadjusted modified Dickey-Fuller t | -2.2575*** | -1.7273** | 1.3556** |
| Pedroni test | H0: No cointegration | -3.7527*** | -2.4902*** | -3.2298*** |
|           | H1: All panels are cointegrated | -2.0852*** | -1.7999** | 1.6756** |
|           | Modified variance ratio | -2.0852*** | -1.7999** | 1.6756** |
|           | Phillips-Perron t | -3.4784*** | -1.3191*** | -1.4926** |
|           | Augmented Dickey-Fuller t | -2.2377*** | -3.0089*** | -1.4741** |
| Westerlund test | H0: No cointegration | 1.2609*** | 1.6999** | 0.8122** |
|           | H1: All panels are cointegrated | -1.3121*** | -3.2098*** | -1.4741** |

4.2.2 Estimation results of the PPCR model

Whether the PPCR model established by using the competitiveness score can avoid multicollinearity needs to be verified. Variance expansion factor (VIF) was a widely used tool for judging multicollinear relationship (Farrar et al., 1967). In all three regions, the VIF value of all independent variables was not greater than 10 (Appendix Table a.4). Therefore, it can be judged that there was no multi-collinear relationship among the independent variables. Furthermore, this work employed the Hausman test (Hausman, 1978) to make model choices. Appendix Table a.5 showed that the Hausman test rejected the null hypothesis of the random effect model in all three regions (Geisser, 1974). Therefore, the fixed effects model was chosen to fit the PPCR model in all three regions. The estimation results of the three regions are shown in Table 6.

From the model estimation results shown in Table 7, it can be seen that the effects of WC, OC, TC, and IC on CO2 emissions were statistically significant in all three regions. Among them, the elastic coefficients of WC were positive in all three regions.
Moreover, it showed the rule that the central region was the largest, the eastern region was the smallest, and the western region was in the middle. Therefore, the WC has a promoting effect on CO₂ emissions in all three regions, and this promotion has the same law to the elasticity coefficients. Regarding OC, its elasticity coefficients were positive in all three regions, and its value increased according to the order of the western region, the eastern region, and the central region. This implied that OC has the effect of promoting CO₂ emissions in all three regions. This promoting effect was most potent in the central region, most minor in the western region, and centered in the eastern region. As far as TC was concerned, its elasticity coefficients were positive in the central region, negative in the western and eastern regions. Therefore, TC has the effect of promoting CO₂ emissions in the central region, and inhibiting CO₂ emissions in the western and eastern regions. Finally, the elasticity coefficients of IC were negative in all three regions, which implied that IC has the effect of inhibiting CO₂ emissions in all three regions. Moreover, the inhibiting effect of IC was most potent in the western region, most minor in the central region, and centered in the eastern region.

### Table 6

| Statistic   | Eastern region | Central region | Western region |
|-------------|----------------|----------------|----------------|
| WC          | 0.410***       | 0.561***       | 0.448***       |
| (43.144)    | (39.139)       | (88.389)       |                |
| OC          | 0.144***       | 0.631***       | 0.030***       |
| (17.392)    | (12.752)       | (5.504)        |                |
| TC          | -0.037***      | 0.058**        | -0.016**       |
| (-7.328)    | (1.987)        | (-3.892)       |                |
| IC          | -0.100***      | -0.064***      | -0.214***      |
| (-1.5102)   | (-3.840)       | (-3.4461)      |                |
| C           | 0.115***       | 0.422***       | -0.261***      |
| (10.041)    | (13.672)       | (-5.206)       |                |

Note: *" represents p < 0.05, "**" represents p < 0.01.

### 5. Discussion

Based on the above empirical conclusions, we have found some valuable phenomena.

The promoting effect of residents’ wealth competitiveness on CO₂ emissions showed the opposite law to residents’ wealth competitiveness. Inevitably, the process of creating wealth and consuming it consumes fossil fuels and brings about CO₂ emissions. The competitiveness of residents’ wealth reflects their ability to create wealth and their ability to consume wealth. And the ability of residents to create wealth and consume wealth promote each other. First, the ability of residents to create wealth is the basis of the ability to consume wealth. On the one hand, the stronger the ability of residents to create wealth, the greater the ability of residents to pay for wealth, which makes residents “able” to consume. On the other hand, the more wealth-generating the residents can provide, the greater the level of social security that can be provided, which makes them “dare” to consume.

Moreover, the consumption power of residents’ wealth is the driving force of residents’ wealth creation. When the ability of residents to create and consume wealth is weak, the consumption demand of residents mainly meets the material needs of basic survival, such as clothing, food, housing, travel, etc. On the contrary, when residents have a solid ability to create and consume wealth, the consumer demand is mainly to meet their development and enjoyment of service needs, such as: culture, health care, art, education, entertainment, tourism. In other words, the improvement of residents’ wealth competitiveness can promote the upgrading of residents’ consumption structure from “survival” consumption to “development and enjoyment” consumption. Obviously, “survival” material consumption is a high CO₂ consumption relative to “development and enjoyment” service consumption. Therefore, it was found that the higher the competitiveness of residents’ wealth, the lower the contribution to CO₂ emissions.

It can be determined that the “pollution refuge” hypothesis is established in all three regions of China. This differs from the conclusion of (Jin et al., 2016), who believed that the “pollution refuge” hypothesis only exists in the western region. At the same time, the promoting effect of opening-up competitiveness on CO₂ emissions is the strongest in the central region, followed by the eastern region and the weakest in the western region. The competitiveness of opening-up included the dependence of economic
development on foreign trade and the foreign capital, which reflected the external dependence of economic development. The economic development of the Eastern region has made remarkable achievements, which has led to the gradual transformation of its economic development from the demand for economic scale to the pursuit of economic efficiency. Moreover, although the eastern region's external trade has maintained a net export model, its dependence on foreign trade has decreased. Besides, its export commodity structure has gradually transitioned from labor-intensive and resource-intensive manufactured goods to technology- and capital-intensive high-value-added commodities. In addition, the dependence on foreign capital of the Eastern region has declined rapidly, and more attention has been paid to guiding foreign investment into high-tech, low-polluting industries. Therefore, the promoting effect of opening-up competitiveness on carbon emissions has been curbed to some degree in the Eastern region. For the central region, its external economic dependence has been low. However, due to its energy endowment, the central region's exports are mainly steel, cement, and other energy-intensive commodities, which undoubtedly increased CO₂ emissions. In addition, the central region's demand for economic scale led to an increase in foreign investment in high-energy-consuming and high-emission industries. Therefore, the opening-up competitiveness of the central region has the most potent effect on CO₂ emissions. In other words, the "pollution refuge" hypothesis is most pronounced in the central region. Similar to the central region, the external economic dependence of the western region has been low, and its foreign trade is also reflected in net exports. However, exports from the western region are mainly primary products, such as unprocessed or initially processed agricultural products and extractive industrial products. At the same time, the economic dependence on FDI in the western region has been low, and there is a more apparent downward trend. Moreover, the economic development of the western region started late, drew lessons from the central region, and strictly controlled foreign investment in high-energy-consuming and high-polluting industries. Therefore, although the competitiveness of opening-up in the western region has a statistically beneficial effect on CO₂ emissions, it is feeble.

The competitiveness of technology inhibits CO₂ emissions in the eastern and western regions, but promotes CO₂ emissions in the central region. This is broadly in line with the conclusion of (J. Chen et al., 2020). They confirmed that technological advances have the effect of reducing CO₂ emissions in the central and western regions and increasing CO₂ emissions in the eastern region. The eastern region has the most potent R&D efforts and is the primary source of Chinese technology. Moreover, benefiting from its economic development and environmental regulation, R&D in the eastern region favors environmentally friendly technologies and low-carbon production technologies. In addition, the eastern region is the area of net technology output, which provides the capital base for technological progress, which is conducive to its technological progress, especially to the progress of environment-friendly technology. As a result, it was found that the technological competitiveness of the eastern region inhibited CO₂ emissions. For the central region, because of the pursuit of the economic scale, the environmental supervision is relatively broad, which leads to the R&D bias towards industrial production technology. At the same time, the central region's technological progress is less dependent and prefers the introduction of industrial production technology. None of this is conducive to the progress of technology, especially environment-friendly technology. As a result, the technological competitiveness of the central region contributed to energy demand and CO₂ emissions. For the western region, although the technological R&D is low, the technological progress is more dependent than that in the central region. So, the introduction of technology in the western region is more efficient than that in the central region, which is more beneficial to the progress of environment-friendly technology. In addition, compared with the central region, the technological R&D in the western region favors environment-friendly technology. Therefore, the technological competitiveness curbs CO₂ emissions in the western region.

The inhibiting effect of the competitiveness of industrial structure on CO₂ emissions shows the same law as the competitiveness of industrial structure. Furthermore, it shows that the rationalization of industrial structure in all three regions has reached the degree of curbing CO₂ emissions. Under China's current background of economy, the lower the proportion of the secondary industry, the higher the proportion of the tertiary industry, the more reasonable the industrial structure. During the research period, under the pressure of the environment, all three regions experienced the process of industrial structure adjustment and optimization of the decline of the proportion of secondary industry and the increase of the proportion of tertiary industry. The adjustment and optimization of the industrial structure are beneficial to the allocation of resources and improve the
rationalization of the industrial structure, which is undoubtedly conducive to curbing CO₂ emissions. Another interesting finding is that the inhibiting effect of the competitiveness of industrial structure on CO₂ emissions is most powerful in the western region, mainly because the nodes of industrial structure adjustment and optimization in the western region are better than those in the eastern and central regions. The lower the node where the proportion of the secondary industry decreases, the fewer CO₂ emissions the secondary industry will cause. On the contrary, the higher the node where the proportion of the tertiary industry increases, the stronger the inhibiting effect on CO₂ emissions. Therefore, for CO₂ emissions, the lower the node where the proportion of the secondary industry decreases, the higher the node where the proportion of the tertiary industry increases, and the more reasonable the industrial structure is. Therefore, it was found that the industrial structure is more reasonable in the western region.

6. Conclusions and policy implications

Based on the economic panel data of China's thirty provinces from 2003 to 2017, this work evaluated the economic competitiveness of the provinces by using the principal component factor analysis method. The results showed that economic competitiveness included four parts: the competitiveness of residents' wealth, the competitiveness of opening-up, the competitiveness of technology, and the competitiveness of industrial structure. Furthermore, the PPCR model was established based on the four-part competitiveness score to fit the effect of economic competitiveness on CO₂ emissions. It was found that the promoting effect of WC on CO₂ emissions presented a law opposite to that of WC. In other words, the stronger the competitive advantage of WC, the weaker of its effect on promoting CO₂ emissions. It can be determined that the "pollution refuge" hypothesis was verified in all three regions. Moreover, the promotion of CO₂ emissions by OC was the most in the central region, followed by the eastern region, and the weakest in the western region. Furthermore, TC promoted CO₂ emissions in the central region and inhibited CO₂ emissions in the eastern and western regions. Finally, the inhibiting effect of IC on CO₂ emissions showed the same law as IC. Based on the conclusions above, some recommendations were put forward.

Compared with the three regions, the improvement of the competitiveness of residents' wealth has the effect of curbing the increase of CO₂ emissions. Therefore, striving to improve the competitiveness of residents' wealth in various regions is an effective measure to curb the increase of CO₂ emissions. Furthermore, wealth creation-ability and consumption-ability are two mutually reinforcing aspects of the competitiveness of residents' wealth. Therefore, the eastern region should take full advantage of its highest wealth creation-ability and consumption-ability to promote the upgrading of its consumption structure. On the contrary, the central and western regions have low wealth creation and consumption power, and their "survival" material consumption patterns are difficult to change in the short term. So, the central and western regions should focus on the ability of create wealth, that is increase GDP per capita, to promote the improvement of their consumption level and the upgrading of consumption structure.

The competitiveness of opening-up promoted CO₂ emissions in three regions. In other words, the external dependence of economic development increases CO₂ emissions in the three regions. Therefore, efforts should be made to reduce the external dependence of the economic development of the three regions. From the perspective of foreign trade, we must first try to reduce the degree of economic dependence on foreign trade, and promote the development of a virtuous "inner circle" of the economy. Furthermore, efforts should be made to improve the commodity structure of foreign trade, promote the export of trade in services, and reduce the export of energy-intensive and polluting commodities. From the perspective of FDI, the government should optimize the industrial layout of FDI. In high-energy- and high-polluting industries, FDI should be guided to adopt advanced production technology to reduce pollution emissions. In addition, it is more important to guide FDI into the clean industry, environmental protection industry, and actively play the FDI technology spillover effect. These measures should be more meaningful in the central region.

As far as technological competitiveness is concerned, the eastern region has apparent advantages. Therefore, the eastern region should fully play its advantages in R&D and technology diffusion. First, the eastern region should continue to increase investment in R&D of production-oriented and environmental-friendly technologies. Furthermore, it is necessary to encourage technology diffusion from the eastern region to the central and western regions. In addition, R&D often has the characteristics of
significant investment and slow return (Hall et al., 2010). On the contrary, the introduction of technology is more targeted and effective. Therefore, for the central and western regions, subject to economic development and R&D capital constraints, emphasis should be placed on increasing investment in technology introduction. Especially in the central region, limited funds should be invested in the introduction of production-oriented technology to improve production efficiency and reduce energy consumption and pollution emissions.

After a period of industrial restructuring in various regions, the industrial structure gradually tends to be rationalized, which is manifested in that the competitiveness of the industrial structure inhibits CO₂ emissions in all regions. However, there are apparent differences in the rationality of the industrial structure in each region. Therefore, differentiated measures should be taken to improve the rationality of the industrial structure in each region. For the eastern and western regions where the industrial structure is relatively reasonable, we should focus on increasing the proportion of the tertiary industry. For example, the government needs to issue policies to encourage the development of high-end service industries such as tourism, finance, cultural industries, and technical services. On the contrary, for the central region where the industrial structure is less reasonable, we should focus on reducing the secondary industry's proportion. The policy should try its best to guide the resources in the secondary industry to resource-saving and environment-friendly industries.

Author contribution
Keliang Chang: Conceptualization, methodology, resources, visualization, writing (review and editing).
Zifang Du: Supervision, Reviewing and Editing.
Wang Gao: Software, Methodology.
Quan Wang: Data curation, Methodology, and funding acquisition.
Guijing Chen: Data curation, Writing- Original draft preparation, and funding acquisition.
Wenbo Ma: Visualization, Investigation.

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Availability of data and materials
The datasets used and analysed during the current study are available from the corresponding author on reasonable request.

Declarations
Ethics approval
Not applicable.
Consent to participate
Not applicable.
Consent for publication
Not applicable.
Competing interests
The authors declare no competing interests.

Appendix

| Table a.1 | Carbon emission coefficients for various energy |
|-----------|------------------------------------------------|
| Fossil fuels | 𝛼ᵢ, TCE (kg) | 𝛽ᵢ, Carbon emission coefficients (C/TCE) | 𝛿ᵢ, CE coefficients |
| 1 kg coal | 0.7143 | 0.7559 | 1.98 |
| 1 kg coke | 0.9714 | 0.8816 | 3.14 |
| 1 kg crude | 1.4286 | 0.9854 | 3.07 |
| 1 kg fuel oil | 1.4286 | 0.6176 | 3.23 |
| 1 kg gasoline | 1.4714 | 0.5552 | 2.99 |
| 1 kg kerosene | 1.4714 | 0.5714 | 3.08 |
| 1 kg diesel | 1.4571 | 0.5913 | 3.16 |
| 1 x 10⁸m³ natural gas | 13,300 | 0.4479 | 2.18 |
| Note: TCE denotes standard coal; 𝛼ᵢ denotes the conversion coefficient form fossil fuels to standard coal; 𝛽ᵢ denotes the carbon emission coefficients of fossil fuels equivalent to one unit of standard coal; 𝛿ᵢ denotes CO₂ emissions coefficients of fossil fuels, and 𝛿ᵢ = 𝛼ᵢ × 𝛽ᵢ × 44/12 |

| Table a.2 | KMO and Bartlett’s Test results |
|-----------|--------------------------------|
| Statistics | value |
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy | 0.792 |
| Bartlett’s Test of Sphericity | 16150.425*** |
| Note: *** represents p < 0.01. |

| Table a.3 | Economic competitiveness index system |
|-----------|----------------------------------|
| Target layer | Criteria Layer | Index layer |
| Comprehensive economic competitiveness (CEC) | Competitiveness of residents’ wealth (WC) | Urban residents’ consumption level |
| Rural residents’ consumption level |
Table a.4  VIF values for multicollinearity of independent variables.

| Variables | Eastern region | Central region | western region |
|-----------|----------------|----------------|----------------|
| WC        | 1.098          | 1.465          | 1.677          |
| OC        | 1.138          | 2.210          | 2.168          |
| TC        | 1.367          | 2.481          | 3.681          |

Table a.5  Panel model selection.

| Statistic | Eastern region | Central region | western region |
|-----------|----------------|----------------|----------------|
| Hausman test | 12.464***    | 40.692***      | 25.799***      |

| Model type | FE              | WC              | IC              |
|------------|-----------------|-----------------|-----------------|
| VIF values for multicollinearity of independent variables. | | | |
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| Province   | CO2 Emissions (2017) |
|------------|----------------------|
| Liaoning   | -0.171               |
| Heilongjiang| -0.549               |
| Shanghai   | 0.619                |
| Jiangsu    | 0.010               |
| Zhejiang   | -0.137               |
| Anhui      | -0.434               |
| Fujian     | -0.159               |
| Jiangxi    | -0.479               |
| Shandong   | -0.330               |
| Henan      | -0.598               |
| Hebei      | -0.423               |
| Hunan      | -0.435               |
| Guangdong  | 0.403                |
| Guangxi    | -0.474               |
| Hainan     | -0.262               |
| Chongqing  | -0.496               |
| Sichuan    | -0.453               |
| Guizhou    | -0.500               |
| Yunnan     | -0.537               |
| Shaanxi    | -0.430               |
| Gansu      | -0.517               |
| Qinghai    | -0.345               |
| Ningxia    | -0.485               |
| Xinjiang   | -0.454               |

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