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

keliang Chang (changkeliang123@163.com)
Renmin University of China
zifang Du
Renmin University of China
Wang Gao
Hebei University of Economics and Trade
Quan Wang
Shanxi Datong University
Guijing Chen
Shanxi Datong University
Wenbo Ma
Renmin University of China

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The effect of China's regional economic competitiveness on CO_2 emissions-based on economic factors

Keliang Chang [a, b *], Zifang Du [a], Wang Gao [c], Quan Wang [b], Guijing Chen [b *], Wenbo Ma [a]

[a] School of Statistics, Renmin University of China, Beijing, 100872, China

[b] School of Mathematics and Statistics, Shanxi Datong University, Datong, 037009, China

[c] School of Finance, Hebei University of Economics and Business, Shijiazhuang, 050062, China

Corresponding author:

Name: Keliang Chang

E-mail: changkeliang123@163.com

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_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_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_2 emissions. The "pollution refuge" hypothesis was verified in all three regions of China. And the promotion of CO_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_2 emissions in the central region, but inhibited CO_2 emissions in the eastern and western regions. Finally, the inhibiting effect of IC on CO_2 emissions showed the same law as IC. Based on the conclusions, some recommendations were put forward.

Keywords: CO_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.(Luan 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., 1988). 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 theprimary reason for the enlargement of emissions. For BRIICS 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 of30 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 CO2 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 CO_2 emissions(Cole et al., 2008). Similarly, Sun et al. (2016)showed that the secondary industry accounts for most of China's total CO_2 emissions. Thus, (Zhang et al., 2014)supported that the enlargement of the proportion the tertiary industry has a crucial role in curbing China's CO_2 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 CO_2 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 CO_2 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 CO_2 emissions and found a significant nonlinear inverse "U" relationship between trade competitiveness and CO_2 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 CO_2 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 CO_2 emissions. In addition, concerning the effect of economic competitiveness on CO_2 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 CO_2 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 CO_2 emissions data were calculated by Eq. (1) based on the carbon emissions coefficient (Appendix Table a.1) published by(IPCC, 2006).

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

Where, $i = 1, \cdots, 30$ denotes 30 provinces of China, $t = 2003, \cdots, 2017$ denotes the study period, $j = 1 \cdots 8$ denotes the eight fossil fuels; CE_{it} denotes the CO_2 emissions; E_{itj} denotes the jth fuel consumption of ith province in the tth year. δ_i

denotes CO_2 emissions coefficients of fossil fuels.

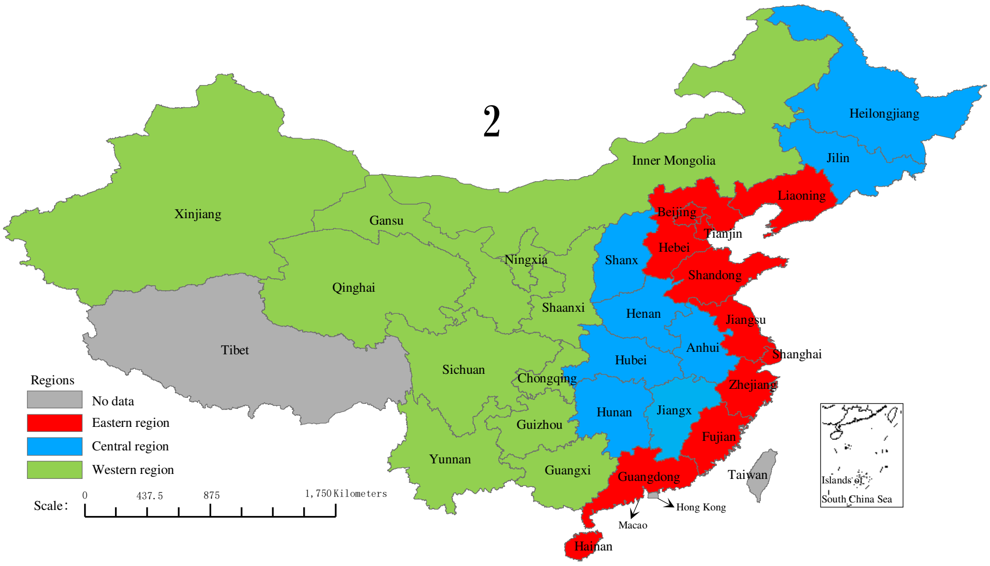

Fig.1. Geographical distribution of the three regions.

Table 1
Variables

Variables	Definition	Unit
CO_2 emission (CE)	Total CO_2 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).

$$\begin{cases} X_1 = a_{11}F_1 + a_{12}F_2 + \cdots + a_{1m}F_m + \varepsilon_1 \\ X_2 = a_{21}F_1 + a_{22}F_2 + \cdots + a_{2m}F_m + \varepsilon_2 \\ \vdots \\ X_p = a_{p1}F_1 + a_{p2}F_2 + \cdots + a_{pm}F_m + \varepsilon_p \end{cases} \tag{2}$$

Where, $X_1, X_2, \cdots, X_p$ are twelve economic factors. $F_1, F_2, \cdots, F_m$ are independent of each other and are common factors, and $COV(F_1, F_2, \cdots, F_m) = I$. $\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_p$ are so-called special factors. The $a_{ij}(i = 1, \cdots, p; j = 1, \cdots, m)$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 $a_{ij}(i = 1, \cdots, p; j = 1, \cdots, m)$. The Factor scores of $F_1, F_2, \cdots, F_m$ can be obtained by the least squares regression method proposed by Thurstone (1934). The comprehensive score F is derived from Eq. (3).

$$F = (\gamma_1 \times F_1 + \gamma_2 \times F_2 + \cdots + \gamma_m \times F_m)/\gamma \tag{3}$$

Where, $\gamma_j(j = 1,2, \cdots, m)$ represents the variance contribution rate of factor F_j, γ 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 CO_2 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:

$$ZCE_{it} = \alpha + \beta_1 WC_{it} + \beta_2 OC_{it} + \beta_3 TC_{it} + \beta_4 IC_{it} + \varepsilon_{it} \quad (4)$$

Where, $i = 1, \cdots, 30$ denotes 30 provinces of China, $t = 2003, \cdots, 2017$ marks the study period. α denotes constant term, $\beta_j (j = 1, \cdots, 4)$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 the 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_3as 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 E q. (5), and shown in the Appendix Table b.5.

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

Table 2
Total variance explained

Component	Rotation Sums of Squared Loadings		
	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

Notes: Extraction method: Principal component analysis. Rotation Method: Equamax with Kaiser Normalization.

Table 3

Rotated Component Matrix

Variables	Component			
	F_1	F_2	F_3	F_4
	competitiveness of residents' wealth (WC)	competitiveness of opening-up (OC)	competitiveness of technology (TC)	competitiveness of industrial structure (IC)
Urban residents' consumption level (URC)	0.905	0.109	0.328	0.207
Rural residents' consumption level (RRC)	0.902	0.128	0.326	0.197
Residents' consumption level (RC)	0.870	0.207	0.367	0.239
GDP per capita (PGDP)	0.851	0.264	0.368	0.168
Foreign trade dependence (FTD)	0.150	0.916	0.243	0.193
Export dependence (ED)	0.212	0.909	0.032	-0.087
Import dependence (ID)	0.078	0.799	0.384	0.399
Foreign direct investment dependence (FDI)	0.085	0.717	0.065	-0.091
Technical output amount (TOA)	0.237	0.073	0.882	0.327
Technical introduction amount (TIA)	0.534	0.078	0.769	0.165
R&D intensity(R&D)	0.361	0.448	0.662	0.241
Secondary industry (SI)	-0.051	0.145	-0.104	-0.956
Tertiary industry (TI)	0.370	0.220	0.380	0.784

Notes: Extraction method: Principal component analysis. Rotation Method: Equamax with Kaiser Normalization

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 CO_2 emissions gradually reduce according to the eastern, central, and western order. From the perspective of time, the CO_2 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.

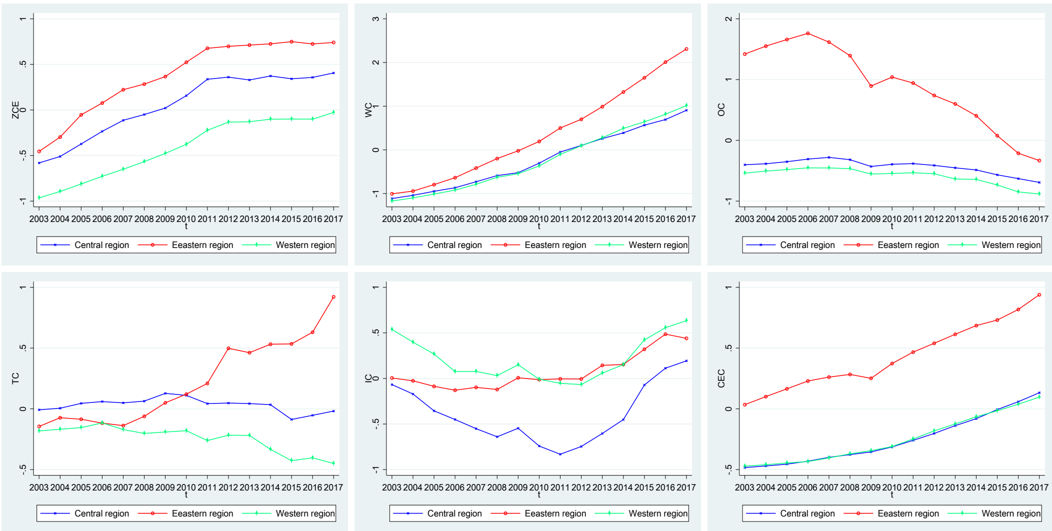

Fig.2. The average values of competitiveness and the average standardized score of CO_2 emission in regions (Eastern, central, and western regions).

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.

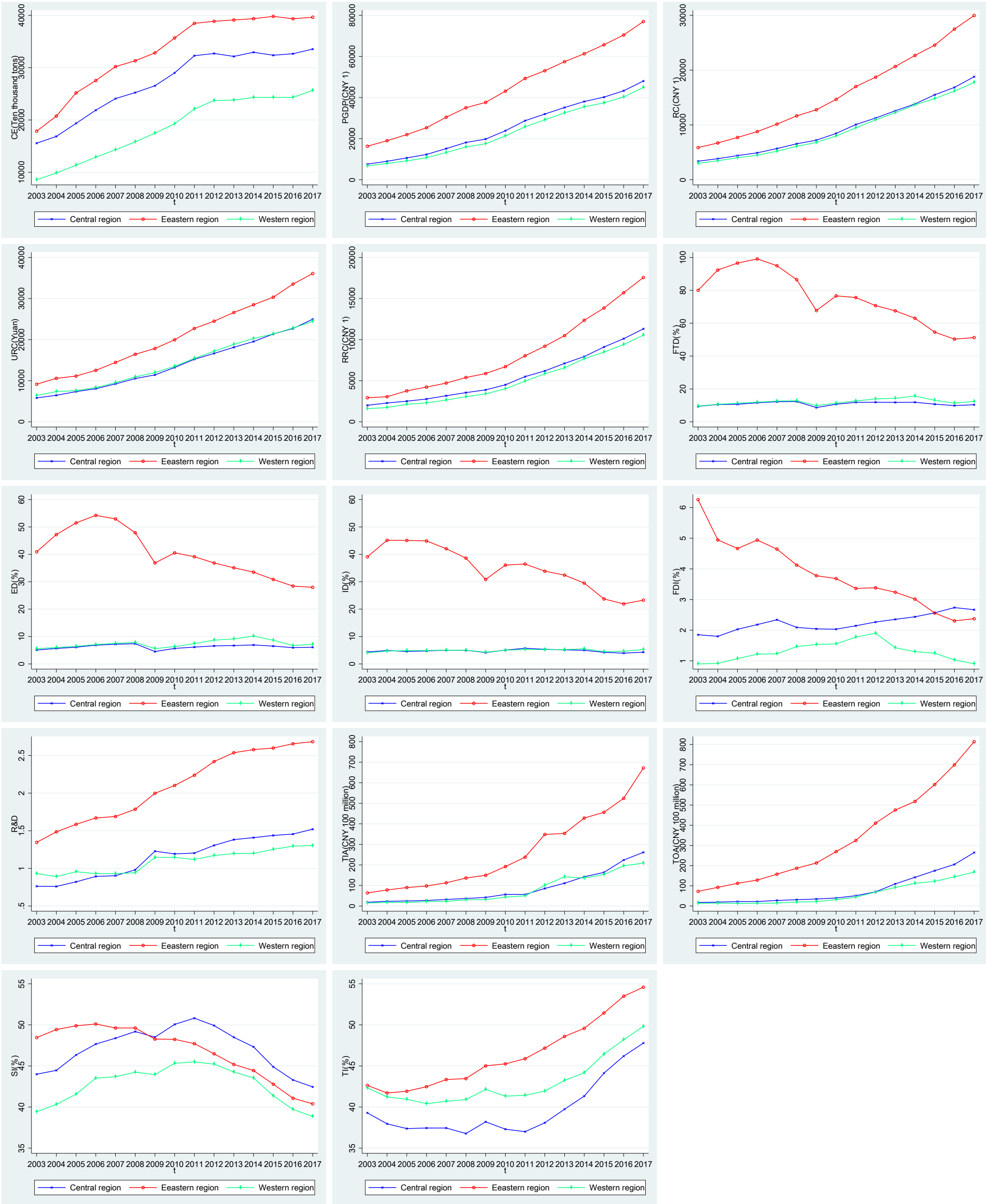

Fig.3. The average values of CO_2 emissions (CE) and thirteen economic factors in regions (Eastern, central, and western regions).

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 estimate 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		Levels				First difference			
		LLC	IPS	Fisher ADF	Fisher PP	LLC	IPS	Fisher ADF	Fisher PP
Eastern region	ZCE	2.87	2.49	8.46	24.31	-8.70***	-5.17***	64.59***	72.13***
	WC	10.22	13.10	0.37	0.41	-4.73***	-2.27**	41.30***	56.20***
	OC	4.54	6.47	1.85	1.76	-9.89***	-7.19***	86.71***	100.02***
	TC	2.75	2.33	24.92	20.88	-6.33***	-7.00***	86.46***	93.19***
	IC	2.11	2.77	17.48	3.42	-6.31***	-5.67***	76.17***	96.01***
Central region	ZCE	0.17	0.66	13.10	11.69	-3.60***	-2.01**	28.07**	71.34***
	WC	4.53	6.62	1.05	0.35	-2.79***	-1.45*	24.33*	36.65***
	OC	2.43	2.91	10.67	4.77	-2.88***	-2.33***	29.44**	47.99***
	TC	1.92	2.63	8.11	5.29	-3.22***	-2.89***	39.44***	72.11***
	IC	-1.04	-0.08	17.78	15.19	-1.86**	-4.53***	38.87***	54.88***
Western region	ZCE	-1.20	1.52	16.41	8.38	-2.14***	-1.84***	35.55***	61.95***
	WC	4.61	7.62	0.63	0.18	-1.66**	-1.42**	35.85***	42.10***
	OC	1.62	3.05	9.12	8.54	-4.17***	-2.47***	40.32***	84.18***
	TC	2.58	4.27	3.44	9.92	-2.78***	-3.63***	50.74***	111.25***
	IC	1.05	1.31	24.16	21.22	-2.19***	-1.52**	32.29**	56.46***

Note: *represents $p < 0.10$, **represents $p < 0.05$, *** represents $p < 0.01$. Exogenous variables: Individual effects, individual linear trends. Automatic lag length selection based on SIC: 0 to 1.

Table 5
Cointegration tests for three regions.

Tests	Hypothesis	Statistics	Regions		
			Eastern region	Cental region	Western region
Kao test	H_0: No cointegration	Modified Dickey-Fuller t	-1.1170**	-1.6673**	1.4335**
	H_a: All panels are cointegrated	Dickey-Fuller t	-3.6250***	-1.7142**	1.2914*
		Augmented Dickey-Fuller t	0.5862	-2.3000***	0.7005*
		Unadjusted modified Dickey-Fuller t	-2.2563**	-1.6965**	1.4886**
		Unadjusted Dickey-Fuller t	-3.2575***	-1.7273**	1.3556**
Pedroni test	H_0: No cointegration	Modified variance ratio	-3.7527***	-2.4092***	-3.2298***
	H_a: All panels are cointegrated	Modified Phillips-Perron t	2.0852***	1.7990**	1.676**
		Phillips-Perron t	-1.4784**	-3.1191***	-1.4926**
		Augmented Dickey-Fuller t	-2.2377***	-3.0089***	-1.4741**
Westerlund test	H_0: No cointegration	Variance ratio	1.2609**	1.6899**	0.812**
	H_a: All panels are cointegrated				

Note: *represents $p < 0.10$, **represents $p < 0.05$, *** represents $p < 0.01$. Exogenous variables: Individual effects, individual linear trends. Automatic lag length selection based on SIC: 0 to 1.

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 CO_2 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 CO_2 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 CO_2 emissions in all three regions. This promoting effect was most potent in the central region, most minor 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 CO_2 emissions in the central region, and inhibiting CO_2 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 CO_2 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
Estimation of PPCR model for three regions

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	-0.170***	-0.064***	-0.214***
	(-15.012)	(-2.840)	(-34.461)
C	0.115***	0.422***	-0.261***
	(10.041)	(13.672)	(-52.206)
R^2	0.987324	0.983783	0.985302
Adjusted R^2	0.986141	0.982131	0.98393
F-statistic	834.5264	595.5969	718.2546
Durbin-Watson	2.024887	1.881128	2.010345
Obs	165	120	165
Cross-sections included	11	8	11
Model selection	FE	FE	FE
Estimation methods	Panel EGLS	Panel EGLS	Panel EGLS

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 CO_2 emissions showed the opposite law to residents' wealth competitiveness. Inevitably, the process of creating wealth and consuming it consumes fossil fuels and brings about CO_2 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 CO_2 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 CO_2 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 CO_2 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 CO_2 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 CO_2 emissions. In other words, the 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 CO_2 emissions, it is feeble.

The competitiveness of technology inhibits CO_2 emissions in the eastern and western regions, but promotes CO_2 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 CO_2 emissions in the central and western regions and increasing CO_2 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 CO_2 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 CO_2 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 CO_2 emissions in the western region.

The inhibiting effect of the competitiveness of industrial structure on CO_2 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 CO_2 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 CO_2 emissions. Another interesting finding is that the inhibiting effect of the competitiveness of industrial structure on CO_2 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 CO_2 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 CO_2 emissions. Therefore, for CO_2 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 CO_2 emissions. It was found that the promoting effect of WC on CO_2 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 CO_2 emissions. It can be determined that the "pollution refuge" hypothesis was verified in all three regions. Moreover, the promotion of CO_2 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 CO_2 emissions in the central region and inhibited CO_2 emissions in the eastern and western regions. Finally, the inhibiting effect of IC on CO_2 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 CO_2 emissions. Therefore, striving to improve the competitiveness of residents' wealth in various regions is an effective measure to curb the increase of CO_2 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 CO_2 emissions in three regions. In other words, the external dependence of economic development increases CO_2 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 CO_2 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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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	α_i TCE (kg)	β_i Carbon emission coefficients (C/TCE)	δ_i 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	0.5854	3.07
1 kg fuel oil	1.4286	0.6176	3.23
1 kg gasoline	1.4714	0.5532	2.99
1 kg kerosene	1.4714	0.5714	3.08
1 kg diesel	1.4571	0.5913	3.16
$1\times 10^4 m^3$natural gas	13,300	0.4479	2.18

Note: TCE denotes standard coal; α_i denotes the conversion coefficient form fossil fuels to standard coal; β_i denotes the carbon emission coefficients of fossil fuels equivalent to one unit of standard coal; δ_i denotes CO_2 emissions coefficients of fossil fuels, and $\delta_i = \alpha_i \times \beta_i \times 44/12$.

Table a.2

KMO and Bartlett's Test results

Statistics	value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	.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

		Residents' consumption level GDP per capita
	Competitiveness of opening-up (OC)	Foreign trade dependence Export dependence Import dependence Foreign direct investment dependence
	Competitiveness of technology (TC)	Technical output amount Technical introduction amount R&D intensity
	Competitiveness of industrial structure (IC)	Secondary industry Tertiary industry

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	1.136	2.210	1.678
TC	1.105	2.687	3.756
IC	1.067	2.481	3.681

Table a.5
Panel model selection.

Statistic	Eastern region	Central region	western region
Hausman test	12.464**	40.692***	25.279***
Model type	FE	FE	FE

Note: FE is fixed effects model, ***represents p < 0.01, **represents p < 0.05.

Table b.1
Competitiveness of residents' wealth.

Provinces	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	-1.413	-1.501	-1.467	-1.424	-1.032	-1.060	-0.641	-0.700	-0.730	-0.749	-0.394	-0.050	0.464	1.165	1.347
Tianjin	-1.008	-0.975	-0.855	-0.748	-0.462	-0.063	0.126	0.449	0.798	1.133	1.558	1.840	2.369	2.872	3.309
Hebei	-1.032	-0.943	-0.860	-0.758	-0.643	-0.522	-0.440	-0.310	-0.051	0.111	0.226	0.295	0.366	0.570	0.723
Shanxi	-1.054	-0.944	-0.853	-0.761	-0.638	-0.475	-0.505	-0.214	0.014	0.146	0.280	0.314	0.511	0.565	1.035
Inner Mongolia	-1.104	-1.023	-0.863	-0.719	-0.492	-0.254	-0.077	0.166	0.571	0.793	1.125	1.565	1.677	1.884	1.989
Liaoning	-1.084	-1.098	-0.948	-0.823	-0.660	-0.389	-0.237	0.014	0.338	0.651	1.042	1.323	1.578	1.266	1.372
Jilin	-1.193	-1.217	-1.072	-0.973	-0.793	-0.605	-0.482	-0.314	-0.028	0.210	0.435	0.461	0.634	0.495	0.596
Heilongjiang	-1.043	-0.979	-0.878	-0.824	-0.694	-0.530	-0.501	-0.321	-0.102	0.000	0.193	0.458	0.592	0.715	0.909
Shanghai	-0.506	-0.352	-0.051	0.190	0.482	0.808	1.022	1.539	2.039	2.198	2.546	3.033	3.296	3.751	4.197
Jiangsu	-1.097	-1.081	-0.890	-0.679	-0.431	-0.163	0.039	0.195	0.620	0.910	1.422	2.072	2.513	3.131	3.671
Zhejiang	-0.565	-0.417	-0.214	0.001	0.223	0.451	0.647	1.016	1.462	1.649	2.004	2.339	2.688	2.963	3.264
Anhui	-1.178	-1.107	-1.072	-1.000	-0.866	-0.751	-0.633	-0.402	-0.156	-0.049	0.039	0.199	0.295	0.487	0.671
Fujian	-0.911	-0.812	-0.695	-0.530	-0.333	-0.059	0.070	0.352	0.644	0.816	0.959	1.308	1.602	2.030	2.446
Jiangxi	-1.168	-1.059	-0.964	-0.898	-0.783	-0.691	-0.630	-0.337	-0.056	0.097	0.288	0.321	0.634	0.844	0.993
Shandong	-1.024	-0.943	-0.806	-0.554	-0.409	-0.191	-0.071	0.035	0.284	0.503	0.698	0.985	1.225	1.824	2.071
Henan	-1.039	-0.944	-0.854	-0.778	-0.671	-0.536	-0.458	-0.256	-0.066	0.086	0.270	0.458	0.638	0.843	1.077
Hubei	-1.157	-1.077	-0.997	-0.901	-0.718	-0.579	-0.521	-0.337	-0.038	0.124	0.227	0.357	0.411	0.615	0.845
Hunan	-1.084	-0.993	-0.896	-0.800	-0.674	-0.540	-0.444	-0.253	0.032	0.201	0.344	0.544	0.812	0.983	1.132
Guangdong	-1.156	-1.004	-0.847	-0.706	-0.442	-0.196	0.005	0.189	0.524	0.698	0.840	1.212	1.327	1.575	1.644
Guangxi	-1.161	-1.102	-1.019	-0.951	-0.803	-0.657	-0.550	-0.384	-0.162	0.008	0.152	0.339	0.470	0.618	0.730
Hainan	-1.257	-1.248	-1.112	-0.970	-0.867	-0.801	-0.750	-0.659	-0.420	-0.223	-0.013	0.216	0.737	0.959	1.361
Chongqing	-1.108	-1.047	-0.962	-0.876	-0.692	-0.540	-0.422	-0.280	0.044	0.268	0.512	0.713	1.031	1.176	1.557
Sichuan	-1.237	-1.133	-1.055	-0.976	-0.851	-0.726	-0.623	-0.409	-0.123	0.047	0.183	0.346	0.422	0.575	0.756
Guizhou	-1.204	-1.161	-1.067	-0.973	-0.870	-0.778	-0.696	-0.588	-0.413	-0.234	-0.040	0.213	0.421	0.683	0.877
Yunnan	-1.175	-1.055	-1.010	-0.940	-0.865	-0.719	-0.648	-0.508	-0.278	-0.107	0.115	0.265	0.386	0.529	0.673
Shaanxi	-1.311	-1.235	-1.140	-1.011	-0.869	-0.680	-0.653	-0.429	-0.212	-0.004	0.013	0.200	0.174	0.300	0.495
Gansu	-1.219	-1.154	-1.138	-1.079	-0.991	-0.892	-0.803	-0.682	-0.467	-0.315	-0.184	-0.032	0.070	0.183	0.311
Qinghai	-1.184	-1.131	-1.022	-0.944	-0.823	-0.639	-0.593	-0.440	-0.185	0.061	0.320	0.541	0.790	1.018	1.180
Ningxia	-1.067	-0.994	-0.906	-0.834	-0.705	-0.451	-0.355	-0.169	0.154	0.331	0.546	0.774	1.008	1.192	1.533
Xinjiang	-1.124	-1.056	-0.946	-0.827	-0.712	-0.573	-0.576	-0.320	-0.074	0.189	0.303	0.493	0.611	0.811	1.054

Table b.2
Competitiveness of opening-up.

Provinces	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	1.717	2.029	2.419	2.410	2.072	2.298	1.210	1.477	1.402	0.830	0.472	-0.113	-0.713	-1.507	-1.441
Tianjin	2.275	2.832	3.360	3.611	3.303	2.783	2.090	2.186	2.075	1.987	1.884	1.758	1.590	0.598	0.500
Hebei	-0.421	-0.324	-0.314	-0.349	-0.364	-0.281	-0.427	-0.441	-0.413	-0.483	-0.473	-0.504	-0.578	-0.621	-0.697
Shanxi	-0.515	-0.470	-0.468	-0.441	-0.262	-0.380	-0.606	-0.573	-0.527	-0.570	-0.579	-0.651	-0.671	-0.747	-0.888
Inner Mongolia	-0.574	-0.510	-0.369	-0.290	-0.325	-0.421	-0.495	-0.513	-0.521	-0.702	-0.664	-0.739	-0.846	-0.818	-0.908
Liaoning	0.931	0.979	0.665	0.870	0.932	0.836	0.816	1.112	0.871	0.779	0.837	0.604	-0.391	-0.504	-0.449
Jilin	-0.239	-0.236	-0.257	-0.280	-0.316	-0.367	-0.455	-0.423	-0.454	-0.485	-0.523	-0.535	-0.624	-0.648	-0.758
Heilongjiang	-0.249	-0.208	-0.126	-0.043	-0.012	-0.008	-0.252	-0.160	-0.140	-0.262	-0.301	-0.365	-0.567	-0.640	-0.634
Shanghai	2.909	3.452	3.421	3.397	3.152	2.837	2.020	2.313	2.264	1.976	1.654	1.461	1.137	0.905	0.649
Jiangsu	2.115	2.122	2.205	2.387	2.247	1.824	1.235	1.213	0.963	0.685	0.297	-0.016	-0.444	-0.550	-0.598
Zhejiang	0.898	1.145	1.315	1.409	1.336	1.127	0.746	0.829	0.749	0.504	0.508	0.457	0.308	0.146	-0.030
Anhui	-0.562	-0.551	-0.489	-0.351	-0.216	-0.266	-0.392	-0.330	-0.326	-0.271	-0.278	-0.303	-0.352	-0.416	-0.477
Fujian	0.990	1.115	1.147	1.609	1.327	1.116	0.482	0.534	0.525	0.332	0.165	0.072	-0.062	-0.140	-0.184
Jiangxi	-0.152	-0.099	-0.084	-0.047	-0.092	-0.117	-0.172	-0.078	-0.089	-0.135	-0.201	-0.164	-0.227	-0.309	-0.304
Shandong	0.558	0.643	0.572	0.588	0.513	0.294	0.045	0.137	0.101	0.011	-0.090	-0.256	-0.421	-0.590	-0.711
Henan	-0.667	-0.689	-0.625	-0.572	-0.533	-0.533	-0.565	-0.553	-0.445	-0.368	-0.404	-0.429	-0.433	-0.473	-0.550
Hubei	-0.366	-0.315	-0.316	-0.308	-0.381	-0.409	-0.484	-0.514	-0.531	-0.654	-0.743	-0.864	-1.023	-1.183	-1.259
Hunan	-0.468	-0.514	-0.448	-0.425	-0.435	-0.466	-0.516	-0.521	-0.548	-0.555	-0.589	-0.585	-0.644	-0.626	-0.670
Guangdong	3.299	3.195	3.223	3.275	2.989	2.360	1.744	1.931	1.736	1.530	1.421	1.138	0.712	0.344	-0.196
Guangxi	-0.567	-0.624	-0.601	-0.587	-0.548	-0.514	-0.527	-0.554	-0.566	-0.576	-0.659	-0.607	-0.497	-0.628	-0.598
Hainan	0.346	-0.131	0.238	0.167	0.274	0.143	-0.132	0.162	0.100	-0.027	-0.077	-0.149	-0.289	-0.418	-0.502
Chongqing	-0.580	-0.526	-0.501	-0.450	-0.411	-0.305	-0.307	-0.409	-0.090	0.323	-0.041	0.057	-0.215	-0.662	-0.543

Sichuan	-0.575	-0.586	-0.558	-0.518	-0.534	-0.435	-0.432	-0.345	-0.276	-0.348	-0.477	-0.523	-0.718	-0.846	-0.993
Guizhou	-0.732	-0.689	-0.710	-0.725	-0.734	-0.738	-0.811	-0.780	-0.762	-0.779	-0.788	-0.863	-0.930	-1.011	-1.062
Yunnan	-0.692	-0.659	-0.628	-0.581	-0.565	-0.581	-0.649	-0.545	-0.592	-0.599	-0.641	-0.642	-0.754	-0.935	-0.954
Shaanxi	-0.371	-0.364	-0.385	-0.378	-0.393	-0.478	-0.517	-0.529	-0.617	-0.724	-0.860	-0.826	-0.842	-0.905	-0.980
Gansu	-0.664	-0.662	-0.617	-0.556	-0.500	-0.557	-0.690	-0.600	-0.665	-0.715	-0.774	-0.835	-0.880	-0.972	-1.052
Qinghai	-0.230	-0.139	-0.211	-0.231	-0.374	-0.604	-0.649	-0.675	-0.749	-0.768	-0.864	-0.890	-0.911	-0.999	-1.079
Ningxia	-0.497	-0.391	-0.433	-0.411	-0.479	-0.562	-0.694	-0.674	-0.667	-0.718	-0.719	-0.636	-0.752	-0.789	-0.733
Xinjiang	-0.459	-0.415	-0.282	-0.256	-0.137	0.072	-0.328	-0.377	-0.366	-0.436	-0.519	-0.569	-0.739	-0.779	-0.811

Table b.3

Competitiveness of technology,

Provinces	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	0.670	1.194	1.136	1.503	1.370	1.534	2.123	2.721	3.495	4.940	5.254	6.106	6.113	7.736	8.513
Tianjin	-0.161	-0.171	-0.279	-0.235	-0.246	-0.116	0.075	-0.125	0.002	0.097	0.103	0.328	0.226	0.264	-0.207
Hebei	-0.020	-0.096	-0.044	-0.011	0.060	0.034	-0.092	0.025	-0.144	-0.089	-0.210	-0.132	-0.223	-0.219	-0.034
Shanxi	0.224	0.299	0.418	0.467	0.486	0.478	0.508	0.452	0.488	0.397	0.254	0.312	-0.458	-0.267	-0.236
Inner Mongolia	-0.558	-0.590	-0.471	-0.436	-0.511	-0.459	-0.507	-0.498	-0.603	-0.197	-0.569	-0.832	-0.853	-1.059	-1.177
Liaoning	0.082	0.042	0.264	0.101	0.086	0.266	0.206	0.334	0.777	0.640	0.030	-0.153	-0.319	-0.299	-0.052
Jilin	-0.096	-0.059	-0.181	-0.383	-0.362	-0.420	-0.297	-0.416	-0.584	-0.612	-0.709	-0.688	-0.710	-0.536	-0.318
Heilongjiang	0.407	0.397	0.428	0.411	0.335	0.311	0.316	0.193	0.086	0.028	-0.099	-0.335	-0.629	-0.673	-0.991
Shanghai	-0.313	-0.360	-0.401	-0.291	-0.327	-0.350	-0.321	-0.392	-0.447	-0.310	-0.388	-0.495	-0.421	-0.677	-0.132
Jiangsu	0.108	0.268	0.181	-0.006	-0.045	0.010	0.131	0.622	0.687	1.008	1.168	1.134	1.663	1.227	1.219
Zhejiang	-0.188	-0.190	-0.319	-0.345	-0.388	-0.382	-0.394	-0.531	-0.710	-0.321	-0.747	-0.789	-0.944	-0.781	-0.396
Anhui	-0.358	-0.384	-0.260	-0.202	-0.203	-0.103	0.033	0.067	0.095	0.194	0.290	0.263	0.199	0.144	0.234
Fujian	-0.398	-0.416	-0.457	-0.628	-0.641	-0.639	-0.432	-0.468	-0.500	-0.194	0.169	0.039	-0.086	-0.492	-0.866
Jiangxi	-0.142	-0.117	-0.047	0.068	0.118	0.060	0.098	0.090	-0.016	-0.065	-0.025	-0.146	-0.304	-0.280	-0.302
Shandong	0.282	0.457	0.534	0.200	0.270	0.320	0.380	0.386	0.438	0.369	0.450	0.716	0.604	0.679	1.082
Henan	0.150	0.160	0.242	0.305	0.273	0.306	0.286	0.212	0.143	0.010	-0.021	-0.122	-0.236	-0.296	-0.270
Hubei	0.027	-0.027	0.056	0.064	-0.001	0.030	0.225	0.419	0.290	0.590	0.745	1.145	1.696	2.012	2.112
Hunan	-0.277	-0.229	-0.296	-0.253	-0.254	-0.153	-0.149	-0.131	-0.158	-0.161	-0.089	-0.157	-0.258	-0.531	-0.375
Guangdong	-0.566	-0.599	-0.490	-0.558	-0.569	-0.269	-0.045	-0.037	-0.085	0.395	0.682	0.610	1.093	1.405	3.034
Guangxi	-0.517	-0.477	-0.489	-0.477	-0.507	-0.526	-0.551	-0.473	-0.502	-0.598	-0.546	-0.686	-0.995	-1.033	-1.078
Hainan	-1.089	-0.934	-1.065	-1.024	-1.087	-1.087	-1.085	-1.206	-1.211	-1.054	-1.427	-1.517	-1.827	-1.910	-2.026
Chongqing	0.040	0.124	0.058	0.160	-0.024	-0.175	-0.169	-0.055	-0.302	-0.177	-0.283	-0.241	-0.463	0.364	-0.539
Sichuan	0.049	-0.004	0.078	0.127	0.133	0.145	0.263	0.225	0.043	0.143	0.422	0.282	0.472	0.409	0.796
Guizhou	-0.162	-0.187	-0.195	-0.193	-0.300	-0.350	-0.317	-0.416	-0.486	-0.546	-0.673	-0.601	-0.590	-0.702	-0.695
Yunnan	-0.172	-0.224	-0.234	-0.268	-0.326	-0.373	-0.439	-0.397	-0.588	-0.500	-0.619	-0.727	-0.638	-0.702	-0.753
Shaanxi	0.731	0.735	0.605	0.590	0.584	0.539	0.670	0.656	0.846	1.088	1.739	1.550	1.558	1.660	2.052
Gansu	-0.035	-0.055	0.007	0.106	0.162	0.144	0.091	0.178	0.052	0.024	0.052	-0.026	-0.277	-0.267	-0.429
Qinghai	-0.656	-0.651	-0.547	-0.556	-0.599	-0.597	-0.469	-0.505	-0.499	-0.570	-0.678	-0.843	-1.060	-1.025	-0.970
Ningxia	-0.241	-0.211	-0.252	-0.129	-0.078	-0.183	-0.245	-0.350	-0.423	-0.490	-0.624	-0.770	-0.906	-0.964	-0.949
Xinjiang	-0.481	-0.309	-0.256	-0.200	-0.410	-0.388	-0.427	-0.346	-0.407	-0.568	-0.627	-0.773	-0.937	-1.119	-1.198

Table b.4

Competitiveness of industrial structure.

Provinces	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	2.949	2.832	3.118	3.274	3.427	3.785	3.327	3.371	3.379	2.955	2.878	2.498	2.415	1.755	1.501
Tianjin	-0.213	-0.304	-0.457	-0.515	-0.511	-0.662	-0.520	-0.290	-0.168	-0.166	-0.021	-0.064	0.032	0.610	0.887
Hebei	-0.355	-0.351	-0.434	-0.453	-0.586	-0.696	-0.360	-0.451	-0.494	-0.474	-0.315	-0.278	0.007	0.037	0.157
Shanxi	-0.827	-1.092	-1.477	-1.585	-1.787	-1.806	-1.370	-1.724	-2.021	-1.645	-1.286	-0.986	0.286	0.356	-0.013
Inner Mongolia	1.147	1.097	0.589	0.321	0.370	0.333	0.372	0.235	0.064	-0.196	-0.047	0.082	0.289	0.379	0.600
Liaoning	-0.540	-0.267	-0.447	-0.571	-0.724	-1.124	-1.084	-1.359	-1.576	-1.340	-0.951	-0.520	0.256	0.751	0.676
Jilin	0.562	0.662	0.720	1.134	0.903	0.836	0.756	0.743	0.881	0.831	0.880	0.859	0.793	0.951	0.991
Heilongjiang	-1.327	-1.445	-1.606	-1.649	-1.574	-1.606	-1.078	-0.953	-0.920	-0.622	-0.448	0.004	0.780	1.061	1.407
Shanghai	0.305	0.306	0.358	0.358	0.620	0.676	1.065	0.818	0.876	1.069	1.353	1.519	1.810	2.171	1.901
Jiangsu	-1.354	-1.365	-1.343	-1.340	-1.300	-1.268	-1.172	-1.169	-1.106	-1.159	-1.066	-0.986	-1.139	-0.870	-0.934
Zhejiang	-0.891	-1.046	-1.027	-1.120	-1.101	-1.062	-0.788	-0.751	-0.671	-0.681	-0.477	-0.563	-0.379	-0.265	-0.254
Anhui	1.014	0.966	0.656	0.415	0.213	-0.007	-0.162	-0.536	-0.804	-0.887	-0.824	-0.716	-0.322	-0.111	0.002
Fujian	-0.266	-0.391	-0.413	-0.583	-0.518	-0.634	-0.526	-0.748	-0.838	-0.967	-1.162	-1.204	-1.027	-0.755	-0.444
Jiangxi	-0.163	-0.372	-0.622	-0.964	-1.053	-0.965	-0.975	-1.348	-1.393	-1.299	-1.299	-1.122	-0.801	-0.550	-0.447
Shandong	-1.215	-1.585	-1.595	-1.504	-1.447	-1.381	-1.261	-1.053	-0.936	-0.753	-0.597	-0.586	-0.408	-0.332	-0.382
Henan	-0.638	-0.787	-1.057	-1.225	-1.268	-1.473	-1.333	-1.339	-1.271	-1.078	-0.932	-0.787	-0.604	-0.446	-0.394
Hubei	0.250	0.172	0.031	-0.006	0.005	-0.100	-0.283	-0.597	-0.724	-0.885	-0.584	-0.616	-0.627	-0.641	-0.496
Hunan	0.589	0.531	0.513	0.277	0.156	0.000	0.075	-0.179	-0.402	-0.386	-0.338	-0.248	-0.076	0.282	0.496
Guangdong	-0.014	-0.002	-0.233	-0.275	-0.268	-0.409	-0.361	-0.428	-0.366	-0.407	-0.378	-0.459	-0.451	-0.321	-0.781
Guangxi	0.970	0.855	0.791	0.711	0.549	0.498	0.584	0.311	0.194	0.402	0.599	0.630	0.912	1.119	1.224
Hainan	1.648	1.892	1.523	1.310	1.331	1.445	1.760	1.915	1.848	1.859	2.320	2.328	2.409	2.564	2.514
Chongqing	0.064	-0.137	-0.080	-0.316	-0.164	0.061	-0.003	0.053	0.011	-0.298	-0.105	-0.157	0.014	-0.053	0.369
Sichuan	0.519	0.403	0.141	-0.104	-0.173	-0.332	-0.512	-0.645	-0.591	-0.554	-0.621	-0.383	-0.223	0.161	0.279
Guizhou	0.366	0.312	0.284	0.272	0.382	0.483	0.535	0.625	0.659	0.615	0.694	0.634	0.623	0.641	0.826
Yunnan	0.397	0.344	0.481	0.377	0.456	0.363	0.579	0.304	0.564	0.489	0.624	0.735	0.876	1.137	1.300
Shaanxi	-0.391	-0.480	-0.370	-0.614	-0.748	-0.833	-0.723	-0.922	-1.227	-1.395	-1.495	-1.308	-0.864	-0.729	-0.921
Gansu	0.374	0.345	0.360	0.063	-0.227	-0.153	0.010	-0.384	-0.222	-0.111	0.057	0.189	0.839	1.079	1.328
Qinghai	1.391	1.263	0.838	0.802	0.926	0.855	0.861	0.843	0.649	0.593	0.683	0.845	1.022	0.936	0.780
Ningxia	0.280	0.077	0.099	-0.157	-0.286	-0.369	-0.074	-0.059	-0.203	-0.080	0.049	0.132	0.329	0.444	0.228
Xinjiang	0.802	0.298	-0.182	-0.524	-0.232	-0.564	0.021	-0.456	-0.487	-0.200	0.206	0.270	0.831	1.014	0.961

Table b.5

Comprehensive economic competitiveness.

Provinces	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	0.691	0.846	1.002	1.124	1.154	1.308	1.196	1.392	1.538	1.625	1.697	1.772	1.760	2.016	2.222
Tianjin	0.226	0.371	0.503	0.606	0.612	0.600	0.539	0.665	0.798	0.903	1.039	1.138	1.257	1.258	1.315
Hebei	-0.516	-0.477	-0.450	-0.423	-0.398	-0.362	-0.344	-0.296	-0.250	-0.201	-0.161	-0.122	-0.090	-0.030	0.062
Shanxi	-0.578	-0.560	-0.572	-0.543	-0.486	-0.471	-0.459	-0.432	-0.390	-0.313	-0.240	-0.183	-0.072	-0.020	0.034
Inner Mongolia	-0.435	-0.407	-0.381	-0.352	-0.297	-0.242	-0.209	-0.157	-0.083	-0.016	0.044	0.129	0.168	0.212	0.234

Liaoning	-0.171	-0.123	-0.143	-0.105	-0.066	-0.036	0.001	0.143	0.243	0.329	0.404	0.465	0.375	0.336	0.428
Jilin	-0.372	-0.353	-0.329	-0.275	-0.263	-0.242	-0.213	-0.179	-0.108	-0.055	-0.006	0.000	0.015	0.031	0.089
Heilongjiang	-0.549	-0.540	-0.507	-0.478	-0.432	-0.389	-0.351	-0.274	-0.215	-0.176	-0.123	-0.027	0.032	0.092	0.146
Shanghai	0.619	0.808	0.896	0.992	1.057	1.081	1.001	1.189	1.334	1.372	1.429	1.538	1.602	1.692	1.839
Jiangsu	0.010	0.052	0.120	0.196	0.237	0.225	0.172	0.328	0.422	0.502	0.613	0.743	0.860	0.980	1.128
Zhejiang	-0.137	-0.049	0.037	0.110	0.155	0.180	0.184	0.302	0.398	0.476	0.532	0.602	0.671	0.772	0.910
Anhui	-0.434	-0.423	-0.421	-0.390	-0.346	-0.339	-0.333	-0.301	-0.262	-0.204	-0.145	-0.087	-0.014	0.055	0.139
Fujian	-0.159	-0.119	-0.086	0.026	0.020	0.031	-0.036	0.022	0.090	0.139	0.186	0.236	0.297	0.371	0.464
Jiangxi	-0.479	-0.461	-0.455	-0.459	-0.438	-0.413	-0.402	-0.349	-0.294	-0.252	-0.199	-0.174	-0.069	0.026	0.089
Shandong	-0.330	-0.306	-0.266	-0.240	-0.188	-0.155	-0.149	-0.052	0.052	0.115	0.195	0.304	0.342	0.520	0.648
Henan	-0.598	-0.597	-0.580	-0.557	-0.527	-0.513	-0.476	-0.425	-0.338	-0.263	-0.194	-0.138	-0.074	-0.004	0.066
Hubei	-0.423	-0.409	-0.390	-0.362	-0.335	-0.310	-0.301	-0.262	-0.222	-0.164	-0.067	0.026	0.122	0.212	0.314
Hunan	-0.435	-0.418	-0.387	-0.382	-0.366	-0.337	-0.305	-0.286	-0.247	-0.193	-0.131	-0.065	0.013	0.076	0.185
Guangdong	0.403	0.419	0.460	0.497	0.502	0.451	0.406	0.507	0.561	0.662	0.747	0.759	0.789	0.861	1.020
Guangxi	-0.474	-0.482	-0.463	-0.448	-0.426	-0.382	-0.342	-0.327	-0.286	-0.219	-0.148	-0.099	-0.047	-0.007	0.046
Hainan	-0.262	-0.312	-0.262	-0.264	-0.212	-0.207	-0.209	-0.099	-0.052	0.014	0.066	0.102	0.175	0.221	0.292
Chongqing	-0.496	-0.479	-0.449	-0.426	-0.371	-0.286	-0.259	-0.206	-0.077	0.082	0.071	0.163	0.172	0.270	0.297
Sichuan	-0.453	-0.455	-0.451	-0.447	-0.422	-0.380	-0.351	-0.290	-0.211	-0.147	-0.088	-0.037	0.006	0.074	0.200
Guizhou	-0.560	-0.550	-0.532	-0.508	-0.481	-0.446	-0.423	-0.386	-0.334	-0.303	-0.257	-0.191	-0.142	-0.101	-0.018
Yunnan	-0.537	-0.510	-0.465	-0.456	-0.426	-0.411	-0.383	-0.349	-0.284	-0.224	-0.167	-0.124	-0.070	-0.042	0.017
Shaanxi	-0.430	-0.418	-0.403	-0.406	-0.390	-0.377	-0.330	-0.300	-0.266	-0.204	-0.106	-0.046	0.022	0.092	0.189
Gansu	-0.517	-0.505	-0.470	-0.466	-0.461	-0.435	-0.426	-0.413	-0.361	-0.312	-0.250	-0.212	-0.132	-0.076	-0.049
Qinghai	-0.345	-0.325	-0.361	-0.350	-0.338	-0.354	-0.322	-0.291	-0.262	-0.214	-0.165	-0.109	-0.052	-0.010	0.005
Ningxia	-0.485	-0.462	-0.450	-0.439	-0.427	-0.407	-0.373	-0.329	-0.265	-0.215	-0.153	-0.075	-0.027	0.030	0.120
Xinjiang	-0.454	-0.471	-0.472	-0.475	-0.401	-0.353	-0.368	-0.366	-0.303	-0.222	-0.149	-0.124	-0.069	-0.024	0.018

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