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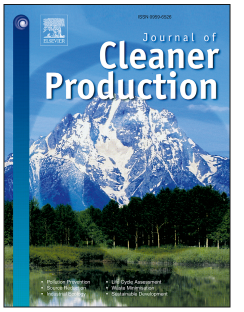

Multi-region and multi-sector comparisons and analysis of industrial carbon productivity in China

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To sort out the contribution of each author, we share an accurate and detailed description of our diverse contributions to the published work. As shown in the table below.

Author	Contribution
Hua Yang	Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation, Visualization, and Investigation.
Zhengnan Lu	Supervision and Funding acquisition.
Xunpeng Shi	Conceptualization, Writing- Original draft preparation, and Writing- Reviewing and Editing.
Isaac Adjei Mensah	Writing- Reviewing and Editing.
Yusen Luo	Visualization and Investigation.
Weijian Chen	Software and Validation.

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Abstract

In the context of global warming, increasing carbon productivity is an important way to balance environmental goals with economic growth and development. In this study, we measure the provincial industrial carbon productivity (ICP) in China. Employing spatial production-theoretical decomposition analysis and data from the industrial sector in each province of China, we investigate the regional disparities in ICP and the driving factors at the provincial and sectoral levels. The results indicate that the ICP discrepancies across different regions are obvious: the eastern region had the highest ICP, followed by the northeastern, central, and western regions. The capital-energy substitution effect and CO_2 emission performance were two principal

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contributors to increasing the regional disparities for most provinces. By contrast, the labor-energy substitution effect and energy consumption structure remained relatively backward and resulted in lower ICP than the average level in most provinces. Furthermore, 12 key industrial subsectors, including electricity generation sector, five energy-intensive manufacturing sectors and six nonenergy intensive manufacturing sectors, in 13 provinces (including Hebei, Liaoning, Heilongjiang, Anhui, and all the other western provinces) were identified as the main drivers of the lower than average ICP in these 13 provinces. For the12 industrial sectors in the 13 provinces, industrial structure, and CO_2 emission performance were the main causes of their backward carbon productivity. Based on the findings of this study, several relevant suggestions for policymakers are provided.

Keywords: Industrial carbon productivity; Production-theoretical decomposition analysis; Multi-region comparisons; Multi-sector comparisons

1. Introduction

Balancing carbon emission mitigation with economic growth in the industrial sector is the keystone for the ultimate achievement of China's emissions targets. Since China is the world's largest CO_2 emitter, accounting for 27.8% of the world's total share in 2018, its efforts in mitigating climate change is vital for the global community in its battle against climate change (U.S. Energy Information Administration (EIA), 2019). The Chinese government has promised to peak its CO_2 emissions near 2030, and to decrease CO_2 emissions per unit of gross domestic product (GDP) by 60-65% (compared with the 2005 level) (Chinese Government, 2015). The rapidly growing industrial sector, as the core pillar of China's economy, is at the core of the emission reduction efforts. CO_2 emissions from the industrial sector exceeded 68% of the country's total CO_2 emissions in 2016, while the industrial value-added averaged only about 33% of GDP (National Bureau of Statistics of China (NBSC), 2017; Shan et al., 2020).

Improving China's industrial carbon productivity (ICP) is a key measure of minimizing the costs (industrial value-added loss) of reducing industrial CO_2 emissions reduction and helping China to balance between industrial growth and emission mitigation. Based on the definition of Kaya and Yokobori (1999), ICP can be defined as the ratio of industrial value-added to CO_2 emissions from the industrial sector (Li and Wang, 2019). Since the average ICP in China was just one-third of the world average from 2000 to 2011 (Long et al., 2016), the potential for improvement is regarded significant.

Further studies on ICP by province and sector can generate additional information that is needed for China's policy formulation. Since China is a large and centralized country, national policy targets are often allocated to provinces (Wang et al., 2020). Due to China's vast territory, there are large disparities in natural resource endowments, economic development, and technological capabilities across regions and sectors (Yang et al., 2014). Identifying the industrial sectors with high abatement costs and formulating appropriate policies to encourage emission reduction can help China achieve its emission commitments at a low cost. Hence, a bottom-up process would be more effective (Shan et al., 2018), by identifying several local regions (each province in China) and their respective low industrial sectors. Information obtained can then be used to establish policies aimed at increasing ICP. To effectively improve ICP, further research needs to be carried out to account for the significant heterogeneity, and thus marginal abatement cost, across regions[1] and sectors. Moreover, identifying the key drivers in the industrial sector of each province can inform effective policy formulation (Nabavi-Pelesaraei et al., 2019).

Our key motivation is to help policymakers to minimize the emission abatement cost in China through identifying the under-performed regions and their sectors. These underperformed regions and sectors can reduce emissions without comprising their outputs in the current technology and thus should be the priority of emissions reduction. Specifically, we focus on the following issues: (i) How the determinants of ICP disparities at both the provincial and sectoral levels are quantified; (ii) Which regions have ICP levels that are below the average level, and the major sectors causing this; and (iii) What drivers are causing industrial sectors' carbon productivity levels to be below average? Based on the outcomes from aforementioned issues, we discuss possible reasons to offer policy.

Our contributions to the literature are in three folds. Firstly, we extended the data to assess carbon productivity in 29 provinces and 22 industrial sectors and as well present detailed information on ICP in each province. Secondly, we compared multiple regions' ICP identifying provinces with below-average ICP and for the first time identifying the key industrial sectors that have contributed to this low carbon

[1]The 'region' implicitly refers to a geographic area, which is a province in this study.

productivity. Thirdly, from the perspectives of production systems, provinces, and industrial sectors, we carried out an in-depth analysis of the driving factors behind low carbon productivity with respect to key industrial sectors which have caused some provinces to have lower than average ICP.

This paper is organized as follows: Section 2 provides a literature review, and Section 3 features the methodology on spatial-production-theoretical decomposition analysis (PDA), the data sources, and variables. The research results are presented in Section 4, while Section 5 further discusses the results. Section 6bfinally, summarizes the main findings and policy implications.

2. Literature review

Carbon productivity is a key indicator for assessing the beneficial outputs gained concerning CO_2 emissions, and ascertaining a country's contributions towards addressing global climate change (Y. Li et al., 2018). Carbon productivity needs to be improved from approximately 740 to 7300 \$/t CO_2eq by 2050 to achieve the 2050 goal proposed by the Intergovernmental Panel on Climate Change (IPCC) for reducing greenhouse gases (GHG) (Beinhocker et al., 2008). As the industrial sector is the largest energy consumer and CO_2 emitting sector in China, research on carbon productivity has recently been focused primarily on the industrial sector (Liu et al., 2019). Since the Chinese government began to transform its economic development patterns and substantially increase its green investment, China's ICP has significantly improved (Long et al., 2020). However, due to the large proportion of heavy industry and coal-based energy consumption, Chinese carbon productivity has been far lower than that in developed countries (Bai et al., 2019). Many scholars have focused on the relationship between ICP and CO_2 emissions (Beinhocker et al., 2008; Cheng et al., 2018; Gazheli et al., 2016). Other scholars have also analyzed the carbon productivity of a special sector within the industrial sector, such as the textile industry, power industry, pulp and paper industry, and other sub-industrial sectors in China (Lin and Jia, 2019; Zhao and Lin, 2019; Zheng and Lin, 2020).

The existing literature also focuses on the influencing factors of ICP. A summary of literature on the influencing factors of ICP arranged in chronological order is shown in Table1. Many scholars have proven that technological innovation has significantly positive effects on carbon productivity (Hu and Liu, 2016; Meng and Niu, 2012). Lu et al. (2015) analyzed the change in China's industrial system carbon productivity from 2000 to 2012, and point out that the structure of CO_2 emissions is a main influencing factor in the industrial system. Some scholars have examined the impacts of substitution effects between energy and non-energy inputs on production activities and emissions performance (GenovaitėLiobikienė and MindaugasButkus, 2017; Ma and Stern, 2016; Shabanzadeh-Khoshrody et al., 2016). Other factors of influencing carbon productivity have been studied, including industrial-scale structure, opening degree, energy structure effect, industrial structure, environmental regulations, GDP per capita, and R&D investment (see Table 1) (Hu and Wang, 2020; Li and Wang, 2019).

To the best of our familiarity, although many of the previous existing studies used the decomposition model to analyze differences in cross-regional carbon productivity, no scholars have applied spatial PDA to compare interprovincial ICP in China. As for methodologies used to measure carbon productivity, the LMDI (Logarithmic Mean Divisia Index) method, the Laspeyres index method (Sun et al., 2018), and spatial analysis approaches have been widely used. Lu et al. (2015) applied the LMDI to analyze the factors influencing carbon productivity, reported that regional economic development patterns had no impact on the differences in regional carbon productivity in China. Index decomposition analysis (IDA) and structural decomposition analysis approach (SDA) were widely used to analyze multi-region comparisons (see Table 1). Compared with the IDA and SDA approaches, the Spatial-PDA has advantages in its theoretical basis, decomposition forms, and its ability to analyze detailed industrial sectoral carbon productivity (Wang et al., 2015). Recently, PDA and spatial decomposition models have been applied to uncover the influencing factors behind differences in absolute energy-emissions and intensity among regions using indicators such as emission performances (Zhang et al., 2020), energy performances (Wang et al., 2019), CO_2 emissions, and energy intensity (Lin and Du, 2014).

Another gap in the literature is that the existing literature does not comprehensively measure China's region-level disparities in ICP and the driving factors. It is crucial to consider regional differences in development patterns and ICP when discussing how emission reduction targets can be achieved fairly and at the lowest cost (Zheng et al., 2019). The relevant measurements focus mainly on the absolute amount of carbon productivity and the influencing factors rather than regional and sectoral disparities in carbon productivity, such as Du and Li (2019, and Hu and Wang (2020). China's carbon productivity and regional carbon productivity only have been examined in the transport industry (Yu et al., 2017). There is still disagreement over the factors which affect carbon productivity (Sun et al., 2018). Also, the research to date has neglected to identify the key industry sectors that have led to weak ICP in each region. Furthermore, most previous studies did not take the resource[2] allocation in production systems into account when seeking the determinants of the disparities in ICP at the sectoral level.

To fill these gaps, this study focuses on multi-region comparisons of China's ICP from the perspective of production systems at the regional and sectoral levels and quantifies the sectoral differences within a particular province. Based on an extension of the comparison model, we used a multi-region spatial decomposition model (M-R) to compare each target region with the reference region given by the overall average of the entire group (Ang et al., 2015). A decomposition approach that integrates the PDA and M-R model was used not only to decompose regional ICP disparities into several pre-defined factors but also to quantify inter-factor substitution effects by specifying different distance functions (Wang et al., 2018). The model also maintained the advantages of the M-R spatial comparison strategy, e.g. satisfying the circularity property and ease of use, and could account for the sectoral heterogeneity. This model was in line with the research motivation of this paper. Therefore, we choose this model as the research method.

Table 1 Summary of various studies on carbon productivity in chronological order

[2]Production resources mainly include capital, labor, energy, and CO_2 emission rights.

Focus	Key references	Domain	Model	Key Findings
Influencing factors	Meng and Niu (2012)	China	Log Mean Divisia Index	Technological innovation and industrial structure adjustment.
	Sun et al. (2018)	China	Laspeyres index method	Regional development mode affects electric carbon productivity improvement.
	Li and Wang (2019).	Province in China	An extended STIRPAT model	GDP per capita, technology level, trade openness, and foreign direct investment, energy consumption structure, industrial proportion, and urbanization level.
	Hu and Wang (2020)	China	Econometric model	There is a threshold for the impact of environmental regulation on carbon productivity in China.
	Long et al. (2020)	Province in China	The generalized space three-stage least-squares estimator method (GS3SLS)	Scale effect, structural effect, technical effect, and environmental effect.
Multi-region comparisons	Ang et al.(2015)	Province in China	IDA	Region's emission performance was decomposed into structure effect and energy intensity effect.
	Su and Ang (2016)	Province in China	SDA	30 geographical regions in China are compared and ranked based on their emission performance.
	Long et al. (2016)	Province in China	Moran's I index and spatial panel data models.	Carbon productivity: high in the east and lower in the west; high in the south and lower in the north.
	Wang and Zhou (2018)	Global	PDA	The driving forces of regional disparities in CO_2 emission intensity from viewpoints of production technology and technical efficiency were revealed.
Sub-industrial sectors	Sun et al. (2016)	Electricity in China	Multi-Dimensional Decomposition	Electric carbon productivity can be decomposed into a technological improvement effect and structure adjustment effect.
	Zhao and Lin (2019)	Textile industry in China	DEA and the Biennial Malmquist–Luenberger (BML)	The average growth rates of technical improvement, labor, capital for energy substitution, and output structural change are the main factors that improve energy productivity.

3. Method and data sources

3.1 Method

Spatial PDA combined with PDA and a M-R model is usually carried out on a spatial dimension for a specific year, revealing the effect of production technology and efficiency on energy and emissions (Wang and Zhou, 2018). Suppose the entire economy includes N regions (N is the number of regions, here N=29) and each region has M industrial sectors (S1, S2, …, here M=22), then based on the M-R model[3], the average of measured regions is defined as a reference region. There are $N+1$ (j=1, …, N, $N+1$, and the reference region R is included) regions and M industrial sectors (i=1, ..., M) in regions to be evaluated. In the process of economic production activities, the GDP of industrial sectors, ie industrial added value (Y), is regarded as desirable output. Energy-related CO_2 emissions (C) are regarded as undesirable output and can be obtained after inputting production factors, i.e. aggregate capital (K) energy consumption (E), and labor (L) at the sector level (Nabavi-Pelesaraei et al., 2013).

According to Färe et al. (2005), the production technology can be defined as

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

where T satisfies the assumptions: (i) if $(K, L, E, Y, C) \in T$ and $0 \leq \theta \leq 1$, then $(K, L, E, \theta y, \theta C) \in T$ and (ii) if $(K, L, E, Y, C) \in T$, and C=0, then Y=0. Suppose the production technology is constant returns to scale (CRS), which has been widely adopted to modelling environmental production technology (Wang, 2013; Bostian et al., 2016). For each sector i, the environmental production technology is defined as follows.

[3]In the M-R model, the average level of all measured regions is defined as the reference region, and then the comparison is made between each target region and the reference region. For more details on this model, refer to Ang et al. (2015).

$$T=\{(K_i, L_i, E_i, Y_i, C_i): \sum_j \lambda_j K_{ij} \leq K_i;\ \sum_j \lambda_j L_{ij} \leq L_i;$$

$$\sum_j \lambda_j E_{ij} \leq E_i;\ \sum_j \lambda_j Y_{ij} \geq Y_i;\ \sum_j \lambda_j C_{ij} = C_i;\ \lambda_j \geq 0, j=1, ..., N+1\} \quad (2)$$

Two Shephard undesirable and desirable output distance functions can be derived by solving the following linear programs, which have been widely used in PDA (Zhou and Ang ,2008; Wang et al., 2015; Wang and Zhou, 2018).

The undesirable output distance function is defined as:

$$D_{in}^{C}(K_i,L_i,E_i,Y_i,C_i)^{-1} = min\,\beta_{in}$$

$$\text{s.t.}\{\sum_j \lambda_j K_{ij} \leq K_{in}; \sum_j \lambda_j L_{ij} \leq L_{in}; \sum_j \lambda_j E_{ij} \leq E_{in}; \sum_j \lambda_j Y_{ij} \geq Y_{in};$$

$$\sum_j \lambda_j C_{ij} = \beta_{in} C_{in}; \lambda_j \geq 0, j=1, ..., N+1\} \quad (3)$$

and the desirable output distance function can be defined as follows

$$D_{in}^{Y}(K_i,L_i,E_i,Y_i,C_i)^{-1} = max\theta_{in}$$

$$\text{s.t.}\{\sum_j \lambda_j K_{ij} \leq K_{in};\ \sum_j \lambda_j L_{ij} \leq L_{in};\ \sum_j \lambda_j E_{ij} \leq E_{in};\ \sum_j \lambda_j Y_{ij} \geq \theta_{in} Y_{in};$$

$$\sum_j \lambda_j C_{ij} = C_{in};\ \lambda_j \geq 0, j=1,..., N+1\} \quad (4)$$

where n represents the region under measurement, and λ represents the intensity variable. The above distance function shows the distance from the technology frontier. C_{in}/β_{in}^{*} in Eq. (3) represents the minimum emissions level, while Y_{in}/θ_{in}^{*} in Eq. (4) represents the maximum desired output level, where * denotes optimal solutions (Wang and Zhou, 2018).

Based on the definition of carbon productivity in Kaya and Yokobori (1999), the ICP of the *jth* region can be modeled as:

$$P_j = \frac{Y_j}{C_j} = \sum_{i=1}^{M} \frac{Y_{ij}}{E_{ij}} \cdot \frac{E_{ij}}{C_{ij}} \cdot \frac{C_{ij}}{C_j} = \sum_{i=1}^{M} \frac{Y_{ij}}{E_{ij}} \cdot \frac{E_{ij}}{C_{ij}} \cdot S_{ij}^{C} \quad (5)$$

Here P_j denotes the carbon productivity of region j, Y_{ij}/E_{ij} represents the energy efficiency of the *ith* sector in region *j*, and E_{ij}/C_{ij} denotes energy consumption per unit of CO_2 emissions of the *i* industrial sector in *j* region. E_{ij}/C_{ij} is the energy emission ratio, which is the reciprocal of the energy-carbon conversion rate. The energy-carbon conversion rate is only affected by the energy mix, under the premise that the carbon emission factors of various types of energy remain unchanged (Xu et al., 2014). According to the Intergovernmental Panel on Climate Change (IPCC), CO_2 emission factors of various types of energy are generally constant. Therefore, the changes in energy emission ratios reflect changes in the energy mix. S_{ij}^{C} in Eqs. (5) represents the proportion of CO_2 emissions from a particular sub-sector *i* to total industrial CO_2 emissions in region *j*, which is named as CO_2 emissions structure (*Str-C*) and reflects industrial structure (Lu et al., 2014).

Combining Eqs. (3), (4) and (5), ICP can be decomposed as follows (6)

$$
\begin{aligned}
P_j &= \sum_{i=1}^{M} \frac{Y_{ij}}{E_{ij}} \cdot \frac{E_{ij}}{C_{ij}} \cdot S_{ij}^{C} \\
&= \sum_{i=1}^{M} \frac{Y_{ij}/D_{ij}^{Y}(K_i, L_i, E_i, Y_i, C_i)}{E_{ij}} \cdot \frac{E_{ij}}{C_{ij}/D_{ij}^{C}(K_i, L_i, E_i, Y_i, C_i)} \cdot \frac{D_{ij}^{Y}(K_i, L_i, E_i, Y_i, C_i)}{D_{ij}^{C}(K_i, L_i, E_i, Y_i, C_i)} \cdot S_{ij}^{C} \\
&= \sum_{i=1}^{M} \left[\frac{1}{Y_{ij}} \left(\frac{1}{E_{ij}}\right)^{-1} \cdot D_{ij}^{Y}(K_i, L_i, E_i, Y_i, C_i)\right]^{-1} \cdot \frac{E_{ij}}{C_{ij}/D_{ij}^{C}(K_i, L_i, E_i, Y_i, C_i)} \cdot \frac{D_{ij}^{Y}(K_i, L_i, E_i, Y_i, C_i)}{D_{ij}^{C}(K_i, L_i, E_i, Y_i, C_i)} \cdot S_{ij}^{C} \\
&= \sum_{i=1}^{M} \left[\frac{1}{Y_{ij}} \cdot D_{ij}^{Y}(k_{ij}, l_{ij}, 1, Y_i, c_{ij})\right]^{-1} \cdot \frac{E_{ij}}{C_{ij}/D_{ij}^{C}(K_i, L_i, E_i, Y_i, C_i)} \cdot \frac{D_{ij}^{Y}(K_i, L_i, E_i, Y_i, C_i)}{D_{ij}^{C}(K_i, L_i, E_i, Y_i, C_i)} \cdot S_{ij}^{C} \\
&= \sum_{i=1}^{M} D_{ij}^{Y}(k_{ij}, l_{ij}, 1, 1, c_{ij})^{-1} \cdot \frac{E_{ij}}{C_{ij}/D_{ij}^{C}(K_i, L_i, E_i, Y_i, C_i)} \cdot \frac{D_{ij}^{Y}(K_i, L_i, E_i, Y_i, C_i)}{D_{ij}^{C}(K_i, L_i, E_i, Y_i, C_i)} \cdot S_{ij}^{C} \\
&= \sum_{i=1}^{M} D_{ij}^{Y}(k_{ij}, l_{ij}, 1, 1, c_{ij})^{-1} \cdot PCF_{ij}^{-1} \cdot CPI_{ij} \cdot S_{ij}^{C} \qquad (6)
\end{aligned}
$$

where $k_{ij} = K_{ij}/E_{ij}$ denotes the capital-energy ratio (KE), $l_{ij} = L_{ij}/E_{ij}$ is the labor-energy ratio (LE), and $c_{ij} = C_{ij}/E_{ij}$ is the carbon factor[4] (CF) (Ang, 1999).

[4]The carbon factor is different from the emission factor. The emissions factor is the amount of carbon oxidized per unit of fuel consumed, and its main match is fuel. The

$(C_{ij}/D_{ij}^{C}(K_i,L_i,E_i,Y_i,C_i))/E_{ij}$ is defined as the potential carbon factor (PCF) which reflects the potential level of the carbon factor when the technical efficiency of an entity in terms of emissions can be promoted to the best practice (Wang and Zhou, 2018; Zhou and Ang, 2008). $D_{ij}^{Y}(K_i,L_i,E_i,Y_i,C_i)/D_{ij}^{C}(K_i,L_i,E_i,Y_i,C_i)$ is defined as the carbon performance index (CPI) and is the ratio of actual carbon productivity to potential carbon productivity, which is between 0 and 1. A larger CPI represents better CO_2 emissions performance, which mainly reflects the technical efficiency of emission (Zhou et al., 2012). If the CPI is equal to unity, it means that the province has the best CO_2 emissions performance in the special sector.

Taking the average level of all regions, as a reference, the ratio in ICP between region j and the reference region r can be decomposed by using LMDI-I as follows.

$$\frac{P_j}{P_r}=\frac{\sum_{i=1}^{M}D_{ij}^{Y}(k_{ij},\,l_{ij},\,1,\,1,\,c_{ij})^{-1}\cdot PCF_{ij}^{-1}\cdot CPI_{ij}\cdot S_{ij}^{C}}{\sum_{i=1}^{M}D_{ir}^{Y}(k_{ir},\,l_{ir},\,1,\,1,\,c_{ir})^{-1}\cdot PCF_{ir}^{-1}\cdot CPI_{ir}\cdot S_{ir}^{C}}$$

$$=exp\left(\sum_{i=1}^{M}w_i^{j,\,r}\,ln\frac{D_{ir}^{Y}(k_{ir},\,l_{ir},\,1,\,1,\,c_{ir})}{D_{ij}^{Y}(k_{ij},\,l_{ij},\,1,\,1,\,c_{ij})}\right)\cdot exp\left(\sum_{i=1}^{M}w_i^{j,\,r}\,ln\frac{PCF_{ir}}{PCF_{ij}}\right)$$

$$\cdot\,exp\left(\sum_{i=1}^{M}w_i^{j,\,r}\,ln\frac{CPI_{ij}}{CPI_{ir}}\right)\cdot exp\left(\sum_{i=1}^{M}w_i^{j,\,r}\,ln\frac{S_{ij}^{C}}{S_{ir}^{C}}\right)=A_{mix}^{j,\,r}\cdot A_{PCF}^{j,\,r}\cdot A_{CPI}^{j,\,r}\cdot A_{str\text{-}C}^{j,\,r} \quad (7)$$

$$w_i^{j,r}=\frac{L(Y_{ij}/C_j,Y_{ir}/C_r)}{L(P_j,P_r)} \quad (8)$$

$$L(a,b)=\begin{cases}\dfrac{a-b}{\ln a-\ln b}, & a\neq b\\ a, & a=b\end{cases} \quad (9)$$

where A represents the multiplicative effects, w represents the weight function and L is the logarithmic mean function (Ang, 2015). The subscript *mix* represents the comprehensive effect involving the *KE*, *LE*, and *CF* difference, and *str-C* represents

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"carbon factor" is the ratio of CO_2 emissions to energy consumption and it can be disaggregated into the emission factor and the fuel share (Ang, 1999).

the CO_2 emission structure effect. Hence the disparity in industrial carbon productivity between region j and r is mainly caused by these four effects. The result of multiplicative decomposition can express the relative contributions of regional ICP attributable to regional differences in one driving factor based on the same absolute amount (here is the national average) (Ang, 2004; Ang et al., 2015).

To quantify the difference of three effects, i.e. *KE*, *LE*, and *CF* between region j and region r, it is necessary to carry out the second stage of decomposition. Putting the three factors in $A_{mix}^{j,r}$ into $D_{ir}^{Y}(k_{ir},l_{ir},1,1,c_{ir})/D_{ij}^{Y}(k_{ij},l_{ij},1,1,c_{ij})$ one by one in different combinations by using Laspeyres-linked methods (Wang et al., 2017), there are six decomposition results. This method coincides with the Siegel formula, and has been used by (Wang and Zhou, 2018). The decomposition form of the second stage can be expressed as Eq. (10).

$$\frac{D_{ir}^{Y}(k_{ir}, l_{ir}, 1, 1, c_{ir})}{D_{ij}^{Y}(k_{ij}, l_{ij}, 1, 1, c_{ij})}$$

$$= \left\{\left[\frac{D_{ir}^{Y}(k_{ir}, l_{ir}, 1, 1, c_{ir})}{D_{i}^{Y}(k_{ij}, l_{ir}, 1, 1, c_{ir})}\right]^{2} \cdot \left[\frac{D_{i}^{Y}(k_{ir}, l_{ij}, 1, 1, c_{ij})}{D_{ij}^{Y}(k_{ij}, l_{ij}, 1, 1, c_{ij})}\right]^{2} \cdot \left[\frac{D_{i}^{Y}(k_{ir}, l_{ij}, 1, 1, c_{ir})}{D_{i}^{Y}(k_{ij}, l_{ij}, 1, 1, c_{ir})}\right] \cdot \left[\frac{D_{i}^{Y}(k_{ir}, l_{ir}, 1, 1, c_{ij})}{D_{i}^{Y}(k_{ij}, l_{ir}, 1, 1, c_{ij})}\right]\right\}^{\frac{1}{6}} \cdot$$

$$\left\{\left[\frac{D_{ir}^{Y}(k_{ir}, l_{ir}, 1, 1, c_{ir})}{D_{i}^{Y}(k_{ir}, l_{ij}, 1, 1, c_{ir})}\right]^{2} \cdot \left[\frac{D_{i}^{Y}(k_{ij}, l_{ir}, 1, 1, c_{ij})}{D_{ij}^{Y}(k_{ij}, l_{ij}, 1, 1, c_{ij})}\right]^{2} \cdot \left[\frac{D_{i}^{Y}(k_{ij}, l_{ir}, 1, 1, c_{ir})}{D_{i}^{Y}(k_{ij}, l_{ij}, 1, 1, c_{ir})}\right] \cdot \left[\frac{D_{i}^{Y}(k_{ir}, l_{ir}, 1, 1, c_{ij})}{D_{i}^{Y}(k_{ir}, l_{ij}, 1, 1, c_{ij})}\right]\right\}^{\frac{1}{6}} \cdot$$

$$\left\{\left[\frac{D_{ir}^{Y}(k_{ir}, l_{ir}, 1, 1, c_{ir})}{D_{i}^{Y}(k_{ir}, l_{ir}, 1, 1, c_{ij})}\right]^{2} \cdot \left[\frac{D_{i}^{Y}(k_{ij}, l_{ij}, 1, 1, c_{ir})}{D_{ij}^{Y}(k_{ij}, l_{ij}, 1, 1, c_{ij})}\right]^{2} \cdot \left[\frac{D_{i}^{Y}(k_{ij}, l_{ir}, 1, 1, c_{ir})}{D_{i}^{Y}(k_{ij}, l_{ir}, 1, 1, c_{ij})}\right] \cdot \left[\frac{D_{i}^{Y}(k_{ir}, l_{ij}, 1, 1, c_{ir})}{D_{i}^{Y}(k_{ir}, l_{ij}, 1, 1, c_{ij})}\right]\right\}^{\frac{1}{6}}$$

$$= KE_{i}^{j,r} \cdot LE_{i}^{j,r} \cdot CF_{i}^{j,r} \tag{10}$$

The ratio of j and r in ICP can be decomposed as Eq. (11)

$$\frac{P_j}{P_r} = A_{KE}^{j,r} \cdot A_{LE}^{j,r} \cdot A_{CF}^{j,r} \cdot A_{PCF}^{j,r} \cdot A_{CPI}^{j,r} \cdot A_{str\text{-}C}^{j,r} \tag{11}$$

Compared with the reference region *r*, the carbon factor effect (CFE), the labor-energy substitution effect (LESE) and the capital-energy substitution effect (KESE) of region *j* are $A_{CF}^{j,r}$, $A_{LE}^{j,r}$, $A_{KE}^{j,r}$, respectively. The CFE is mainly influenced by the energy consumption structure. The KESE and LESE represents the level of substitution of capital for energy and labor for energy, respectively. If the decomposition value is greater than 1, it means that the relevant factors cause the gap between region *j* and *r* to increase in terms of ICP and vice versa. Hence the disparity in ICP between region *j* and *r* was found to be caused mainly by these six effects (ref. Eqs. 11).

3.2 Data sources and description

Our research employs sectoral level data for various industries in 29 of China's provinces/regions. (Unfortunately, the ICP for Hong Kong, Macao, Taiwan, Hainan and Tibet could not be calculated due to excessive gaps in the published data.) All input and output variables in this study were aggregated into a unified classification with 22 sectors (Appendix A2), and the price was converted to the 1997 constant level by using the double deflation method (United Nations, 1999). [5]

The spatial-PDA decomposition model involves six variables, i.e. industrial added value, capital, labor, energy consumption (*E*), energy-related CO_2 emissions (*C*), and ICP (*P*). The industrial value added (in one hundred million CNY) collected from the *China Industry Statistical Yearbook*, 2017 (NBSC, 2017), eliminated the influence of price fluctuations. The data for capital (in one hundred million CNY) was gathered

[5] The data can be shared upon reasonable request.

from *China Fixed Assets Investment Statistics Yearbook, 2017* (NBSC, 2017a). The labor was measured using the average number of sectoral employed people working in each sector at the end and beginning of the year 2016 with the unit as 10,000 people, and derived from *China Population and Employment Statistics Yearbook, 2017* (NBSC, 2017b). The data pertaining to the different types of energy consumed in the various regions and industrial sectors were collected from *China Energy Statistical Yearbook* (NBSC, 2017c) and *Provincial Statistical Yearbooks* (NBSC, 2017d) and converted into a calorific value in Tega joule (TJ).

The industrial CO_2 emissions from 22 industrial sectors in each of the 29 provinces were estimated using the method from Shan et al. (2020). Although this method required high-quality and quantitative data sets, a more detailed emission inventory could be obtained, which included the emissions of 47 industrial subsectors and 17 energy types in each region. In this research, we classified these 40 industrial sectors into 22 industrial sectors according to the method of Geng et al. (2013). The CO_2 emissions were caused mainly by fossil fuel combustion and industrial production.

Industrial CO_2 emissions from fossil fuel combustion were derived based on the relation:

$$C_{ui} = \sum_{u=1}^{17} \sum_{i=1}^{22} AD_{ui} \cdot NCV_u \cdot EF_u \cdot O_{ui} \tag{12}$$

where C_{ui} refers to the CO_2 emissions from fossil fuel u combusted in industrial sector i; AD_{ui} refers to the activity level of fossil fuel u in sector i; NCV_u and EF_u represent the net caloric value and emission factor of different fuel types, respectively. In this study, EF_u was based on the result of Liu et al. (2015), which was measured by analyzing 602 coal samples from the 100 largest coal-mining areas in China (Liu et al., 2015). O_{uj} represents a carbon oxidation ratio for different sectors and fuel types.

Industrial CO_2 emissions from industrial production on the other hand was computed as:

$$C_v = \sum_v AD_v \cdot EF_v \tag{13}$$

where C_v indicates CO_2 emissions from industrial processes v; AD_v indicates activity data; and EF_v refers to the emissions factor. Most of this information was collected from IPCC (2006), except for the cement process from Liu et al. (2015).

Accounting to Eq. (5), ICP was calculated as follows:

$$P = Y/C \tag{14}$$

The statistical result of the input and output variables showed significant differences across the 29 provinces, with the maximum value being approximately 13 times larger than the minimum value in ICP (see Table 2). r as a reference region was built by the average number of three input variables (K, L, E) and two output variables (Y, C) for the 29 provinces in the M-R model (see Table Appendix B). Moreover, the average value of all variables except ICP was larger than the median value, indicating a right-skewed data distribution.

Table 2. The statistical description of industrial inputs and outputs of 29 provinces, 2016

	Capital (10^8 CNY)	Labor (10^4 persons)	Energy Consumption (10^{16} Joules)	Industrial value-added (10^8 CNY)	CO_2 emissions (10^4 tons)	ICP (CNY/kg)
Maximum	26442.71	2277.93	867.79	32650.89	73658.16	10.32
Minimum	709.81	45.10	51.27	901.68	3902.35	0.77
Mean	7820.72	570.83	308.40	9814.06	27688.33	3.54

Median	6370.01	345.14	236.28	7219.11	20118.87	3.70
Standard deviation	6507.21	527.17	189.50	8194.00	18010.40	2.28

4. Results

4.1 Empirical results and analysis at the provincial level

4.1.1 Spatial distribution characteristics

Figure 1 portrays the variation tendencies present in industrial carbon emissions, China's ICP, and the ICP of eastern, northeast, central, and western China from 2000 to 2016. In terms of carbon emissions, there was an upward trend until 2013, and a downward trend after 2013 until 2016. It is clear that China's overall and regional ICP were generally on an upward trend, only to decrease briefly between 2008 and 2009. After 2009, it improved dramatically again, with the ICP reaching a peak in eastern China (4.7 CNY/Kg), the central region (3.4 CNY/Kg) and western region (2.5 CNY/Kg) in 2016, respectively, whereas in the northeast region (3 CNY/Kg) in 2014.

Figure 2 shows the industrial CO_2 emissions and carbon productivity of the 29 provinces and the reference region in China during the period studied. Regarding industrial CO_2 emissions, Shandong (736.58 million tons), Hebei (658.89 million tons) and Jiangsu (654.50 million tons) were the top three provinces, while Shanghai (116.65 million tons), Qinghai (45.63 million tons), and Beijing (39.02 million tons) were the bottom three provinces. This is consistent with the results of Shan et al. (2020). The regional distribution of CO_2 emissions and carbon productivity varied greatly due to the differences in GDP.

China's ICP of 3.54 yuan value added per unit of CO_2 (CNY/kg) in 2016, was lower than China's overall carbon productivity, 4.576 CNY/Kg (Li and Wang, 2019).

The ICP of the reference region (3.54 CNY/Kg) ranked seventeenth among 30 regions. Beijing (10.32 CNY/kg), Guangdong (8.54 CNY/kg) and Shanghai (6. 48 CNY/kg) were the top cities in terms of ICP in 2016. Xinjiang (0.77 CNY/kg) had the worst ICP, followed by Ningxia (0.78 CNY/kg) and Shanxi (1.06 CNY/kg). The results indicate that the ICP of Beijing was 13.33 times that of Xinjiang.

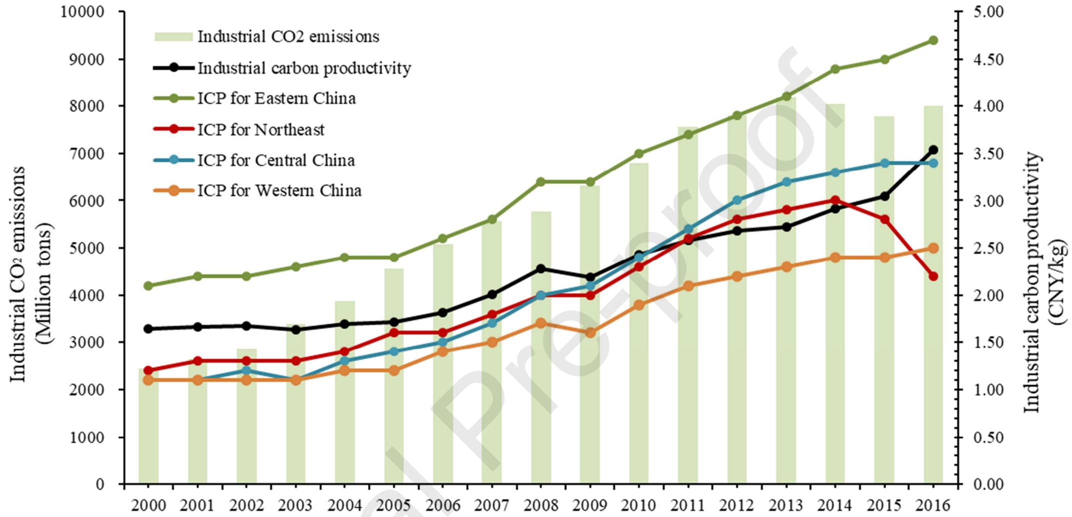

Figure 1. China's industrial CO_2 emissions and ICP from 2000 to 2016. *Source*: the China Emission Accounts and Datasets (CEADs)

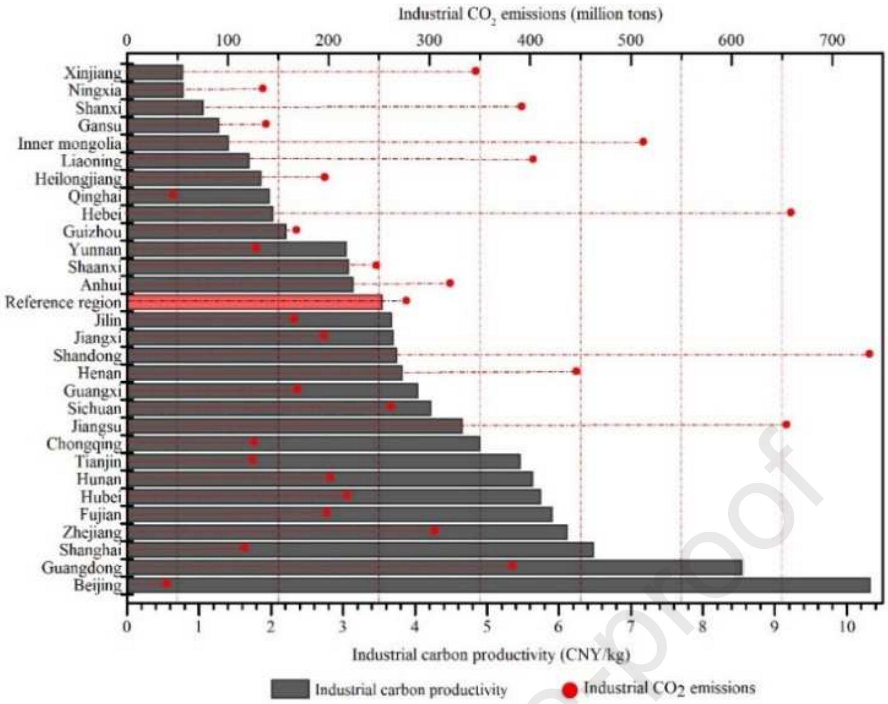

Figure 2. Industrial CO_2 emissions and ICP in 29 provinces and the reference region, 2016.

Notes: The top X-axis is the scale that matches the industrial CO_2 emissions, while the bottom X-axis is the scale that matches the ICP.

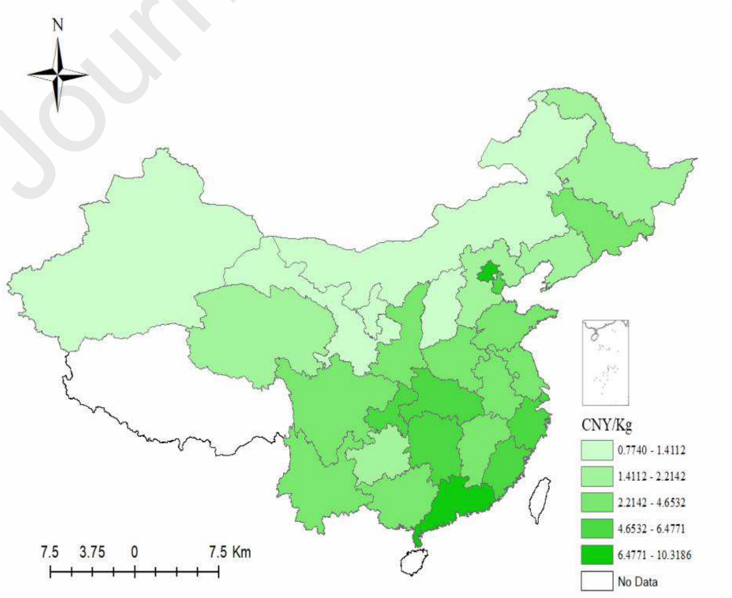

Figure 3. The spatial distribution of ICP in China, 2016.

The geographical spatial distribution of ICP is plotted in Figure 3. The ICP in the southeast coastal provinces was the highest, followed by that in the mid-west provinces. It can be observed from Figure 3 that the ICP of most of the eastern provinces was above the average level (3.54 CNY/Kg) in 2016, except for Hebei and Liaoning. In contrast, the ICP for most of the western provinces was less than that of the reference region, except for Chongqing, Sichuan, and Guangxi. In the middle of China, the ICP for five out of the eight provinces was higher than the average level. This result is roughly consistent with the work result of Long et al. (2016).

4.1.2 Provincial-level disparities

Figure 4 reports the provincial aggregated ICP and its decomposition results compared to the reference region. Among the 29 provinces, the KESE played a positive role in 20 provinces in driving up their ICP compared to the reference region. This means that it is an important component in understanding the provincial disparities in ICP. By contrast, the LESE contributed negatively to the increase in the regional disparities in ICP for all provinces except Beijing, Liaoning, Anhui, Jiangxi, and Hunan. Relative to the average level, KESE drives most provinces' ICP higher. LESE was a more potent factor than KESE in terms of improving technological efficiency in production for 24 out of the 29 provinces. This is consistent with the results obtained by Wang and Zhou (2018). Lin and Du (2014) analyzed these two driving factors when examining the decline in China's energy intensity and reported similar findings.

Next, the carbon performance index effect (CPIE) in most of the eastern and central provinces was higher than 1, particularly for Beijing, Guangdong and Shanghai, which drove their ICP higher than in the reference region. In contrast, the CPIE for

Hebei, Liaoning, Heilongjiang, Shanxi, and most of the western provinces played a negative role in increasing their ICP compared to the average level. This is consistent with most literature (Lin and Du, 2015; Yao et al., 2016; Zhou et al., 2013) and suggests that compared to the average level, the technical efficiency of Hebei, two northeast provinces and most of the western provinces in terms of CO_2 emissions, has not promoted their overall ICP. Compared to the average level, the CFE and potential carbon factor effect (PCFE) contributed negatively to the increase in regional disparities in ICP for all provinces in China. These results reveal that there is an imbalance in the energy consumption structure regarding most of the provinces in China (Wang et al., 2015). This therefore suggests that the CFE and PCFE could be further improved.

CESE was another factor contributing to increasing the regional disparities between each province and the reference region in terms of ICP. There was no evidence of any significant improvement with regards to the diversities in ICP among most provinces, except for Shanghai, Zhejiang, Fujian, Guangdong, Jilin, Hubei, Sichuan, Chongqing, and Qinghai. Compared to the reference region, emission structure only drove up carbon productivities in nine provinces Hence, there is great potential to improve regional ICP through industrial structure adjustment. This is consistent with the results reported in (Meng and Niu, 2012).

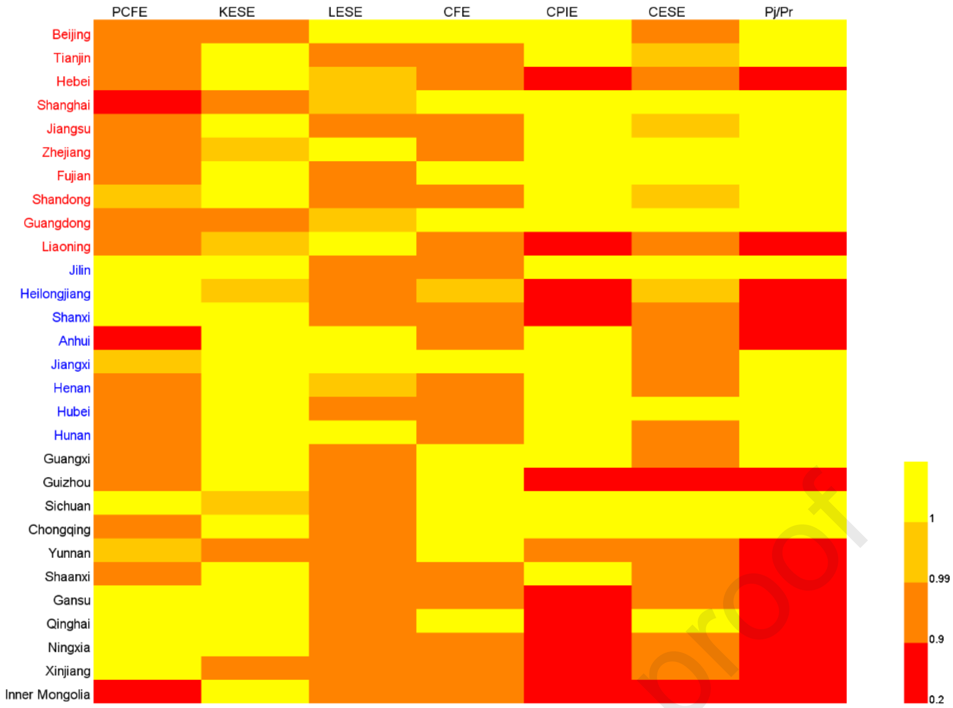

Figure 4. Decomposition results compared with those of the reference region

Notes: The red, blue, and black fonts in the title on the vertical axis portray provinces in eastern, central, and western China, respectively

4.2 Empirical results and analysis at the sectoral level

4.2.1 Sectoral level disparities for the ICP in China

Figure 5 portrays the industrial CO_2 emissions and ICP of 22 industrial sectors in China. The top three sectors in CO_2 emissions were the electricity sector (S20), smelting and pressing of metals (S13) together with nonmetal mineral products (S12), followed by petroleum processing and coking (S10), coal mining and dressing (S1) and the chemical sector (S11). All of these are energy-intensive industrial subsectors. However, the carbon productivity for these sectors was low. The absolute difference in sectoral carbon productivity was significant. The ICP of sectors categorized as low-carbon industries was generally higher than that included in carbon-intensive industries. This is consistent with the results of (W. Li et al., 2018), in the sense that carbon productivity of the top sector, namely, manufacturing of electronics, instruments, culture and office equipment (S18) (388.20 CNY/kg) was 109.52 times the level of overall ICP (3.54 CNY/kg) in China, while the electricity sector (S20) (0.34 CNY/kg) had the lowest carbon productivity. Although the electricity sector is a high energy-consuming industry striving for a low-carbon development, the continued heavy reliance on coal to generate electricity has not changed. In 2016, the proportion of fossil energy generating electricity reached 73% (Li et al., 2017). Moreover, coal prices have risen sharply since March 2016, increasing the cost of electricity and posing a huge challenge to the growth of carbon productivity in the electricity sector (National Energy Administration in China, 2016).

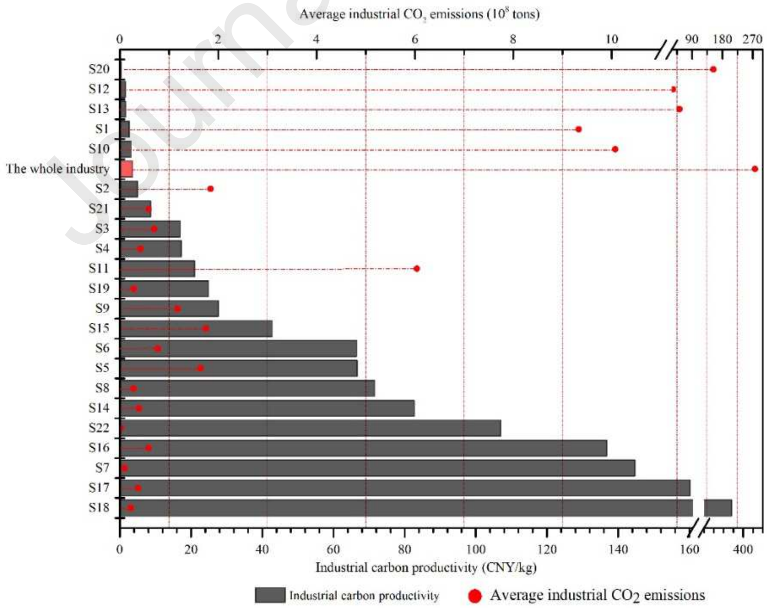

Figure 5. Average industrial CO_2 emissions and ICP in 22 industrial sectors in China, 2016

Notes: *The top X-axis is the scale that matches the industrial CO_2 emissions, while the bottom X-axis is the scale that matches the ICP. The term "industry" denotes China's overall industrial sector.*

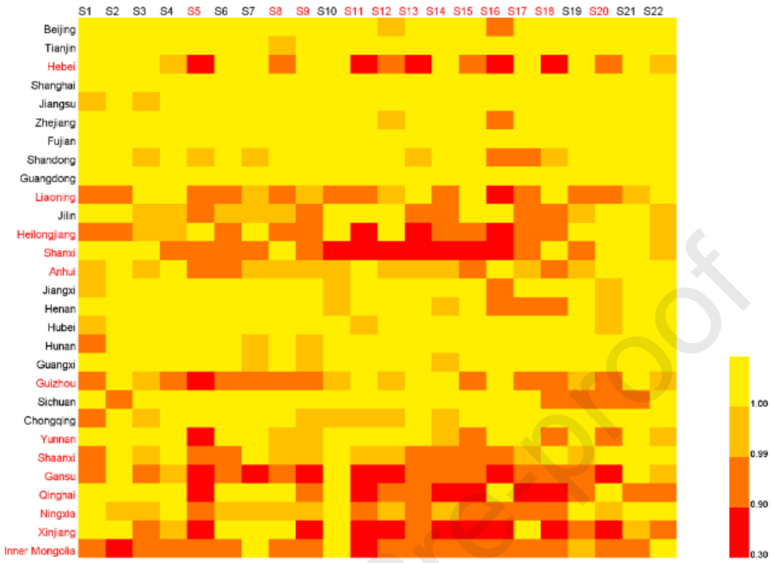

Figure 6. Sectoral decomposition results of comparing industrial sectors in 29 regions to the reference region

Notes: *The horizontal axis represents 22 industrial sectors and the vertical axis represents 29 provinces. The red font in the title on the vertical axis portrays the 13 provinces with a below-average ICP level (the ICP of reference region). The red font in the title on the horizontal axis indicates that 12 industrial subsectors were the main cause of the below-average ICP in these 13 provinces. The yellow area indicates that the decomposition value was greater than 1. The other color areas were less than 1, where red represents the minimum value.*

Next, carbon productivity was considered at the sectoral level (horizontal axis in Figure 6). From Figure 6, the value below 1 indicates that a specific industrial sector contributed to the overall ICP of its corresponding region and was lower than the reference region (average level). For instance, petroleum and natural gas extraction (S2) contributed to the lower ICP of 5 regions, including Liaoning, Heilongjiang, Sichuan, Ningxia and Inner Mongolia, and contributed to the higher ICP for the other 24 regions compared to the reference region. The result points out that compared to the reference region, improvements in the carbon productivity of S2 in these five provinces should be prioritized for effectively increasing these provinces' overall ICP. In contrast to the reference region, the petroleum and natural gas extraction and processing sectors (including S2, S10, and S21) contributed the most to increasing most regions' ICP. Meanwhile, the paper, printing, culture articles manufacturing and metal products sectors (S9 and S14) were the weak sectors in most of the northeast, central and western regions, and caused these regions' ICP to be lower than that of the reference region. In addition, the chemicals sector (S11) in seven regions, Hebei, Heilongjiang, Shanxi, Gansu, Qinghai, Xinjiang, and Inner Mongolia, obviously resulted in levels of carbon productivity that were worse than the average level.

From the regional level (the vertical axis in Figure 6), we found that industrial subsectors with below-average carbon productivity were distributed mainly in **13 regions**, that is **Hebei, Liaoning, Heilongjiang, Shaanxi, Anhui, Shanxi, Yunnan, Guizhou, Qinghai, Inner Mongolia, Gansu, Ningxia, and Xinjiang.** This result is completely consistent with that of the regions in Figure 2 where the overall ICP was lower than the average level. These 13 provinces deserve more attention to effectively improve China's overall ICP. Hence, this study focused on these 13 regions.

We further investigated the major industrial sectors affecting the ICP for the 13 regions in 2016, From Figure 6, the driving industrial sectors affecting ICP had significant heterogeneity among regions. For example, for Hebei province, the main industrial sectors that caused its ICP to be below average level were S4, S5, S8, S11, S12, S13, S15, S16, S18, S20, and S22, while for Yunnan, they were S5, S8, S9, S14, S15, S18, S20, and S22, for Shanxi, they were S4, S5, S6, S7, S9, S10, S11, S12, S13, S14, S15, S16, S17, S19, and S22. However, for the 13 provinces, the following **12 major industrial sectors** contributed to their below-average carbon productivity, including five **energy-intensive manufacturing** sectors (including food and tobacco (**S5**), paper and painting (**S9**), chemicals (**S11**), non-metallic minerals (**S12**) and refining (**S13**)), six **nonenergy intensive manufacturing sectors** (including wood products (**S8**), fabricated metal products (**S14**), and ordinary and special equipment (**S15**), transportation equipment (**S16**), machinery and electrical equipment **(S17**), and computer and electronic products (**S18**)), and the sector for production and supply of electric power, steam and hot water (**S20**)[6].

4.2.2 Contributions to ICP from the industrial sectors in each region

The driving factors behind the regional disparities in carbon productivity across 12 industrial sectors in the 13 regions mentioned above need further analysis. From the sectoral perspective, the contribution of each driving force in 22 sectors in each region was significantly different. Taking Hebei as an example in Table 3, according to the analysis in Section 4.1.2, PCFE, LESE, CFE, CPIE, and CESE contributed to a lower overall ICP than the reference region at the provincial level,. This reveals that the improvements in PCFE, CFE, LESE, CPIE, and CESE had greater potential than

[6]These 12 industrial sectors are the most important driving factors behind ICP in the 13 provinces (Hebei, Liaoning, Heilongjiang and most of the central and western provinces) selected in this paper, but not for all provinces in China.

KESE to increase Hebei's ICP. However, that proposal is not targeted for all 22 industry sectors in Hebei. From Table 3, in terms of transportation equipment (S16) (0.7791) in Hebei, CFE, CPIE, and CESE values were less than 1, suggesting that the local government of Hebei should pay more attention to the improvement of transportation equipment manufacturing and CO_2 emission performance. The decomposition result of each industrial sector in every region was similarly conducted.

Table 3 Sectoral decomposition results of comparing industrial sectors in Hebei to the reference region

Sector	PCFE	KESE	LESE	CFE	CPIE	CESE	Total
S1	0.9939	0.9969	1.0006	0.9969	1.1356	1.0011	1.1235
S2	0.9942	0.9998	1.0001	0.9991	1.1351	0.9994	1.1268
S3	0.9994	0.9999	0.9994	0.9945	1.0530	0.9997	1.0455
S4	1.0000	1.0004	0.9993	0.9962	0.9981	0.9991	0.9932
S5	0.9997	1.0014	0.9999	0.9874	0.8770	0.9949	0.8625
S6	0.9958	1.0003	0.9995	0.9918	1.1065	0.9959	1.0881
S7	0.9987	1.0001	0.9999	0.9915	1.0146	1.0001	1.0047
S8	1.0005	1.0001	0.9993	0.9962	0.9788	0.9987	0.9737
S9	0.9983	1.0006	1.0000	0.9965	1.0298	0.9971	1.0221
S10	0.9979	1.0011	1.0013	1.0067	1.0355	0.9976	1.0403
S11	0.9982	1.0038	1.0005	0.9749	0.8581	0.9921	0.8321
S12	0.9997	1.0014	0.9988	0.9949	0.9890	0.9963	0.9801
S13	1.0028	1.0053	0.9933	1.0162	0.8393	1.0137	0.8657
S14	0.9981	1.0000	1.0001	0.9932	1.0590	0.9993	1.0492
S15	1.0002	1.0002	1.0000	1.0042	0.9243	0.9983	0.9269
S16	1.0051	1.0019	1.0022	0.9953	0.7795	0.9951	0.7791
S17	0.9994	1.0001	1.0006	0.9933	1.0177	0.9941	1.0051
S18	0.9994	1.0012	1.0012	0.9942	0.7876	0.9971	0.7822
S19	1.0005	1.0002	1.0000	1.0035	1.0051	0.9989	1.0082
S20	1.0027	1.0004	0.9978	0.9981	0.9517	0.9975	0.9484
S21	0.9997	1.0002	1.0003	0.9999	1.0249	0.9984	1.0233
S22	0.9999	1.0000	1.0000	0.9996	0.9969	0.9999	0.9963

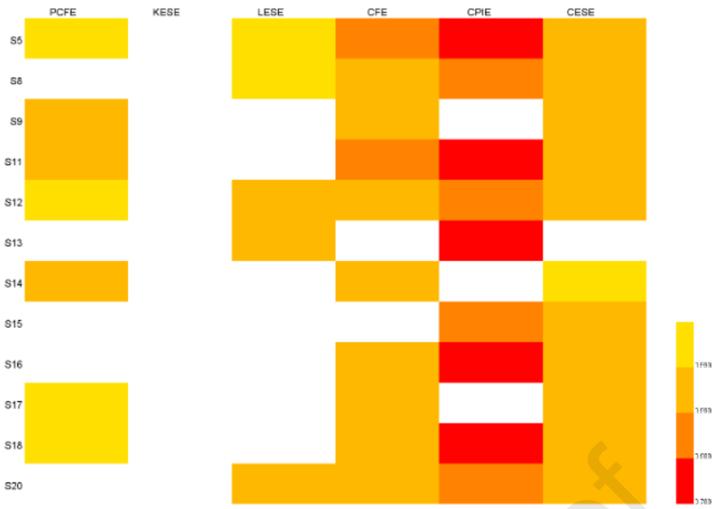

Figure 7. ICP's decompositions for Hebei

Notes: The blank area indicates the decomposition result is higher than 1 and vice versa. The red indicates the minimum decomposition value. For instance, for chemical sector (S11), the driving factors of KESE and LESE increase its carbon productivity compared to the average level. The primary contributor to below-average carbon productivity in S11 of Hebei is CPIE, followed by CFE, CESE and PCFE.

Taking the 12 industrial sectors in Hebei as an example, in Figure 7, if the decomposition index value of the driving forces was less than 1, the influencing factor caused the regional ICP to be lower than that of the reference region. In contrast to the reference region, manufacturing for transportation equipment (S16) with a minimum decomposition value of 0.7791 (see as Table 3) contributed the most to reduce the Hebei's ICP, with CPIE, CFE, and CESE being the main driving forces. This suggests that the carbon technical performance, energy consumption structure and industrial structure played a very large role in decreasing the carbon productivity of S16. CESE, PCFE, CFE, and KESE increased carbon productivity across all 12 sectors. The LESE for most of the 12 industrial sectors was more than 1, except for the refining of metals

(S13), electricity sector (S20), and manufacturing for food (S5), wood (S8), and non-metallic minerals (S12). A similar analysis was extended to the other 12 provinces. The ICP can be promoted more effectively by improving targeted sector-level impact factors with limited resources. The sectoral driving factors (where the decomposition result was less than 1) that have the most potential to improve ICP were combined to inform a particular sector of how to improve its carbon productivity.

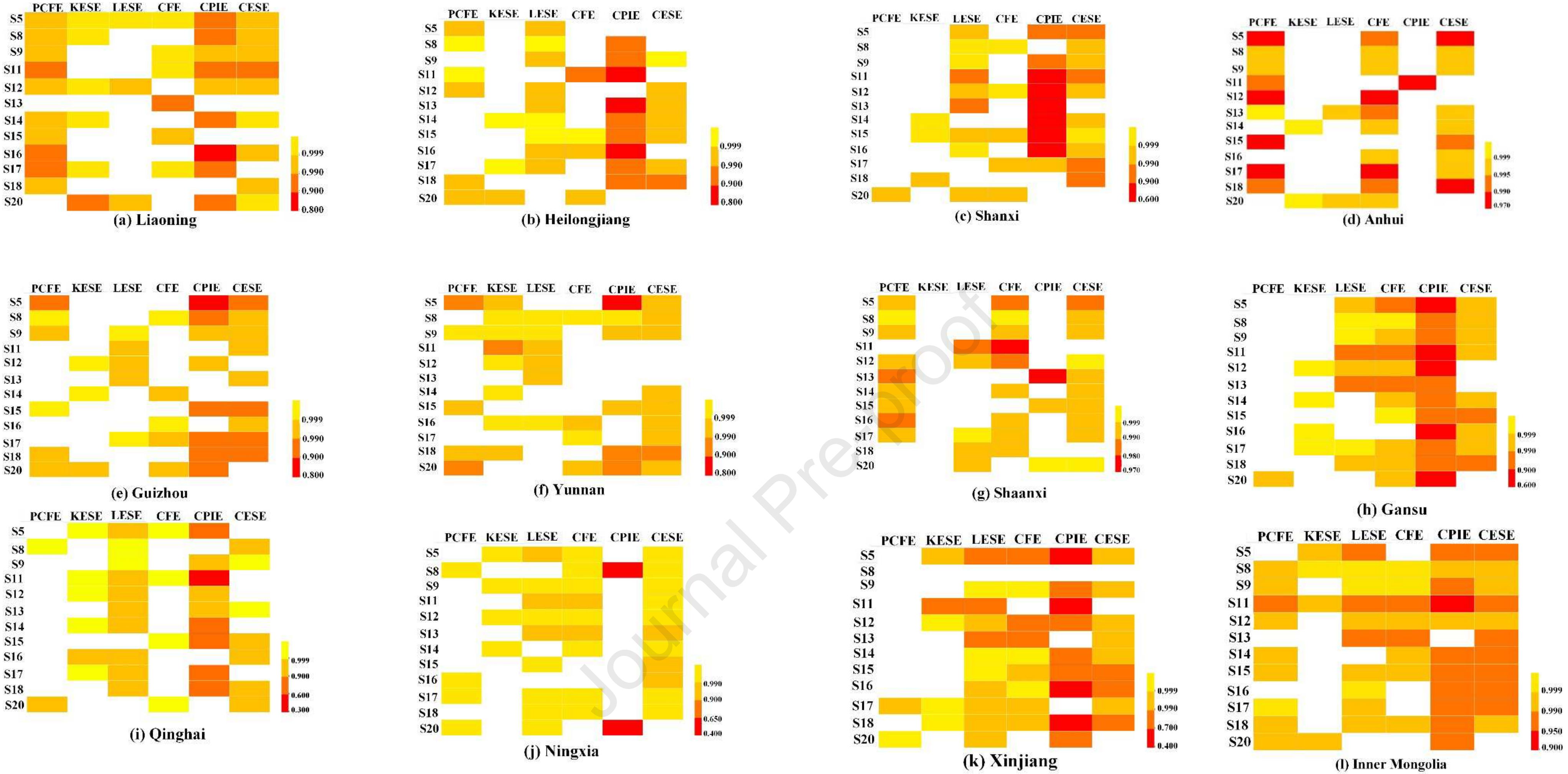

Figure 8. Decomposition results of 13 industrial sectors in 12 regions.

Notes: *The blank area indicates that the decomposition result was higher than 1, meaning that the driving factor increased the target sector's ICP compared to the reference region, and vice versa. The red indicates the minimum decomposition value. For instance, for S16 in (a) LN, the driving factors of KESE, LESE and CFE increased its carbon productivity compared to the average level. The primary contributor to below-average carbon productivity in S16 of LN was CPIE, followed by PCFE and CESE.*

Figure 8 shows the potential factors for improving the 12 industrial sectors' carbon productivity in 12 regions (except Hebei). We found that the CESE had the potential to improve the corresponding industrial sectors' carbon productivity for all 13 regions. The CPIE was the dominant cause of the below-average carbon productivity for 12 industrial sectors in 9 provinces except for Anhui, Shaanxi, and Ningxia. This means that for these industries, the ICP can be improved more effectively by upgrading the production and emission technologies. Further, for the 12 industrial sectors in these 8 western provinces, the LESE and CFE are other two important factors that have great potential to increase sector carbon productivity. This is consistent with the decomposition results at the provincial level.

Also, Figure 8 reports that the heterogeneities among drivers in different sectors of different regions were large. Taking Liaoning as an example, the PCFE and CPIE were the two most promising driving forces to increase carbon productivity across all 12 industrial sectors, especially for the chemical sector (S11) and transportation equipment (S16). This was mainly due to Liaoning's energy emission structure still being fossil fuel-based, notably coal (Geng et al., 2013), and its emission technology level which could be improved. For Heilongjiang, the CPIE for the chemical sector (S11), refining of metals (S13) and transportation equipment (S16) was the most noteworthy factor for increasing the ICP. This coincides with the fact that the northeast region had a single industrial structure and was overly dependent on resource-based industries. Furthermore, for the high carbon industry sectors (S11, S12, S13, and S20) in several provinces rich in natural resources, especially Shanxi, Shaanxi, Xinjiang and Inner Mongolia, resource advantage did not significantly promote the improvement of ICP. This was mainly due to the low resource utilization resulting from the slow transfer of production technologies from the east to central and western China.

5. Discussion

A decomposition technique was used here to conduct multi-region comparisons of ICP in China. The results isolated the drivers behind the regional differences in ICP and further identified the provinces and industries with poor ICP together with their driving factors.

At the provincial level, the capital-energy substitution effect was the main driver which increased most regions' ICP compared to the reference region. As for the labor-energy substitution effect, only five provinces were above average. These findings differed from other studies (Salim et al., 2017) which found a significant potential to replace energy with labor in China. This difference could be due to differences in the measurement of the labor impacts of ICP: we assessed the number of employed as labor impacts, while the aforementioned studies focused on the impacts of the employees' education level. Our study and the previous studies together provide key insights: Salim et al. (2017) determined that energy conservation in China could be achieved by improving post-school human-capital components, while we believe that energy cost reductions and output increases can be achieved by optimizing the allocation of two inputs (labor and energy). Due to China's energy endowment structure characterized as "rich coal, meager oil, and poor gas", most provinces' energy consumption is still dominated by coal (Li and Wang, 2019). Therefore, improving the energy consumption structure is another important challenge for China in its quest to improve ICP. Also, the CO_2 emission performance of the western provinces was worse than the average. This is mainly a function of their backward emission reduction technologies. Meanwhile, the CO_2 emissions structure effect had a less significant effect on raising provincial ICPs higher than the ICP of the reference region. This may be due to the fact that the nature of China's industrialization has remained unchanged, and economic growth still relies too much on industries that are high energy consumers and emit high levels of pollution.

In terms of the absolute ICP (29 provinces as a total) in 2016, 13 provinces were below the national average level including Anhui, Hebei, Heilongjiang, Liaoning, and all the nine western provinces. These 13 provinces are mainly located in northeastern, central, and western China. Most have abundant natural resources, especially Shanxi, Shaanxi, Inner Mongolia, and Xinjiang, causing them to continue their specialization in heavy industries. At the same time, most of the industries which have been relocated from the east to the west regions are heavy industries. Although this over-reliance on resource-based industries and heavy industries has been the mainstay of the economy in these regions, the ICP is still backward, reflecting the low resource utilization and unbalanced industrial structure.

For the industrial sectors within each province, there were significant differences in those that have a major impact on the provincial ICP. These 12 industrial sectors were the main drivers causing ICP in the 13 regions to be below that in the reference region, including five energy-intensive manufacturing sectors, six nonenergy intensive manufacturing sectors and the sector for production and supply of electric power, steam, and hot water (see in chapter 4.2.1). For the wood products sector, one possible reason for its weak carbon productivity could be the lower investment in environmental protection, especially in the wood-based panel industry (high pollution, and high environmental risk). The production and supply of electric power, steam, and hot water mainly involves heating and electricity. Nine of the 13 provinces require winter heating. The heating industry involves high energy consumption, high emissions, high investment, and low efficiency. Therefore, increasing its carbon productivity is a huge challenge (Chinabaogao, 2018). The sudden increase in energy prices (mainly coal prices) (National Energy Administration in China, 2016) makes increasing the carbon productivity levels even more difficult.

The major industrial sectors of the provinces with low ICP need to be targeted for efforts geared to improving China's overall ICP more effectively. Therefore, the 12 industrial sectors in the 13 provinces mentioned above were selected as the key research cases for this study.

From the perspective of the provincial industrial sectors, the driving factors behind the ICP in the 12 industrial sectors in the 13 provinces were revealed to clarify the necessary development direction needed to increase overall ICP. From Figure 8 it can be seen that an industrial structure upgrade needs to be carried out to promote ICP for the 12 industrial sectors in the 13 provinces (Ma et al., 2019). However, industrial restructuring is unavoidably a long-term strategic goal and is particularly difficult for regions with a single industrial structure and excessive dependence on heavy industry development, especially in China’s northeast and western provinces. Moreover, we found that the driving sectors in most of the regions with a lower than average ICP levels were not only high-carbon industrial sectors, but also six low-carbon industrial sectors (6 nonenergy intensive manufacturing sectors) out of 13 sectors. This indicates that industries with low-carbon emissions also have a significant impact on the regional overall ICP, suggesting that it will be more efficient to increase the ICP by improving resource allocation among the industrial sectors (including technology, financial assets, and human capital, and energy resources), than to transform regions’ economic structures from high-carbon industries to low-carbon industries, especially in those provinces that rely on heavy industries.

The carbon performance index effect (CPIE) for the 12 sectors in the 13 provinces reflects the level of CO_2 emissions performance, and also the level of technology (Lin and Du, 2015; Zhou et al., 2012). According to the industry classification found in Li et al. (2018), there were five low-carbon and high-technology industry sectors in the 12 industrial sectors, including manufacturing with food and tobacco, ordinary and special equipment, transportation equipment, machinery and electrical equipment, and computer and electronic products. (W. Li et al., 2018) reported that low-carbon and high-technology industries were the technology leaders and had a positive effect on the improvement of carbon productivity. However, due to the backward technical level of the 12 sectors in the 13 provinces, except for Anhui, Shaanxi, and Ningxia, the role of technology in promoting carbon productivity has not been exerted. This differs from the results of (Y. Li et al., 2018), as we considered regional heterogeneity and focused on low-carbon emission technologies, while the aforementioned studies focused on industrial production technology. In addition, the 12 industrial sectors had significantly different energy consumption structures, technical levels, industrial structure and energy and non-energy substitution effects. This complicates the standardization of policies geared to increasing the carbon productivity of each local government.

6. Conclusions and policy implications

Increasing carbon productivity is crucial for China because it is the largest carbon dioxide emitter in the world (Peters et al., 2012). It must find ways to mitigate emissions while maintaining high levels of economic growth. Measuring ICP by province and industrial sector can help Chinese policymakers prioritize the sectors and regions so as to minimize the costs of carbon mitigation. We quantified the causes of the disparities in ICP, at both the provincial and sectoral levels. We also put forward targeted recommendations after conducting a comparative analysis of ICP in 29 provinces and 22 industries in 2016 by applying the spatial-PDA model.

The main conclusions and implications are as follows: a) At the provincial level, the capital-energy substitution effect was the main cause of the higher ICP compared to the reference region, while the labor-energy substitution effect had the greatest potential to increase most provinces' ICP; b) the ICP in 13 regions (Anhui, Hebei, Heilongjiang, Liaoning, and all the nine western provinces) was below the average level. A total of 12 key industrial sectors were identified as the main cause of the ICP in the 13 regions being lower than the average level. These were mainly the electricity sector, five energy-intensive manufacturing sectors with food and tobacco, paper and paint, chemicals, non-metallic minerals and refining, and six nonenergy intensive manufacturing sectors with fabricated metal products, ordinary and special equipment, transportation equipment, machinery and electrical equipment, and computer and electronic products; c) For the 12 industrial sectors in the 13 provinces, the differences in driving factors were significant. The industrial structure and carbon performance index effect were the main factors that contributed to the sub-average ICP.

Based on the above analysis, the following policy recommendations are proposed.

First, provincial governments should give priority to improving the labor-energy substitution effect and energy emission structure because these two factors were the main reason why ICP in many provinces was below the average level. Due to the significant regional disparities in resources, economics, and technology, local governments should carry out differentiated energy strategies. To significantly improve their CO_2 emission efficiencies, the local governments in most of the western provinces should focus on technology updates in production and energy conservation and emission reduction.. Also, strengthening technology exchanges and other forms of cooperation between the eastern provinces and western regions could help actively guide technological innovation and flows of assistance to the western regions' most backward areas.

Second, priority should be given to increasing ICP in the identified 13 provinces and 12 industrial sectors that had lower than the average national performance across the country. The governments of the 13 provinces (Anhui, Hebei, Heilongjiang, Liaoning, and all the nine western provinces)should increase investment in science and technology research and development on production technology, and introduce low-carbon technologies to the main industries. This could help these provinces catch up to the carbon productivity levels found in the eastern region, and achieve more balanced development among all of China’s regions, thus improving the overall carbon productivity of China. Policymakers should also redistribute more factors of production (capital, labor, and CO_2 emission rights) to the 12 identified industrial sectors (main drivers causing ICP in the 13 provinces being lower than average level), to narrow the differences in carbon productivity and thus improve the overall ICP. In addition, since most of the manufacturing sectors are included in the sectors that result in low productivity, it is particularly important to upgrade manufacturing equipment and processes in the manufacturing industry. However, the transformation from high carbon industries to low carbon industries may not necessarily improve ICP because some low carbon industries also have low ICP.

Third, due to the vast differences among China’s provinces and their industrial sectors, a holistic analysis of each province’s industrial sectors is needed in order to propose appropriate carbon productivity promotion policies for each department. For example, the transportation equipment sector in Hebei has the lowest decomposition index (0.7832) relative to the average level due to its backward technological capabilities and an unbalanced industrial structure (see Table 3). Therefore, based on the Beijing-Tianjin-Hebei coordinated development strategy, promotion policies for this sector should pay more attention to absorbing Beijing and Tianjin's advanced industrial management experience and scientific research results, such as technologies for cleaner production and resource recycling, and be geared to improving technological innovation. In the same way, other provincial governments should focus on identifying the key industrial sectors that lead to low ICP and the key drivers that affect these industries, in order to efficiently optimize the allocation of production factors with limited resources.

The model in this paper combined with PDA and M-R model focused on comparing provinces' ICP in a particular year, while the changing pattern of regional disparities over time cannot be analyzed. Therefore, an integrated spatial-temporal decomposition approach needs to be further proposed. The changing pattern of regional disparities overtime should also be considered when exploring the influence of carbon productivity. The ICP level and targeted measures for each province are discussed in this paper. However, due to limited resources and environmental constraints, even if the ICP of some specific provinces improves, it does not mean that the whole country's carbon productivity will increase. Based on this study, a comparative analysis of carbon productivity between any two provinces can be performed to achieve a more detailed assessment of ICP by province, thus making resource allocation more effective. A resource allocation problem worthy of further study is to balance national resource allocation through the comparative advantage between any two provinces to improve the carbon productivity of the whole country, more detailed studies of carbon productivity, such as at the municipal level and enterprise-level, are other directions worth exploring. In addition, provinces and their sub-industries with above-average ICP are also worthy of investigating to improve the overall ICP of China from the frontier regions.

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Appendix A1

Table A1. Region classification in China

Regional group	Code (*i*)	Region	Short name
	1	Beijing	BJ
	2	Tianjin	TJ
	3	Hebei	HE
	4	Shanghai	SH
Eastern China	5	Jiangsu	JS
	6	Zhejiang	ZJ
	7	Fujian	FJ
	8	Shandong	SD
	9	Guangdong	GD
	10	Liaoning	LN
Northeast	11	Jilin	JL
	12	Heilongjiang	HL
	13	Shanxi	SX
	14	Anhui	AH
Central China	15	Jiangxi	JX
	16	Henan	HA
	17	Hubei	HB
	18	Hunan	HN
	19	Guangxi	GX
	20	Guizhou	GZ

	21	Sichuan	SC
	22	Chongqing	CQ
	23	Yunnan	YN
Western China	24	Shaanxi	SN
	25	Gansu	GS
	26	Qinghai	QH
	27	Ningxia	NX
	27	Xinjiang	XJ
	29	Inner Mongolia	IM
Reference region	30	Reference region	*R*

Note: According to the new situation of accelerating economic and social development in China, the country is divided into four economic regions. The whole Inner Mongolia is allocated to the west of China. The "Reference region" represents the average level in socio-economic and CO_2 emissions of the other 29 provinces.

Appendix A2

Table A2. Industrial sector classification

Code	Sector	Code	Sector
S1	Coal Mining and Dressing	S12	Nonmetal Mineral Products
S2	Petroleum and Natural Gas Extraction	S13	Smelting and pressing of metals
S3	Metals Mining and Dressing	S14	Metal Products
S4	Nonmetal and other Minerals Mining and Dressing	S15	Ordinary and special equipment
S5	Food production and tobacco processing	S16	Transportation Equipment
S6	Textile	S17	Electric Equipment and Machinery
S7	Leather, Furs, Down and Related Products	S18	Electronic and Telecommunications Equipment; Instruments, Meters, Cultural and Office Machinery
S8	Wood products	S19	Other industrial activities
S9	Papermaking, printing, cultural, educational and sports articles	S20	Production and Supply of Electric Power, Steam and Hot Water
S10	Petroleum Processing and Coking	S21	Production and Supply of Gas
S11	Chemical industry	S22	Production and Supply of Tap Water

Appendix B

Table B1. Data for the hypothetical reference region

Sector	Energy consumption (10^{16} Joules)	Industrial value-added (10^8 CNY)	CO_2 emissions (10^4 tons)	Industrial Carbon productivity (CNY/Kg)
S1	17.75	249.48	933.48	2.67
S2	3.33	92.72	184.62	5.02
S3	1.86	118.27	69.64	16.98
S4	1.25	72.78	42.00	17.33
S5	8.46	1096.90	164.51	66.68
S6	7.09	515.55	77.46	66.56
S7	0.59	142.50	9.85	144.69
S8	1.47	203.78	28.46	71.60
S9	6.49	323.80	117.06	27.66
S10	26.08	319.10	1007.70	3.17
S11	49.58	1270.54	604.07	21.03
S12	31.02	527.79	3386.94	1.56
S13	78.32	876.92	5299.71	1.65
S14	2.83	325.57	39.38	82.67
S15	3.94	749.74	175.20	42.79
S16	3.12	804.04	58.78	136.78
S17	2.32	590.47	36.87	160.16
S18	3.08	860.34	22.16	388.20
S19	0.58	71.32	28.64	24.90
S20	57.62	527.04	15340.55	0.34
S21	0.94	51.03	58.94	8.66
S22	0.66	24.38	2.28	106.97
Total	308.40	9814.07	27688.31	3.54

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Declaration of interests

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

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

None