Petroleum Science 21 (2024) 1415–1428

Contents lists available at ScienceDirect

Petroleum Science

journal homepage: www.keaipublishing.com/en/journals/petroleum-science

Original Paper

How can technology and efficiency alleviate the dilemma of economic growth and carbon emissions in China's industrial economy? A meta-frontier decoupling decomposition analysis

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ARTICLE INFO

Article history:
Received 23 April 2023
Received in revised form
2 October 2023
Accepted 2 October 2023
Available online 5 October 2023

Handling editor: Kang-Yin Dong
Edited by Jia-Jia Fei

Keywords:
China's industrial sector
Decoupling process
Meta-frontier DEA
Index decomposition method
Driving factors

ABSTRACT

This paper attempts to explore the decoupling relationship and its drivers between industrial economic increase and energy-related CO_2 emissions (ICE). Firstly, the decoupling relationship was evaluated by Tapio index. Then, based on the DEA meta-frontier theory framework which taking into account the regional and industrial heterogeneity and index decomposition method, the driving factors of decoupling process were explored mainly from the view of technology and efficiency. The results show that during 2000–2019, weak decoupling was the primary state. Investment scale expansion was the largest reason hindering decoupling process of industrial increase from ICE. Both energy saving and production technology achieved significant progress, which facilitated the decoupling process. Simultaneously, the energy technology gap and production technology gap among regions have been narrowed, and played a role in promoting decoupling process. On the contrary, both scale economy efficiency and pure technical efficiency have inhibiting effects on decoupling process. The former indicates that the scale economy of China's industry was not conducive to improve energy efficiency and production efficiency, while the latter indicates that resource misallocation problem may exist in both energy market and product market.

1. Introduction

As a pillar of modern economic development, industrial production has been a major driving force for China's economic development. However, for a long time, China's extensive industrial development mode of “high input, high energy consumption, high carbon emission, and high pollution” has exerted tremendous pressure on resources, the environment and has caused a series of serious environmental and climate problems. According to the China Energy Statistical Yearbook (CESY), industrial energy consumption accounts for more than 65% of all energy consumption in China. China is now in the middle and late stage of industrialization development, the contradiction between industrial development and resources and environment is constantly emerging and intensifying. Resources and the environment have become the rigid conditions restricting the result of an industrial economy (Hou et al., 2023; Wang and Feng, 2023). As a major CO_2 emissions source in China, emission reduction in industrial sector is crucial to the realization of China's dual carbon target.

Many previous studies have found that economic development, technology level, energy structure and other factors have significant impacts on industrial CO_2 emissions (ICE), among which economic growth is the most critical force driving the ICE increase. However, it is obviously unrealistic to reduce ICE by inhibiting industrial economic development at present. Then, how to reduce ICE without hindering the development of industrial economy, that is, to gain the decoupling of industrial economic increase from ICE, is an urgent problem to be solved. However, it is unclear that the decoupling status and its drivers between industrial economic increase and ICE in China. Insufficient understanding of the decoupling status and its driving factors may lead to less effective decoupling efforts in industrial sector. This paper attempts to fill this gap, compared with the existing literature, this study makes the following two aspects contributions:

Firstly, Tapio decoupling index is constructed to estimate the decoupling degree between industrial economic increase and ICE.

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https://doi.org/10.1016/j.petsci.2023.10.004
1995-8226/

At the same time, in order to further clarify the factors affecting the decoupling process between the two, this study constructs a comprehensive decomposition framework on the basis of meta-frontier DEA, production theory and index decomposition method. Such comprehensive analysis framework can not only quantitatively analyze the effects of energy structure, potential energy intensity, investment efficiency, investment scale, energy saving technology, production technology and other factors on the decoupling process, but also quantitatively analyze the impacts of technology gap, scale economy efficiency and management efficiency on decoupling process.

Secondly, on account of the differences in economic advance, industrialization level, geographical conditions, cultural environment and others among different provinces, the decoupling degree of industrial economic increase and ICE and its driving factors will be quite different. Therefore, the decoupling characteristics of the provinces need to be fully taken into account when formulating policies for the decoupling of industrial economic increase and ICE. Considering this, the results analysis will be carried out at the national level, regional level and provincial level.

The rest of this paper is organized as follows. Section 2 reviews the literature. Section 3 conducts the comprehensive analysis framework. Besides, the results at the national level, regional level and provincial level are discussed in Section 4. Section 5 concludes the whole paper.

2. Literature review

In the existing literature, the environmental Kuznets curve (EKC) and decoupling index are two commonly adopted ways to study the relation between economy and carbon emissions (Shan et al., 2021; Rao et al., 2022). Churchill et al. (2018) tested the existence of the EKC hypothesis in 20 OECD countries from 1870 to 2014, and the results showed that there were EKC in nine of these OECD countries. Among them, five countries showed a traditional inverted “U”-shaped relation between economic growth and carbon emissions, three countries exhibited an “N”-shaped relation, and one country exhibited an inverted “N”-shaped relation. Based on the data of Malaysia from 1971 to 2016, Aslam et al. (2021) estimated that Malaysia's CO_2 emissions increased steadily with the rapid economic growth through the regression distribution lag constraint test method, and there was a “U”-shaped relationship between the two. However, the hypothesis of EKC theory also has some limitations. In the empirical study, the environment-income relationship takes on various forms, such as: no relationship, monotonically rising relationship, monotonically falling relationship, inverted “U” relationship, “U” relationship, “N” relationship, inverted “N” relationship and so on. Therefore, the inverted “U” shaped relation described by EKC can only be applied in part of the case. In addition, an important assumption in the EKC theory is that income is an exogenous variable. However, in practice, the development of economic level and the improvement or deterioration of the environment have mutual influences, so the assumption of EKC is obviously divorced from reality (Arrow et al., 1995).

Compared to EKC, the decoupling index can quantitatively and more straightforwardly reflect the relation for environmental indicators and economic relevant indicators. Zhang (2000) used the conception of decoupling to discuss the elasticity of energy use in countries with various income levels at the earliest. OECD (2002) proposed the notion of decoupling in due form: decoupling comes up when the growth rate of variables related to environmental stress is lower than that of the economy. Nevertheless, the “decoupling elasticity” theory come up with by OECD is not credible enough to evaluate the decoupling relationship. Some scholars built Environment Impact-GDP-Technology model (IGT) based on IPAT. Through the IGT model, the degree of decoupling between economy and environment can be judged. For instance, Wu et al. (2018) used this model to study and compare the decoupling state between economy and energy use in countries with different development levels. They found that the decoupling degree between the two was relatively high in developed countries, while the decoupling degree between the two was relatively low in developing countries. It can be seen that IGT model can quantitatively judge the degree of decoupling between economy and environment. However, IGT model presents some shortcomings in evaluating the decoupling state between them. For example, the definition of absolute decoupling and relative decoupling is not clear enough in this model, and the undecoupled state cannot be further divided and defined in detail.

On the basis of the decoupling definition in OECD (2002), Tapio (2005) brought into a fresh decoupling system to reveal the relationship between GDP, traffic flow and carbon emissions in the European Union. This index is called Tapio decoupling index. Tapio decoupling index divides the relationship between economy and carbon emissions into eight states. It has the merits of simple evaluation, easy to understand and unambiguous classification criterion, and has been broadly adopted in the research of decoupling relationship. For example, Ma et al. (2019) carried out the relative studies for the carbon intensity of commercial construction industry and economic growth of service industry in China's five major urban agglomerations, and found that the overall decoupling situation of the five major urban agglomerations was weak from 2001 to 2005; while the degree of decoupling gradually strengthened from 2006 to 2015. Song et al. (2020) used Tapio model to explore the decoupling status and dynamic path of provincial GDP per capita and CO_2 emissions in China from 2000 to 2016. Thanks to its merits, Tapio decoupling index is the most popularly adopted method to study the relations between economic increase and carbon emissions.

Tapio index can unambiguously reflect the decoupling states, but it cannot explain the driving factors of various decoupling states. It is of great significance to clarify the drivers of decoupling state for formulating relevant policy measures to facilitate the decoupling course. Therefore, after assessing the decoupling degree between economy and carbon emissions, it is necessary to further explore the drivers of various decoupling degrees. Many scholars have combined decomposition methods and Tapio decoupling index to solve this problem.

For example, Wang and Han (2021) studied the decoupling degree of carbon emissions embodied in Sino-US trade and its drivers by using multi-regional input-output, Tapio index and structural decomposition method. Xu et al. (2021) combined single-region input-output analysis, Tapio model and structural decomposition method to study the dynamic change characteristics and decoupling state of multi-sector carbon emissions in Guangdong Province from 2002 to 2017, and revealed its driving factors. Chen et al. (2018) used LMDI to explore the impact of CO_2 emission intensity, energy consumption structure, energy consumption intensity, per capita gross output value and population size on CO_2 emissions in OECD countries, and then further used Tapio decoupling to explore the decoupling relationship of the above driving factors and CO_2 emissions. Xie et al. (2019) discussed the decoupling degree of GDP and CO_2 emissions in China's power industry and its drivers. Wang et al. (2020) combined Tapio and LMDI to evaluate the relationship between the development of transport sectors and CO_2 emissions in 29 countries of the Eurasian logistics corridor from 2001 to 2014. Liu and Feng (2020) combined Tapio and LMDI to quantify the impact of various socio-economic factors (such as energy intensity, spatial pattern, per capita service output value, reciprocal ratio of service industry to GDP, and population size) on the decoupling process between transport CO_2 emission and economic development in China. Huo et al. (2021) explored the decoupling relationship and its main drivers between residential building carbon emissions, per capita carbon emissions, residential carbon intensity and per capita income in 30 provinces of China.

As a vital engine of China's economic development and an important field of energy use and carbon emissions, studies on the relations of industrial economic increase and ICE have drawn extensive attention from scholars. Zhao et al. (2016) used the extended LMDI to decompose ICE into emission coefficient, energy structure/intensity, process carbon intensity, investment scale/structure/efficiency, and then combined with Tapio decoupling index to explore the impacts of the above drivers on the decoupling degree of industrial economic increase and ICE. Based on China's provincial panel data from 2000 to 2013, Wang et al. (2017) found an inverted “U”-shaped nonlinear relationship between economic increase and carbon emissions in power generation and heating sectors. However, the per capita income of manufacturing industry was almost linearly correlated with carbon emissions, while the relevance between the two was small in mining industry. Zhou et al. (2017) adopted LMDI and Tapio models to quantitatively analyze the impact of decoupling elasticities of different factors on the decoupling process of ICE and economic increase in China's eight regions. The results showed that there was a weak decoupling relationship between the two in most regions; among them, energy intensity is the primary forces driving the decoupling process of ICE from industrial economy increase. Based on China's industrial data from 1996 to 2015, Yang et al. (2018) combined LMDI and Tapio index, found that the decoupling state had obvious periodicity, that is, showed an overall inverted “U”-shaped trend, and from strong decoupling to expansion coupling, and then from weak decoupling to strong decoupling.

So far, we are aware that most of the existing literatures discuss the driving factors of ICE, but the relevant research on the driving factors of the decoupling degree of industrial economy increase and ICE is still insufficient. Existing about decoupling relationship research for the industrial growth and ICE, less to study the decoupling drivers, even though there are a few literatures concerned about the driving factors of decoupling relationship between them, is confined to some traditional factors (such as energy/economic structure, carbon/energy intensity, economic level, population scale). However, it neglects the influence of various technology and efficiency relevant factors on their decoupling relationship. This study tries to fill this gap by building a new decoupling index decomposition analysis framework to explore the drivers of industrial economic increase and ICE decoupling process from the perspective of technology and efficiency.

3. Methods

3.1. Shephard distance function and meta-frontier approach

Energy, capital stock, and labor were set as inputs, total industrial output value and ICE were “good output” and “bad output”, respectively. Then, we obtain:

$$P^t = \left\{ \left(E_i^t, K_i^t, L_i^t, Y_i^t, C_i^t\right) \middle| CRS : \left(E_i^t, K_i^t, L_i^t\right) \text{ can produce } \left(Y_i^t, C_i^t\right) \right.$$
$$\sum_{i=1}^{n} z_i E_i^t \le E^t; \sum_{i=1}^{n} z_i K_i^t \le K^t; \sum_{i=1}^{n} z_i L_i^t \le L^t; \sum_{i=1}^{n} z_i Y_i^t \ge Y^t$$
$$\left. \sum_{i=1}^{n} z_i C_i^t = C^t; z_i \ge 0, i = 1, 2, ..., n \right\} \tag{1}$$

In Eq. (1), *CRS* represent constant returns to scale; i is decision-making unit (DMU), n is the number of DMUs; z is the intensity variable linking input and output. Besides, the production possible set (P) is a closed and bounded set.

With reference to Pastor and Lovell (2005), this paper adopts global production frontier technology (P^G) so that the efficiency of different DMUs is comparable across time periods:

$$P^G = P^1 \cup P^2 \cup, \cdots, P^t \tag{2}$$

Then, we can define the Shephard distance functions (SDF) of E and Y in period t as:

$$D_{i,E}^t\left(L_i^t, K_i^t, E_i^t, Y_i^t, C_i^t \middle| CRS\right) = \sup\left\{\vartheta : \left(L_i^t, K_i^t, E_i^t / \vartheta, Y_i^t, C_i^t\right) \in P_{CRS}^t\right\} \tag{3}$$

$$D_{i,Y}^t\left(L_i^t, K_i^t, E_i^t, Y_i^t, C_i^t \middle| CRS\right) = \inf\left\{\varphi : \left(L_i^t, K_i^t, E_i^t, Y_i^t / \varphi, C_i^t\right) \in P_{CRS}^t\right\} \tag{4}$$

where ϑ and φ represent energy efficiency and production efficiency, respectively.

Meanwhile, global SDF can be indicated as:

$$D_{i,E}^G\left(L_i^t, K_i^t, E_i^t, Y_i^t, C_i^t \middle| CRS\right) = \sup\left\{\vartheta : \left(L_i^t, K_i^t, E_i^t / \vartheta, Y_i^t, C_i^t\right) \in P_{CRS}^G\right\} \tag{5}$$

$$D_{i,Y}^G\left(L_i^t, K_i^t, E_i^t, Y_i^t, C_i^t \middle| CRS\right) = \inf\left\{\varphi : \left(L_i^t, K_i^t, E_i^t, Y_i^t / \varphi, C_i^t\right) \in P_{CRS}^G\right\} \tag{6}$$

The above SDF can be calculated by the following equations:

$$\begin{aligned}
&\left[D_{i,E}^t\left(L_i^t, K_i^t, E_i^t, Y_i^t, C_i^t \middle| CRS\right)\right]^{-1} = \min \vartheta \\
&\text{s.t. } \sum_{t=1}^{t}\sum_{i=1}^{n} z_i \cdot L_i^t \le L^t;\ \sum_{t=1}^{t}\sum_{i=1}^{n} z_i \cdot K_i^t \le K^t; \\
&\sum_{t=1}^{t}\sum_{i=1}^{n} z_i \cdot E_i^t \le \vartheta E^t;\ \sum_{t=1}^{t}\sum_{i=1}^{n} z_i \cdot Y_i^t \ge Y^t; \\
&\sum_{t=1}^{t}\sum_{i=1}^{n} z_i \cdot C_i^t = C^t; \\
&z_i \ge 0, i = 1, 2, \cdots, n;\ t = 1, 2, \cdots, t.
\end{aligned} \tag{7}$$

$$
\begin{aligned}
&\left[D_{i,Y}^{t}\left(L_i^t,K_i^t,E_i^t,Y_i^t,C_i^t|CRS\right)\right]^{-1}=\max\varphi\\
&\text{s.t. } \sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot L_i^t\le L^t;\ \sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot K_i^t\le K^t;\\
&\sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot E_i^t\le E^t;\ \sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot Y_i^t\ge \varphi Y^t;\\
&\sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot C_i^t= C^t;\\
&z_i\ge 0, i=1,2,\cdots,n;\ t=1,2,\cdots,t.
\end{aligned}
\tag{8}
$$

$$
\begin{aligned}
&\left[D_{i,E}^{G}\left(L_i^t,K_i^t,E_i^t,Y_i^t,C_i^t|CRS\right)\right]^{-1}=\min\vartheta\\
&\text{s.t. } \sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot L_i^t\le L^t;\ \sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot K_i^t\le K^t;\\
&\sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot E_i^t\le \vartheta E^t;\ \sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot Y_i^t\ge Y^t;\\
&\sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot C_i^t= C^t;\\
&z_i\ge 0, i=1,2,\cdots,n;\ t=1,2,\cdots,t.
\end{aligned}
\tag{9}
$$

$$
\begin{aligned}
&\left[D_{i,Y}^{t}\left(L_i^t,K_i^t,E_i^t,Y_i^t,C_i^t|CRS\right)\right]^{-1}=\max\varphi\\
&\text{s.t. } \sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot L_i^G\le L^t;\ \sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot K_i^G\le K^t;\\
&\sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot E_i^t\le E^t;\ \sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot Y_i^t\ge \varphi Y^t;\\
&\sum_{t=1}^{t}\sum_{i=1}^{n}z_i\cdot C_i^t= C^t;\\
&z_i\ge 0, i=1,2,\cdots,n;\ t=1,2,\cdots,t.
\end{aligned}
\tag{10}
$$

Then, the meta-frontier is brought into to decompose the distance function, considering the influence of technology gap and scale economy (Yang and Fukuyama, 2018). As shown in Fig. 1, there are three regional grouping fronts (I, II and III), and the meta-frontier encloses three regional grouping fronts. Next, this paper takes the energy SDF as an example, for the DMU A in period t, if DMU A respectively reaches the regional frontier and meta-frontier by improving its efficiency, its energy input will be able to reduce QR and PR.

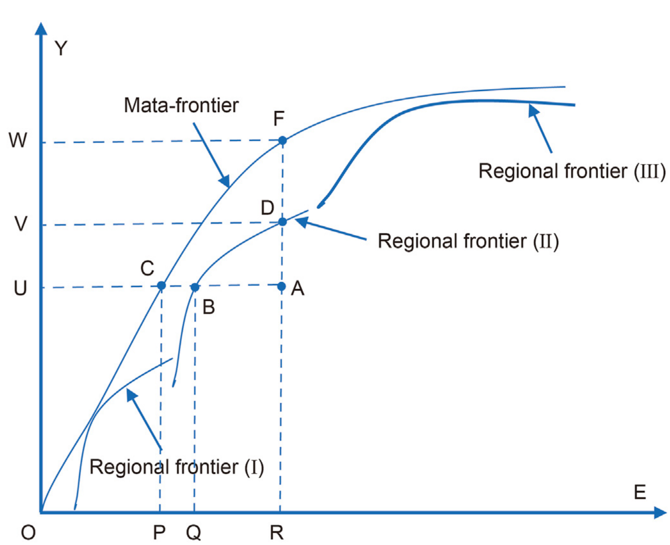

Fig. 1. Mata-frontier approach.

Accordingly, the energy SDF between DMU A and two different frontiers can be defined as:

$$
D_{GE}^t\left(L^t,K^t,E^t,Y^t,C^t|CRS\right)=\frac{OR}{OQ},D_{E}^t\left(L^t,K^t,E^t,Y^t,C^t|CRS\right)=\frac{OR}{OP}
\tag{11}
$$

Then, the energy technology gap ratio (ETG) and energy technical efficiency (TE) can be expressed as:

$$
\begin{cases}
D_{E}^t\left(L^t,K^t,E^t,Y^t,C^t|CRS\right)=ETG\times TE\\
ETG=\dfrac{D_{E}^t\left(L^t,K^t,E^t,Y^t,C^t|CRS\right)}{D_{GE}^t\left(L^t,K^t,E^t,Y^t,C^t|CRS\right)},\\
TE=D_{GE}^t\left(L^t,K^t,E^t,Y^t,C^t|CRS\right);
\end{cases}
\tag{12}
$$

Under the assumption of variable returns to scale (VRS), TE can be expressed as energy-oriented scale economy efficiency (SEE) and energy-oriented pure technical efficiency (PEE), please see:

$$
\begin{aligned}
TE&=\frac{D_{GE}^t\left(L^t,K^t,E^t,Y^t,C^t|CRS\right)}{D_{GE}^t\left(L^t,K^t,E^t,Y^t,C^t|VRS\right)}\times D_{GE}^t\left(L^t,K^t,E^t,Y^t,C^t|VRS\right)\\
&=SEE\times PEE
\end{aligned}
\tag{13}
$$

Thus, the energy SDF can be decomposed into:

$$
D_{E}^t\left(L^t,K^t,E^t,Y^t,C^t|CRS\right)=ETG\times SEE\times PEE
\tag{14}
$$

Similarly, the output SDF can be decomposed into:

$$
D_{Y}^t\left(L^t,K^t,E^t,Y^t,C^t|CRS\right)=\frac{1}{YTG\times SYE\times PYE}
\tag{15}
$$

In Eq. (15), YTG, SYE and PYE represent the production technology gap, output-oriented scale economy efficiency and output-oriented pure technical efficiency, respectively.

Assuming that there exist n DMUs under the meta-frontier, these DMUs are divided into H groups, and each group has N_h number of DMU. Thus, the distance function $D_{GE}^t(L^t, K^t, E^t, Y^t, C^t|CRS)$, $D_{GE}^t(L^t, K^t, E^t, Y^t, C^t|VRS)$, $D_{GY}^t(L^t,K^t,E^t,Y^t,C^t|CRS)$ and $D_{GY}^t(L^t,K^t,E^t,Y^t,C^t|VRS)$ can be calculated by Eqs. (16)–(19):

$$
\begin{cases}
\left[D_{GE,i}^t\left(L_i^t,K_i^t,E_i^t,Y_i^t,C_i^t|CRS\right)\right]^{-1}=\min\vartheta\\
\text{s.t. } \sum\limits_{n=1}^{N_h}w_n\cdot L_n^t\le L_i^t;\sum\limits_{n=1}^{N_h}w_n\cdot K_n^t\le K_i^t;\\
\sum\limits_{n=1}^{N_h}w_n\cdot E_n^t\le \vartheta E_i^t;\ \sum\limits_{n=1}^{N_h}w_n\cdot Y_n^t\ge Y_i^t;\\
\sum\limits_{n=1}^{N_h}w_n\cdot C_n^t=C_i^t; w_n\ge 0, n=1,2,\cdots,N_h.
\end{cases}
\tag{16}
$$

$$\begin{cases} \left[D^{t}_{GY,i}\left(L_i^t, K_i^t, E_i^t, Y_i^t, C_i^t | CRS\right)\right]^{-1} = \max \varphi \\ \text{s.t. } \sum_{n=1}^{N_h} w_n \cdot L_n^t \le L_i^t; \sum_{n=1}^{N_h} w_n \cdot K_n^t \le K_i^t; \\ \sum_{n=1}^{N_h} w_n \cdot E_n^t \le E_i^t; \ \sum_{n=1}^{N_h} w_n \cdot Y_n^t \ge \varphi Y_i^t; \\ \sum_{n=1}^{N_h} w_n \cdot C_n^t = C_i^t; w_i \ge 0, n = 1, 2, \cdots, N_h. \end{cases} \tag{17}$$

$$\begin{cases} \left[D^{t}_{GE,i}\left(L_i^t, K_i^t, E_i^t, Y_i^t, C_i^t | VRS\right)\right]^{-1} = \min \vartheta \\ \text{s.t. } \sum_{n=1}^{N_h} (w_n' + w_n'') \cdot L_n^t \le L_i^t; \sum_{n=1}^{N_h} (w_n' + w_n'') \cdot K_n^t \le K_i^t; \\ \sum_{n=1}^{N_h} (w_n' + w_n'') \cdot E_n^t \le \vartheta E_i^t; \ \sum_{n=1}^{N_h} w_n' \cdot Y_n^t \ge Y_i^t; \\ \sum_{n=1}^{N_h} w_n' \cdot C_n^t = C_i^t; \ \sum_{n=1}^{N_h} (w_n' + w_n'') = 1; \\ w_n', w_n'' \ge 0, n = 1, 2, \cdots, N_h. \end{cases} \tag{18}$$

$$\begin{cases} \left[D^{t}_{GY,i}\left(L_i^t, K_i^t, E_i^t, Y_i^t, C_i^t | VRS\right)\right]^{-1} = \max \varphi \\ \text{s.t. } \sum_{n=1}^{N_h} (w_n' + w_n'') \cdot L_n^t \le L_i^t; \sum_{n=1}^{N_h} (w_n' + w_n'') \cdot K_n^t \le K_i^t; \\ \sum_{n=1}^{N_h} (w_n' + w_n'') \cdot E_n^t \le E_i^t; \ \sum_{n=1}^{N_h} w_n' \cdot Y_n^t \ge \varphi Y_i^t; \\ \sum_{n=1}^{N_h} w_n' \cdot C_n^t = C_i^t; \ \sum_{n=1}^{N_h} (w_n' + w_n'') = 1; \\ w_n', w_n'' \ge 0, n = 1, 2, \cdots, N_h. \end{cases} \tag{19}$$

3.2. Production theory decomposition and index decomposition models

On the strength of Kaya identity, ICE can be represented as:

$$\begin{aligned} C &= \sum_j C_j = \sum_j \frac{C_j}{E_j} \times \frac{E_j}{E} \times \frac{E}{Y} \times \frac{Y}{I} \times I \\ &= CF_j \times ES_j \times EI \times IE \times I \end{aligned} \tag{20}$$

In Eq. (20), C, E, Y and I respectively represent ICE, energy use, gross industrial output value and fixed asset investment (i.e., investment scale); j represents the jth energy type; CF, ES, EI, and IE represent the is the carbon dioxide emission coefficient, energy structure, energy intensity, investment efficiency.

Based on production theory decomposition and Eqs. (3)–(6), the EI in Eq. (20) can be further decomposed into:

$$\begin{aligned} EI^t = & \frac{E^t \Big/ D_E^G\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)}{Y^t \Big/ D_Y^G\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)} \times D_E^t\left(L^t, K^t, E^t, Y^t, C^t | CRS\right) \\ & \times \frac{D_E^G\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)}{D_E^t\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)} \times \frac{1}{D_Y^t\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)} \\ & \times \frac{D_Y^t\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)}{D_Y^G\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)} \end{aligned} \tag{21}$$

Then, according to Eqs. (14) and (15), Eq. (21) can be rewritten as:

$$\begin{aligned} C^t = & CF_j^t \times ES_j^t \times \frac{E^t \Big/ D_E^G\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)}{Y^t \Big/ D_Y^G\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)} \times ETG^t \times SEE^t \times PEE^t \\ & \times \frac{D_E^G\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)}{D_E^t\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)} \times YTG^t \times SYE^t \times PYE^t \\ & \times \frac{D_Y^t\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)}{D_Y^G\left(L^t, K^t, E^t, Y^t, C^t | CRS\right)} \times IE^t \times I^t \\ = & CF_j \times ES_j \times PEI^t \times ETG^t \times SEE^t \times PEE^t \times EST^t \times YTG^t \times SYE^t \times PYE^t \times PT^t \times IE^t \times I^t \end{aligned} \tag{22}$$

To facilitate understanding, the comprehensive decomposition framework constructed in this paper is drawn as shown in Fig. 2.

According to LMDI model, the changes of ICE (ΔC_{tot}) can be expressed as:

$$\begin{aligned} \Delta C_{tot} &= C^t - C^{t-1} \\ &= \Delta C_{CF} + \Delta C_{ES} + \Delta C_{PEI} + \Delta C_{ETG} + \Delta C_{SEE} + \Delta C_{PEE} + \Delta C_{EST} \\ &\quad + \Delta C_{YTG} + \Delta C_{SYE} + \Delta C_{PYE} + \Delta C_{PT} + \Delta C_{IE} + \Delta C_I \end{aligned} \tag{23}$$

The right hand in Eq. (23) respectively represents the effects of various decomposed factors on ICE.

The effects of various factors can be calculated by Eq. (24):

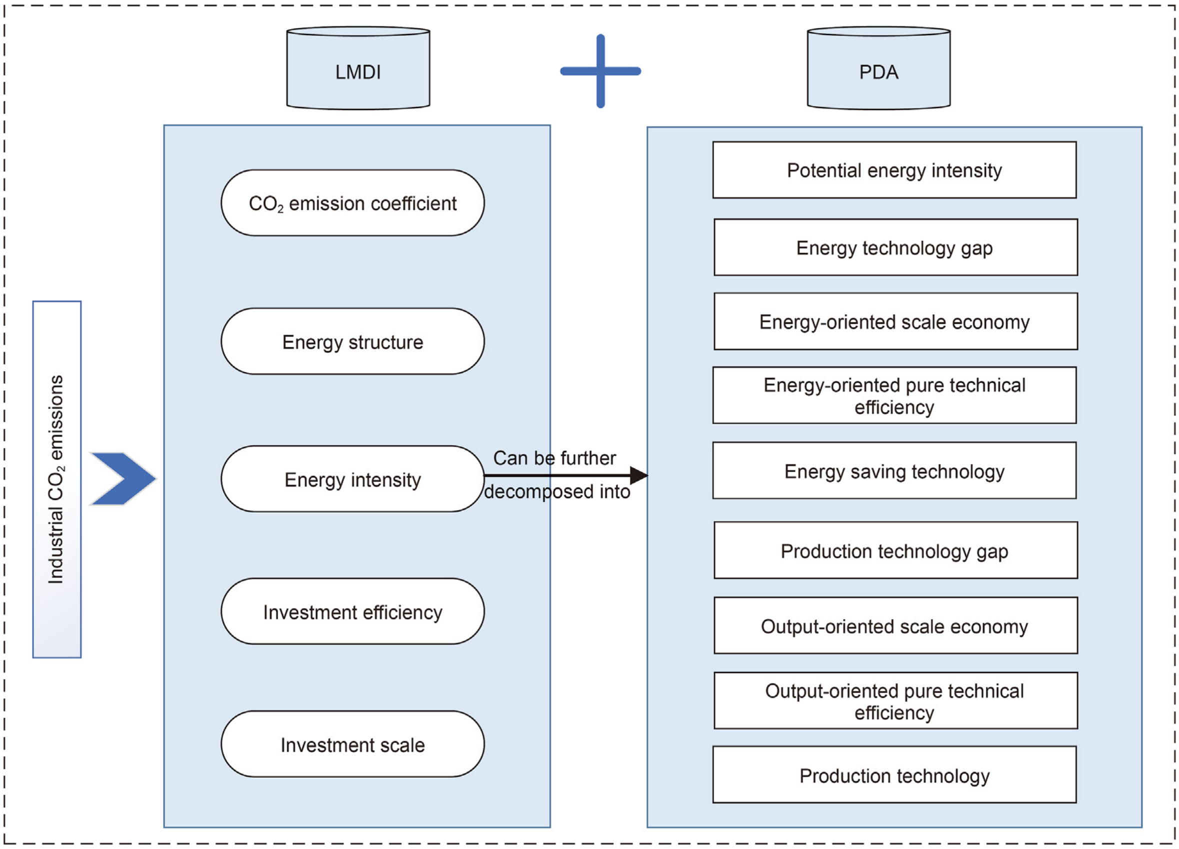

Fig. 2. The comprehensive decomposition framework.

$$\Delta C_X = \sum_{ij} \frac{C_{ij}^t - C_{ij}^{t-1}}{\ln C_{ij}^t - \ln C_{ij}^{t-1}} \cdot \left(\ln X_{ij}^t - \ln X_{ij}^{t-1}\right) \tag{24}$$

Here, X indicates the CF, ES, PEI, ETG, SEE, PEE, EST, YTG, SYE, PYE, PT, IE, and I.

3.3. Construction and decomposition of decoupling index

On the basis of Tapio's definition (2005), decoupling index can be defined as:

$$D = \frac{\Delta C_{t-1\to t} \big/ C^{t-1}}{\Delta Y_{t-1\to t} \big/ Y^{t-1}} = \frac{\frac{C^t - C^{t-1}}{C^{t-1}}}{\frac{Y^t - Y^{t-1}}{Y^{t-1}}} \tag{25}$$

Then, Tapio (2005) divides decoupling into eight states based on the changes of two relative indicators (see Fig. 3).

For the sake of further uncover the driving factors of the decoupling degree between industrial economic increase and ICE, the decoupling index can be decomposed into:

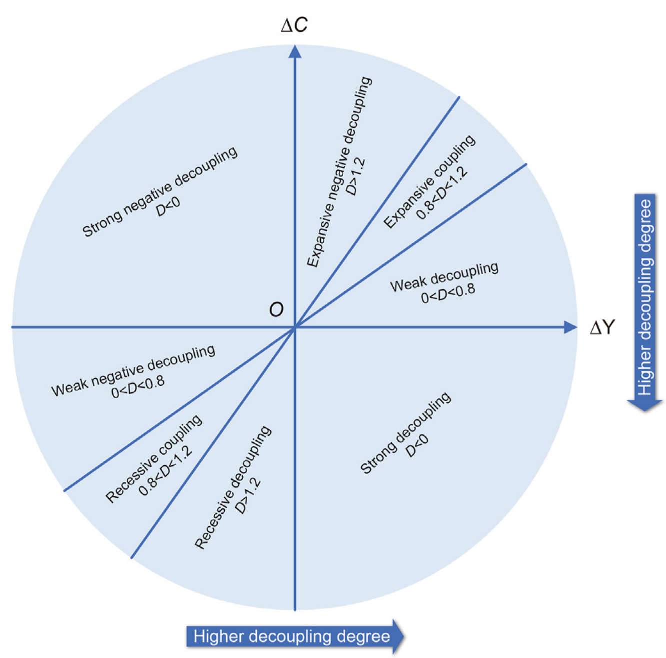

Fig. 3. Tapio decoupling index and its eight states.

$$
\begin{aligned}
D &= \frac{\Delta C \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} = \frac{\Delta C_{tot} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} \\
&= \frac{\left(\begin{array}{l} \Delta C_{CF} + \Delta C_{ES} + \Delta C_{PEI} + \Delta C_{ETG} + \Delta C_{SEE} + \Delta C_{PEE} + \Delta C_{EST} \\ + \Delta C_{YTG} + \Delta C_{SYE} + \Delta C_{PYE} + \Delta C_{PT} + \Delta C_{IE} + \Delta C_{I} \end{array} \right) \Big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} \\
&= \frac{\Delta C_{CF} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{ES} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{PEI} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{ETG} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{SEE} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} \\
&+ \frac{\Delta C_{PEE} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{EST} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{YTG} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{SYE} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{PYE} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} \\
&+ \frac{\Delta C_{PT} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{IE} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} + \frac{\Delta C_{I} \big/ C^{t-1}}{\Delta Y \big/ Y^{t-1}} \\
&= D_{CF} + D_{ES} + D_{PEI} + D_{ETG} + D_{SEE} + D_{PEE} + D_{EST} \\
&\quad + D_{YTG} + D_{SYE} + D_{PYE} + D_{PT} + D_{IE} + D_{I}
\end{aligned} \tag{26}
$$

In Eq. (26), D_X ($X = CF, ES, PEI, \ldots, I$) reflects the factor's effects on decoupling degree. (1) When ΔY>0, the smaller the value of decoupling index, the greater the degree of decoupling (i.e., the more ideal the decoupling state). At this point, D_X<0 implies that the factor has a positive impact on decoupling process, while D_X>0 implies that the factor has a negative impact on decoupling process. (2) Conversely, when ΔY<0, the greater the value of decoupling index, the greater the degree of decoupling (*i.e.* the more ideal the decoupling state). At this point, D_X>0 implies that the factor has a positive impact on decoupling process, and D_X<0 implies that the factor has a negative impact on decoupling process.

3.4. Data

The study covers 30 provinces in Mainland China (Tibet is not included in this study due to missing data), and the time interval is from 2000 to 2019. The East-central-west regional division is adopted. Relevant variables are described as follows:

(1) Industrial labor (L). This data are from China Industrial Statistical Yearbook and China Statistical Yearbook.
(2) Industrial capital stock (K). This paper adopts perpetual inventory method to reckon the data. The data of original value of fixed assets, accumulated depreciation, and investment price index ($P_{2000} = 1$) are from the National Bureau of Statistics.
(3) Total industrial output value (Y) and fixed-asset investment (I). The data of Y are from China Industrial Statistics Yearbook and China Economic Census Yearbook, and converted into comparable prices in 2000.[1] Besides, I is from the National Bureau of Statistics and China Statistical Yearbook, and is converted into 2000 comparable prices using the fixed asset investment price index.
(4) Industrial energy consumption (E). The data are from the "Regional Energy Balance Tables" in China Energy Statistical Yearbook. To keep the data consistent across years, 18 energy sources are considered: 17 fossil energy and electricity.
(5) ICE (C). ICE data include two parts: direct ICE induced by fossil energy combustion and indirect ICE induced by electricity of thermal power generation. With reference to Mi et al. (2017), the former one are estimated by the way proposed in IPCC, while the later one are estimated via the CO_2 emissions coefficient of electricity.

4. Results and discussions

4.1. Discussions for decoupling

4.1.1. Decoupling analysis at national level

As can be seen from Fig. 4(a), ICE increased in most years and decreased only in 2012–2013, 2014–2015 and 2016–2017. Fig. 4(b) shows that the total industrial output value is increasing in all years and shows an inverted "U"-shaped change trend of rising first and then declining. Combining Figs. 4 and 5, it is not difficult to know that the relationship between the two has experienced four kinds of relationships but dominated by weak decoupling during the study period: weak decoupling, expansive coupling, strong decoupling and expansive negative decoupling. This result is similar with previous relevant studies, such as Zhou et al. (2017), Wang and Feng (2021). Besides, the details are as follows.

Strong decoupling: as shown in Fig. 5, the decoupling index of 2012–2013, 2014–2015 and 2016–2017 is lower than zero, showing a strong decoupling, which is the most ideal decoupling state between industrial economy increase and ICE. In these three periods, ICE decreased while industrial output still maintained the growth state. In accordance with the definition of Tapio decoupling, the smaller the decoupling index is, the stronger the decoupling degree.

Weak decoupling: the decoupling index is between 0 and 0.8 in most years, indicating that industrial economic increase and ICE are weakly decoupled in most years during the study period. In weak decoupling, ICE grew in tandem with industrial economy, but its growth rate is lower than that of total industrial output. In addition, this state also indicates that the possible factors promoting the decoupling process (such as the improvement of energy efficiency, the progress of energy saving technology, the optimization of energy structure, etc.) have not fully offset the hindering effect brought by the industrial economic increase.

[1] Among them, the Y data from 2012 to 2019 are estimated by industrial sales output value and production and sales ratio.

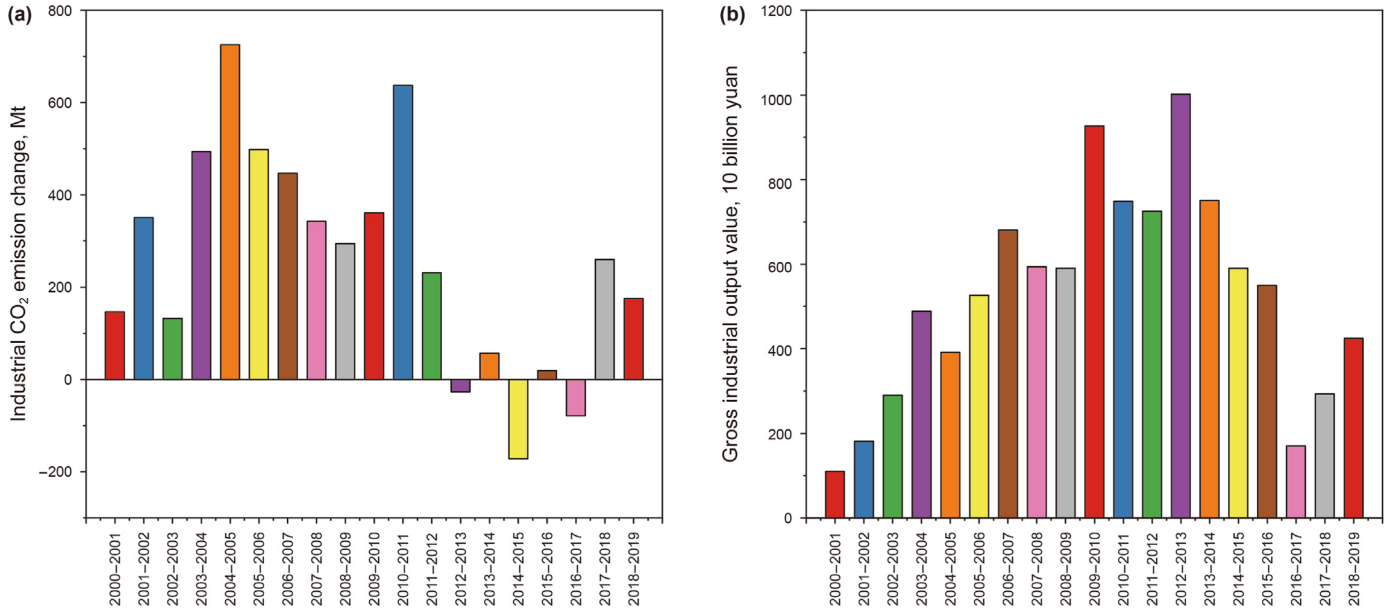

Fig. 4. The change tendency of ICE and total industrial output value, from 2000 to 2019.

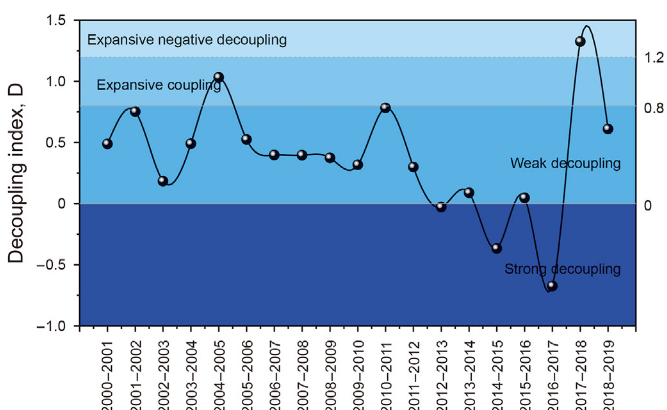

Fig. 5. The decoupling tendency of industrial growth and ICE from 2000 to 2019.

Expansive coupling and expansive negative decoupling: only one year during the study period, 2004–2005, showed expansive coupling. In other words, ICE grew faster than industrial economic increase during 2004–2005. Compared with the weak decoupling, the expansive coupling is a state with a lower decoupling degree, which indicates that the possible factors promoting the decoupling process can only offset a small part of the inhibitory effect brought about by industrial economic increase. In addition, during the study period, only that in 2017–2018 had a decoupling index greater than 1.2, showing a state of expansive negative decoupling. This state indicates that ICE are growing in tandem with industrial output, but the former is growing much faster than the latter, and a higher value indicates a lower degree of decoupling. In comparison with the expansive coupling, expansive negative decoupling is a lower decoupling state.

4.1.2. Decoupling analysis at regional level

As reported in Table 1, during the whole study period, total industrial output value and ICE in three regions have increased, and their decoupling index values are between 0 and 0.8, showing a weak decoupling. Concretely, eastern region showed strong decoupling in the four years 2002–2003 and 2014–2017; while for other years, the growth of industrial output value in eastern region is always accompanied by the growth of ICE with different degrees. The relationship between the two shows the weak decoupling, expansive coupling and expansive negative decoupling, and the weak decoupling is the main one. In most years, the total industrial output value of central region and its ICE show weak decoupling, that is, the growth rate of the total industrial output value is higher than the growth rate of ICE. From the whole study period, the degree of decoupling between industrial economic increase and ICE in the central region has gradually increased. Finally, the industrial economic increase and ICE in the western region exhibits strong decoupling only in 2014–2015, while weak decoupling, expansive coupling and expansive negative decoupling in the rest years. Among them, weak decoupling is the main state.

4.1.3. Decoupling analysis at provincial level

The changes of industrial economic increase and ICE vary greatly among different provinces, and accordingly, the decoupling process among different provinces is also obviously different. As shown in Fig. 6(a), during 2000–2019, only Beijing's ICE decreased, while the ICE in other provinces increased to varying degrees. As for the changes of total industrial output value, it can be seen from Fig. 6(b) that the growth of total industrial output value of Jiangsu, Guangdong and Shandong is the highest. In addition, Heilongjiang, Qinghai, Ningxia, Gansu and Xinjiang all recorded lower gross industrial output growth.

Fig. 7 indicates that the decoupling index of most provinces was between 0 and 0.8, implying that the total industrial output value of most provinces had a weak decoupling relationship with their ICE. That is, the total industrial output value and ICE grew simultaneously, but the former grew faster than the latter. Among the 30 provinces, only Beijing has completely decoupled its industrial economic increase from its ICE, showing a strong decoupling relationship. That is, the total industrial output value of Beijing increased while its ICE decreased, which is the most ideal decoupling relationship. In addition, only Xinjiang showed a negative decoupling relation between its industrial economy increase and ICE, which was the worst kind of decoupling relationship. In the

Table 1
Change tendency of decoupling index in three regions, from 2000 to 2019.

Period	Eastern region			Middle region			Western region		
	ΔC, Mt	ΔY, ten billion yuan	D	ΔC, Mt	ΔY, ten billion yuan	D	ΔC, Mt	ΔY, ten billion yuan	D
2000–2001	81	86	0.5103	52	14	0.8896	13	9	0.2395
2001–2002	236	140	0.9737	59	25	0.5645	56	17	0.6311
2002–2003	−38	234	−0.0951	93	32	0.7369	77	23	0.6541
2003–2004	292	385	0.5811	129	57	0.5934	72	46	0.3295
2004–2005	447	295	1.3061	131	57	0.6517	148	39	0.9532
2005–2006	234	395	0.4842	151	78	0.5940	113	53	0.5347
2006–2007	221	475	0.4210	136	127	0.3524	90	79	0.3130
2007–2008	145	405	0.3627	66	114	0.2220	132	75	0.5717
2008–2009	123	375	0.3645	60	122	0.2194	110	93	0.4128
2009–2010	159	622	0.3036	106	194	0.2756	97	110	0.3425
2010–2011	257	389	0.8820	157	225	0.4135	224	135	0.7244
2011–2012	54	474	0.1539	33	172	0.1275	144	80	0.8254
2012–2013	12	626	0.0280	−113	225	−0.3757	74	151	0.2295
2013–2014	9	449	0.0329	−1	190	−0.0039	49	111	0.2312
2014–2015	−92	314	−0.5236	−55	175	−0.3252	−24	101	−0.1383
2015–2016	−8	260	−0.0567	11	168	0.0795	15	121	0.0784
2016–2017	−38	159	−0.4861	−63	7	−11.2796	22	4	3.6276
2017–2018	225	207	2.2685	−74	29	−3.3022	109	56	1.3165
2018–2019	42	230	0.3720	31	120	0.3644	101	75	0.9087
2000–2019	2361	6519	0.1959	909	2132	0.1016	1622	1378	0.2066

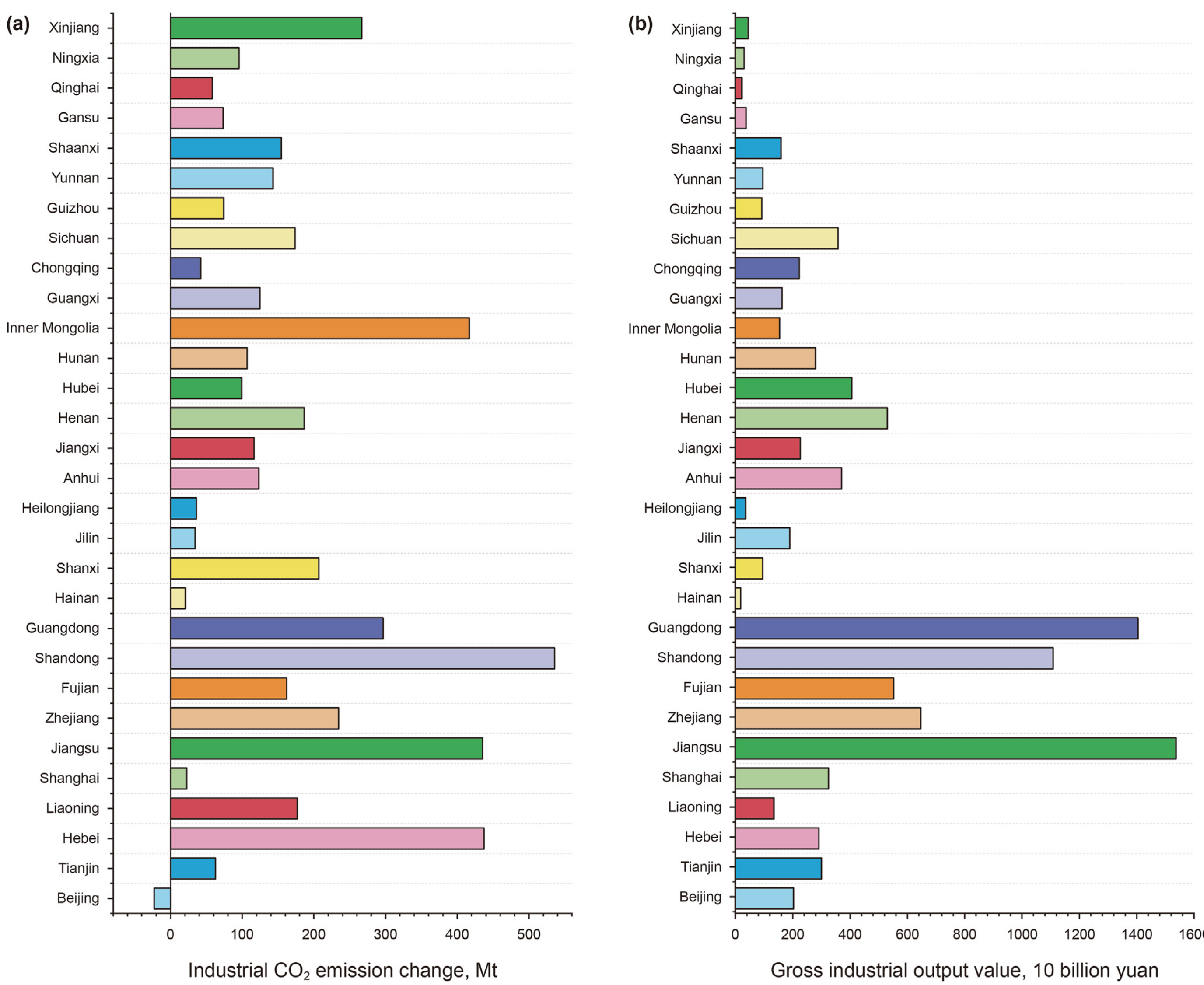

Fig. 6. Total change of gross industrial output value and ICE by province from 2000 to 2019.

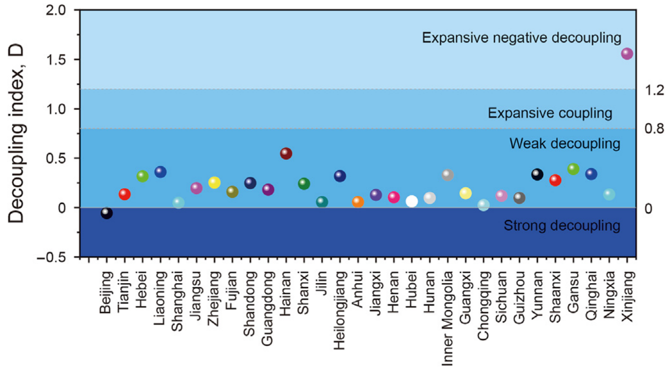

Fig. 7. Overall decoupling process in provinces from 2000 to 2019.

negative decoupling, the growth rate of ICE is much higher than that of its total industrial output. The results show that during the past two decades, Xinjiang's industrial development has come at the cost of high energy use and high emissions.

4.2. Discussions for the drivers of decoupling

4.2.1. Analysis in national level

Intensity factor: CO_2 emissions coefficient (D_{CF}) and potential energy intensity (D_{PEI}). As reported in Table 2, D_{CF} promotes the process of decoupling in most years, mainly thanks to the reduction of the CO_2 emissions coefficient, which contributes to the reduction of ICE and further promotes the process of decoupling. The potential energy intensity in this paper is different from the actual observed energy intensity (i.e., energy use per unit of gross output), which is an intensity measure that eliminates all potential technical efficiencies. The decomposition results in Table 2 show that this factor has a certain degree of hindering effect on the decoupling process of industrial economic increase and ICE during 2000–2019.

Structure factor: since it is difficult to obtain complete data on renewable energy for industries in different provinces, the energy structure effect studied in this paper refers to the impact of changes in the proportion of various fossil energy and electricity consumption on the decoupling relationship, the value of D_{ES} is greater than zero in most years, implying that the adjustment of industrial energy use structure in the past twenty years has not promoted the reduction of ICE, but also hindered the decoupling of industrial

Table 2
The effects of various drivers on decoupling degree.

Period	D_{tot}	Intensity factor		Energy-oriented factor			
		D_{CF}	D_{PEI}	D_{ETG}	D_{SEE}	D_{PEE}	D_{EST}
2000–2001	0.4880	0.0061	0.4748	−0.2191	−0.1070	0.2648	−0.8072
2001–2002	0.7516	0.0128	0.7962	0.0439	0.0221	0.1386	−0.9477
2002–2003	0.1841	−0.0052	0.7544	0.0994	0.1444	0.1061	−1.2375
2003–2004	0.4899	0.0508	0.5436	−0.0266	0.0488	−0.1805	−0.6021
2004–2005	1.0325	−0.0470	0.4145	0.2166	−0.1307	−0.0688	−0.0558
2005–2006	0.5241	−0.0266	0.1728	−0.1900	−0.1063	0.0426	−0.2474
2006–2007	0.3979	−0.0879	0.3832	−0.1591	−0.0049	0.0779	−0.5932
2007–2008	0.3963	0.0223	−0.4072	0.0569	0.2064	−0.3760	−0.2886
2008–2009	0.3744	−0.0121	−0.1432	−0.4013	0.0565	−0.0169	−0.0673
2009–2010	0.3182	−0.0046	0.0634	0.5296	0.4159	−0.0929	−1.7231
2010–2011	0.7829	−0.0355	0.3514	0.1641	0.2660	0.0821	−0.9135
2011–2012	0.2998	0.0070	−0.1021	−0.1252	−0.2572	−0.0121	−0.2467
2012–2013	−0.0277	0.0113	0.1068	0.2090	0.5140	0.1559	−2.0337
2013–2014	0.0881	−0.2741	−0.3938	0.4565	0.1667	−0.0915	−0.9391
2014–2015	−0.3668	−0.2226	0.4773	−0.5023	−0.1315	0.0893	−0.7392
2015–2016	0.0473	−0.0949	0.3388	0.1121	0.5339	−0.0013	−1.6634
2016–2017	−0.6735	−0.0076	5.8330	2.0634	−2.3735	4.4609	−9.5779
2017–2018	1.3255	−0.3491	5.7458	−3.0542	0.1327	0.4210	−0.7678
2018–2019	0.6105	−0.0728	1.4117	−1.3113	−1.0990	−0.4799	1.9235
2000–2019	0.0578	−0.0061	0.0558	−0.0030	0.0100	0.0039	−0.1258

Period	Structure factor	Investment factor		Output-oriented factor			
	D_{ES}	D_{IE}	D_I	D_{YTG}	D_{SYE}	D_{PYE}	D_{PT}
2000–2001	0.1454	−0.5423	1.5119	0.0057	0.0155	0.0632	−0.3237
2001–2002	0.1888	−0.1212	1.1002	−0.0372	0.0175	−0.0058	−0.4567
2002–2003	−0.1865	−0.5197	1.4310	0.0295	0.0251	0.0196	−0.4763
2003–2004	0.0603	0.1346	0.7952	−0.0657	−0.0133	−0.0390	−0.2163
2004–2005	−0.0275	−0.5399	1.5424	−0.0854	−0.0385	−0.1257	−0.0216
2005–2006	0.0433	−0.0338	0.9873	0.0678	0.0743	−0.0309	−0.2291
2006–2007	0.0634	0.0859	0.8524	−0.1004	−0.0154	0.0252	−0.1292
2007–2008	−0.0129	0.0813	0.8733	0.0975	0.1861	−0.0810	0.0383
2008–2009	−0.0364	−0.8062	1.7655	−0.2779	−0.1490	0.0015	0.4612
2009–2010	0.2610	0.0774	0.8600	0.0224	0.0629	0.0570	−0.2108
2010–2011	0.0808	0.5940	0.3928	0.0009	0.2076	−0.0326	−0.3750
2011–2012	0.0263	−0.5795	1.5426	0.1389	−0.0544	−0.1098	0.0719
2012–2013	0.1538	−0.1976	1.1304	−0.0075	0.0776	0.0342	−0.1821
2013–2014	0.0356	−0.2562	1.2164	0.0729	0.2088	0.0773	−0.1914
2014–2015	0.1580	−0.4814	1.4375	0.3309	0.1797	0.1404	−1.1030
2015–2016	0.2313	0.2845	0.6834	−0.1033	−0.2821	−0.0056	0.0138
2016–2017	1.0363	3.3211	−2.3356	1.9125	1.3843	1.1237	−7.5141
2017–2018	0.6085	0.2598	0.7429	0.0897	0.6579	0.7114	−3.8732
2018–2019	0.0416	0.6809	0.3105	−1.0856	−1.9343	−0.0085	2.2336
2000 to −2019	0.0128	−0.0123	0.1559	−0.0010	0.0024	0.0024	−0.0372

Table 3
Effects of intensity, technology and technology gap on the decoupling process from 2000 to 2019 [a].

Region	Province	D_{tot}	Intensity factor		Technology factor		Technology gap factor	
			D_{CF}	D_{PEI}	D_{EST}	D_{PT}	D_{ETG}	D_{YTG}
Eastern provinces	BJ	−0.0562	−0.0087	0.1286	−0.2476	−0.1017	0.0000	0.0000
	TJ	0.1353	−0.0156	0.3151	−0.3702	−0.1425	0.0000	0.0000
	HB	0.3163	−0.0227	0.0030	−0.7309	−0.1187	0.0000	0.0000
	LN	0.3596	−0.0391	−0.0559	−1.2079	−0.3442	0.0000	0.0000
	SH	0.0486	−0.0225	0.2843	−0.5640	−0.2043	0.0000	0.0000
	JS	0.1966	−0.0243	0.1843	−0.2810	−0.0876	0.0000	0.0000
	ZJ	0.2526	−0.0369	0.0710	−0.5330	−0.1403	0.0000	0.0000
	FJ	0.1592	−0.0149	0.1773	−0.2939	−0.0687	0.0000	0.0000
	SD	0.2477	−0.0226	0.2297	−0.3705	−0.0711	0.0000	0.0000
	GD	0.1812	−0.0269	0.2077	−0.4014	−0.1238	0.0000	0.0000
	HN	0.5469	−0.0376	0.3496	−0.9743	−0.5122	0.0000	0.0000
Central provinces	SX	0.2409	−0.0222	−0.0240	−0.6471	−0.1766	0.0385	−0.0624
	JL	0.0559	−0.0096	0.2133	−0.3450	−0.0837	−0.0895	−0.0609
	HLJ	0.3187	−0.0628	−0.1448	−2.1703	−0.7240	0.1120	−0.2776
	AH	0.0568	−0.0063	0.0882	−0.1715	−0.0332	−0.0263	−0.0240
	JX	0.1280	−0.0093	0.0413	−0.2430	−0.0423	0.0027	−0.0427
	HeN	0.1042	−0.0162	0.1241	−0.3875	−0.0795	−0.0440	−0.0191
	HB	0.0632	−0.0101	0.1394	−0.2983	−0.0743	−0.0355	−0.0233
	HuN	0.0979	−0.0096	0.1052	−0.3348	−0.0604	−0.0064	−0.0463
Western provinces	IM	0.3293	−0.0222	0.2291	−0.4046	−0.2172	0.3907	0.0193
	GX	0.1451	−0.0128	0.1414	−0.3149	−0.0623	−0.0106	−0.0396
	CQ	0.0257	−0.0042	0.0540	−0.1258	−0.0267	−0.0387	−0.0109
	SC	0.1192	−0.0114	0.0503	−0.3381	−0.0708	0.0189	−0.0108
	GZ	0.0978	−0.0136	0.0928	−0.3161	−0.0855	0.0193	0.0059
	YN	0.3343	−0.0297	0.1345	−0.7071	−0.2679	−0.0492	0.0562
	ShX	0.2757	−0.0189	0.0938	−0.4878	−0.1915	0.0431	0.0072
	GS	0.3900	−0.0559	0.1549	−1.0830	−0.3892	0.0489	0.0441
	QH	0.3381	−0.0446	0.4843	−0.6358	−0.4737	0.1176	0.0628
	NX	0.1327	−0.0141	0.0821	−0.2526	−0.1287	0.0213	0.0123
	XJ	1.5572	−0.1043	0.5555	−1.7273	−1.3454	−0.0680	0.2489

[a] The names of various provinces and their abbreviations are attached in Appendix A.

Table 4
The effects of structure, investment, scale economy efficiency, and pure technical efficiency on the decoupling process from 2000 to 2019.

Region	Province	Structure factor D_{ES}	Investment factor		Scale economy efficiency factor		Pure technical efficiency factor	
			D_{IE}	D_I	D_{SEE}	D_{SYE}	D_{PEE}	D_{PYE}
Eastern provinces	BJ	0.0243	0.1289	0.1389	−0.0141	−0.0037	−0.0810	−0.0201
	TJ	0.0100	0.0293	0.3785	−0.0162	−0.0031	−0.0332	−0.0167
	HB	0.0474	−0.2830	0.8937	0.0767	0.0130	0.3351	0.1027
	LN	0.0758	0.1803	0.3858	0.1262	0.0456	0.8381	0.3549
	SH	0.0241	0.3849	0.0497	0.0033	0.0028	0.0727	0.0176
	JS	0.0641	−0.0029	0.4260	−0.0728	−0.0091	0.0000	0.0000
	ZJ	0.0723	0.0765	0.4449	0.0556	−0.0019	0.1560	0.0883
	FJ	0.0100	−0.0572	0.4744	0.0407	−0.0052	−0.0711	−0.0321
	SD	0.0590	0.1089	0.3917	0.1132	−0.0010	−0.1531	−0.0366
	GD	0.0603	0.0414	0.4239	0.0000	0.0000	0.0000	0.0000
	HN	0.0217	0.1180	0.6599	0.7592	0.1626	0.0000	0.0000
Central provinces	SX	0.0255	0.1941	0.3742	0.1888	0.1058	0.0891	0.1573
	JL	0.0141	0.0122	0.4048	0.0000	0.0000	0.0000	0.0000
	HLJ	0.0912	−1.4946	2.3500	1.5585	1.2635	−0.0651	−0.1170
	AH	0.0181	−0.0589	0.2889	0.0147	0.0057	−0.0334	−0.0053
	JX	0.0211	−0.0626	0.3813	−0.0121	0.0025	0.0520	0.0392
	HeN	0.0410	−0.0988	0.5603	0.0109	0.0130	0.0000	0.0000
	HB	0.0265	−0.0544	0.4072	−0.0064	−0.0056	−0.0011	−0.0009
	HuN	0.0126	−0.1092	0.5339	−0.0104	0.0113	0.0028	0.0092
Western provinces	IM	0.0387	0.1494	0.2723	−0.0109	−0.0032	−0.0842	−0.0280
	GX	0.0294	−0.0984	0.4822	0.0975	0.0134	−0.0527	−0.0276
	CQ	0.0088	−0.0189	0.1879	0.0000	0.0000	0.0000	0.0000
	SC	0.0080	0.0428	0.3319	0.0671	0.0313	0.0000	0.0000
	GZ	0.0280	0.0009	0.3932	0.0204	−0.0081	−0.0344	−0.0051
	YN	0.0473	−0.0194	0.6744	0.1611	−0.0004	0.2569	0.0776
	ShX	0.0295	−0.0356	0.5542	0.0314	0.0079	0.1598	0.0826
	GS	0.1174	0.1327	0.6038	0.5434	−0.0062	0.0828	0.1964
	QH	0.0048	−0.0777	0.7129	0.2609	−0.0734	0.0000	0.0000
	NX	0.0081	0.0195	0.2412	−0.0202	−0.0341	0.1294	0.0684
	XJ	0.4626	0.3530	0.9640	0.7517	−0.0563	0.9254	0.5972

economic increase from its carbon dioxide emissions.

Energy-oriented factor: D_{EST} has acted a momentous role in promoting the decoupling of industrial economic increase and ICE in almost all years. D_{ETG} also contributed to the decoupling process in most years, but the role was relatively small. It shows that during the study period, the energy-saving technology gap between technologically advanced regions and technologically backward regions has been narrowed in most years, but from the whole study period perspective, the reduction range of energy-saving technology gap is low. In addition, D_{SEE} and D_{PEE} have different effects in different years, but from the whole study period perspective, both of them have hindered the decoupling course. The results show that from 2000 to 2019, the change of scale economy efficiency failed to promote the energy efficiency improvement, and further hindered the decoupling process. At the same time, the resource allocation efficiency in energy market has not been obviously optimized, and it has formed a certain obstacle to the decoupling course of industrial economic increase and ICE.

Output-oriented factor: Table 2 shows that D_{PT} promotes the decoupling process in most years, and the promoting effect is significant. The results show that the technology level of industrial production has been significantly improved in the past two decades, which inhibits ICE and further promotes the decoupling process. D_{YTG} has different effects on decoupling in different years, but from the whole study period, this factor plays a promoting but weak role in decoupling industrial economic increase from its ICE. Both D_{SYE} and D_{PYE} hinder the decoupling of industrial economic increase from its ICE. It indicates that the change of scale economy efficiency during the sample period failed to improve production efficiency and further hindered the decoupling process. At the same time, product markets are less efficiently managed, which increases ICE and further impedes decoupling process.

Investment factor: investment efficiency (D_{IE}) and investment scale (D_I). Over the past two decades, China's industrial development has not completely changed its investment-driven growth model. Therefore, the expansion of investment has promoted the increase of industrial output and further restrained the decoupling of industrial economy from ICE. The expansion of investment scale is the biggest driver impeding the decoupling process. During 2000–2019 period, D_I is negative only in 2016–2017, which contributes positively to the decoupling process. This is caused by the decline of industrial fixed asset investment in 2016–2017. In addition, it is not difficult to know from Table 2 that the D_I exhibited a mild role in facilitating the decoupling of the two during the whole study span.

4.2.2. Analysis in provincial level

As can be seen from Section 4.2, decoupling at the regional level and provincial level both show great differences. This paper focuses on analyzing its driving factors at the provincial level (see Table 3 and Table 4).

Intensity factor (D_{CF} and D_{PEI}) and structure factor (D_{ES}). D_{CF} throughout the study period promoted the decoupling process of industrial economic increase from ICE in all provinces. However, D_{PEI} hinders the decoupling course in most provinces. In addition, the decomposition results also show that the D_{ES} is positive in all provinces, which hinders the decoupling process. This is because the adjustment of industrial energy mix in all provinces during the whole study period failed to reduce ICE, meaning that the industrial energy use structure in all these provinces failed to become more “low-carbon”.

Technology factor (D_{EST} and D_{PT}). D_{EST} motivated the decoupling process between industrial economic increase and ICE in all provinces, implying that the energy saving technology in all provinces had made significant progress during the study period, which also proved by previous studies (e.g., Zhao et al., 2016). Of all the factors, the advance of energy-saving technology in most provinces is the most critical driver to promote their decoupling process. On the other hand, D_{PT} also promotes the decoupling of industrial economic increase from its ICE in all provinces, indicating that all provinces have made progress in industrial production technology (Liu et al., 2022; Jiang et al., 2023).

Technology gap factor (D_{ETG} and D_{YTG}). The technology gap effect refers to the impact of the gap change between technologically backward and technologically advanced regions on the decoupling of industrial economic increase and ICE. The narrowing of technology gap is conducive to the decoupling process, and vice versa. The values of D_{ETG} and D_{YTG} were both zero in eastern provinces, meaning that the two technology gaps between eastern provinces and technologically developed provinces did not change during the study period. This is due to the early start of economic development, convenient transportation, coupled with the high density of talents, eastern provinces have always been at the forefront of technology, which is also the forefront of technology among all the provinces considered in this paper. Besides, D_{ETG} and D_{YTG} positively promoted the decoupling process in Jilin, Anhui, Henan, Hubei and Hunan. The results show that the technology gaps between these provinces and the technologically developed provinces has been narrowed during the study period. The D_{ETG} in Shanxi, Heilongjiang and Jiangxi hindered the decoupling process between industrial economic increase and ICE, while the D_{YTG} promoted their decoupling process. In the western provinces, the gap between the energy-saving technologies of Guangxi, Chongqing, Yunnan and Xinjiang and those of the developed provinces has narrowed, which has motivated the decoupling in these provinces. However, the D_{ETG} in other western provinces has impeded the decoupling. In addition, D_{YTG} of Guangxi, Chongqing and Sichuan promoted their decoupling process, while the D_{YTG} of other provinces hindered their decoupling process.

Investment factors (D_{IE} and D_I): D_I lowered the decoupling degree in all provinces. For the vast majority of provinces, D_I is the largest factor hindering their decoupling process. In addition, D_{IE} promoted the decoupling of industrial economic increase and ICE only in Hebei, Jiangsu and Fujian. D_{IE} promoted the decoupling process in most central provinces, while had a hindering effect in Shanxi and Jilin. In the western provinces, D_{IE} promoted the decoupling of industrial economic increase and ICE in Guangxi, Chongqing, Yunnan, Shaanxi and Qinghai, but hindered the decoupling process in Inner Mongolia, Sichuan, Guizhou, Gansu, Ningxia and Xinjiang.

Scale economy efficiency factor (D_{SEE} and D_{SYE}). D_{SEE} and D_{SYE} hindered the decoupling of industrial economic increase from ICE in most provinces (e.g., Hebei and Liaoning), but only promoted the decoupling in Beijing, Tianjin, Ningxia, Hubei, Inner Mongolia and Jiangsu. In addition, D_{SEE} and D_{SYE} have completely opposite impacts on the decoupling in some provinces. Concretely, in Gansu, Qinghai, Xinjiang, Fujian, Guizhou, Shandong, Zhejiang and Yunnan, D_{SEE} inhibited the decoupling process between industrial economy and ICE, while D_{SYE} promoted their decoupling process. The results suggest that these provinces' scale economy are currently at the stage of more conducive to improving their output efficiency rather than energy efficiency. For Jiangxi and Hunan, the D_{SEE} acted a positive role in facilitating decoupling process, while D_{SYE} impeded their decoupling process. It indicates that the scale economy in Jiangxi and Hunan are currently at the stage of more conducive to improving their energy efficiency rather than output efficiency.

Pure technical efficiency factor (D_{PEE} and D_{PYE}): D_{PEE} and D_{PYE} hindered the decoupling process in mot provinces (e.g., Hebei, Liaoning, and Shanxi), while exerted a negative impact in the decoupling process of Beijing, Tianjin, Fujian, Shandong, Heilongjiang, Anhui, Hubei, Inner Mongolia, Guangxi and Guizhou. Overall, the effects (positive or negative) of pure technical efficiency are relatively mild in all provinces. The above results indicate that resource misallocation may exist in the energy market and product market during the study period, and we should focus on improving the resource allocation efficiency of these provinces in the future.

5. Conclusion and policy implications

The research objective of this article is to reveal the decoupling relation between China's industrial economic increase and ICE, and further uncover the effects of various driving factors on the decoupling process. We found that:

(1) From the perspective of the whole country, China's industrial economic increase and its ICE experienced four decoupling states from 2000 to 2019, and the weak decoupling was the main one. Among them, investment scale expansion is the primary driver hindering the decoupling process, potential energy intensity and energy structure also acts a certain role in hindering the decoupling process. Investment efficiency and CO_2 emissions coefficient promote the decoupling, but their effect is relatively weak. Energy-saving technology, production technology, technology gaps play important roles in promoting the decoupling process. On the contrary, scale economy and pure technical efficiency change have inhibited the decoupling of industrial economic increase from its ICE.

(2) At the provincial level, 28 provinces showed a weak decoupling between industrial output value and ICE, Beijing showed a strong decoupling, while Xinjiang exhibited an expansive negative decoupling. Among them, the changes of investment scale, potential energy intensity and energy structure hinder the decoupling of the two in most provinces. Technology advance in all provinces has exerted vital role in promoting the decoupling degree. Energy saving technology gap change hindered the decoupling of Shanxi, Heilongjiang, Jiangxi, Inner Mongolia, Guizhou, Shaanxi, Gansu, Qinghai and Ningxia, but promoted the decoupling process of other provinces. The effect of production technology gap motivated decoupling process in all central provinces while hindered decoupling in most western provinces. Moreover, scale economy efficiency hindered the decoupling of industrial economic increase and ICE in most provinces, but promoted the decoupling process in Beijing, Tianjin, Jiangsu, Hubei, Inner Mongolia and Ningxia. In the future, each province should be targeted to improve its own scale efficiency and industrial structure efficiency. Besides, for the relatively backward provinces, it should narrow the gap with the technologically developed provinces.

Declaration of competing interest

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

Acknowledgement

We gratefully acknowledge financial support from the China Postdoctoral Science Foundation project (No. 2023M733253).

Appendix A

Table A
The names of various provinces and their abbreviations.

Regions	Provinces
Eastern region	Beijing (BJ), Tianjin (TJ), Hebei (HB), Liaoning (LN), Shanghai (SH), Jiangsu (JS), Zhejiang (ZJ), Fujian (FJ), Shandong (SD), Guangdong (GD), Hainan (HN)
Central region	Shanxi (SX), Jilin (JL), Heilongjiang (HLJ), Anhui (AH), Jiangxi (JX), Henan (HeN), Hubei (HB), Hunan (HuN)
Western region	Inner Mongolia (IM), Guangxi (GX), Chongqing (CQ), Sichuan (SC), Guizhou (GZ), Yunnan (YN), Shaanxi (ShX), Gansu (GS), Qinghai (QH), Ningxia (NX), Xinjiang (XJ)

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