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RESEARCH ARTICLE

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Decomposition and decoupling analysis of electricity consumption carbon emissions in China

Abstract Electricity consumption is one of the major contributors to greenhouse gas emissions. In this study, we build a power consumption carbon emission measurement model based on the operating margin factor. We use the decomposition and decoupling technology of logarithmic mean Divisia index method to quantify six effects (emission intensity, power generation structure, consumption electricity intensity, economic scale, population structure, and population scale) and comprehensively reflect the degree of dependence of electricity consumption carbon emissions on China's economic development and population changes. Moreover, we utilize the decoupling model to analyze the decoupling state between carbon emissions and economic growth and identify corresponding energy efficiency policies. The results of this study provide a new perspective to understand carbon emission reduction potentials in the electricity use of China.

Keywords electricity consumption carbon emission measurement, LMDI model, decoupling model, data driven

1 Introduction

The rapid growth of China's economy has led to drawbacks, such as massive energy consumption and a sharp increase in carbon emissions, to which the power industry is the major contributor. The national carbon market was implemented in 2021. The power industry, which accounts for more than 40% of the country's total carbon emissions, was included first. As the level of end-use electrification continues to grow, some carbon emissions will be gradually transferred from the direct fossil fuel consumption to the power consumption, the power sector will become the most important source of carbon emissions. In 2016, China officially pledged to reduce its carbon emission intensity per unit of gross domestic product (GDP) by 60%–65% compared with that in 2005, to hit peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (Zhou et al., 2022). However, China's current economy is characterized by a large volume and high intensity of carbon emissions, and considerable challenges need to be resolved to achieve carbon neutrality.

Carbon emission measurement models are key to understanding the emission structure and designing effective decarbonization policies. A carbon emission measurement model can be categorized into production-based (Zhang and Da, 2015; Liu et al., 2015a; 2015b) and consumption-based (Feng et al., 2013; Lin et al., 2014; Shan et al., 2016) methods. The production-based method attributes the responsibility of carbon emissions to the principle of the place of production, whereas the consumption-based method attributes the same responsibility to the principle of the place of consumption. The local electricity consumption in each province is measured to help obtain the actual total carbon emissions contributed by electricity in each province. Electricity consumption needs to be calculated and decomposed to explore the causes of carbon emissions because it remains to be the primary contributor to carbon emissions.

Existing studies have focused on exploring power generation-based approaches (Yousuf et al., 2014; Quick, 2014; Howard et al., 2017; Jiang et al., 2021), and some power consumption models use the multi-regional input–output (MRIO) method. MRIO is a carbon emission assessment model based on the principle of consumption. It can measure carbon emission of electricity consumption through an input–output table. Its disadvantage is

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that, first, in the input–output table, electricity consumption is the sum of renewable energy and thermal power generation, and thermal power generation is not separated from it. Second, due to data availability, fully obtaining each electricity sector's consumption by province is difficult. Lastly, the calculation is performed from the perspective of the economic input–output ratio table, and the unit is the economic unit; meanwhile, extant literature performed calculations from the perspective of the power consumption end, including the power generation factor and electricity consumption of power plants, thus certain differences exist in the calculation (Kucukvar et al., 2016; Mi et al., 2018). Some studies have examined carbon emissions from the power consumption side (Zhang et al., 2019; 2021; Abokyi et al., 2021). For the Clean Development Mechanism Project, the Ministry of Ecology and Environment of China calculated the emission factor "operating margin" (OM) and "build margin" (BM) of China's regional power grid baselines. The OM factor is used to analyze pure thermal power plants, calculated based on the total net power generation, fuel type, and total fuel consumption of all plants in the power system (excluding low-cost/must-run units), whereas the BM factor is a comprehensive analysis factor for both thermal and renewable energy power plants, calculated by the weighted average of the power supply emission factors of the selected m newly added unit samples with electricity as the weight.

Most researchers have utilized the logarithmic mean Divisia index (LMDI) decomposition model to obtain the emission factors of carbon emissions (Zhang and Da, 2015; Zhao et al., 2017; Chen et al., 2020; Liu et al., 2021). Carbon emission intensity and Tapio decoupling (Tapio, 2005) models are currently available in literature and can be used to measure the relationship between carbon emissions and the economy. Carbon intensity is the ratio of carbon emissions to GDP. It is an important indicator for evaluating the level of urban development, mainly used to measure the relationship between the economy and carbon emissions. The level of intensity does not indicate the level of efficiency. Countries with high GDP per capita tend to have low carbon intensity. In other words, using carbon intensity indicators is ineffective because these indicators mask the net increase in carbon dioxide emissions, but economic development has not yet been decoupled from carbon emissions. For developing countries, the expansion of the economic scale requires the reuse of the same technology, so the intensity does not decrease linearly with economic growth. Therefore, in the long run, it may be unfavorable for developing countries. The rate of decline in carbon intensity is determined by the elasticity of carbon emissions to GDP and directly related to the growth rate of GDP. The future economic growth rate of a country is uncertain, and the reduction rate of carbon emission intensity, as the country's commitment indicator for reducing greenhouse gas emissions, has some uncertainty. Therefore, a decoupling model is generally adopted, and decoupling emphasizes trends. Decoupling is not a random fluctuation and deviation of energy consumption or carbon emissions in the short term; it can be maintained stably and continuously at a low level for a certain period from the economic growth trend, and it quantitatively reveals the relationship between carbon emissions and economic growth in one or more sectors to facilitate the decarbonization of countries or enterprises (Chen, 2011; Andersson and Karpestam, 2013; Ma and Cai, 2019; Liu et al., 2021; Xi et al., 2021). On the basis of the decomposition results, a decoupling index is introduced to analyze the decoupling relationship between China's carbon emissions and economic growth. Then, policy recommendations are provided to measure the relationship between carbon dioxide emissions and China's economic growth at the national level, and the decoupling relationship of the influencing factors is explored. The motivation for studying decoupling is to analyze the relationship between the economy and carbon emissions. This analysis can help policy makers understand how decarbonization could interact with economic growth for an effective policy design. These data provide the basis for China's decision-making to achieve carbon neutrality. Decoupling of carbon emissions is an idealized process in which the relationship between economic growth and greenhouse gas emissions is constantly weakening or even disappearing, that is, energy consumption is gradually reduced due to economic growth (Andreoni and Galmarini, 2012; Lu et al., 2015; Wang et al., 2016).

In existing literature, carbon emission estimates are mainly based on input–output tables and carbon emissions from initial energy calculations, while electricity consumption carbon emission analysis is primarily based on the evaluation of the electricity consumption of power plants. Research on electricity consumption mostly involves the use of coal, oil, natural gas, and traditional input–output models, and only a few studies have explained the relationship between electricity consumption carbon emissions and the economy, power generation structure, and population.

Given this context, a carbon emission model for electricity consumption based on the OM factor is developed in the current study to analyze the carbon emissions of electricity consumption in each provincial-level region in China (Hong Kong, Macao, and Taiwan are not included) from 2015 to 2019. The calculation results help understand the electricity consumption intensity of each region. On the basis of calculation results, an LMDI decomposition model is utilized to decompose the carbon emissions of the electricity consumption of each region. The carbon emissions of electricity consumption are decomposed into six effects (emission intensity, power generation structure, consumption electricity intensity, economic scale, population structure, and population size) to study the main influencing factors of electricity consumption carbon emissions. Then, the Tapio decoupling elasticity index is adopted to measure the decoupling relationship between carbon emissions and economic development in China's provinces and regions during the five-year period of 2015–2019. The decoupling index is further decomposed into a causal chain. Combining the elasticity index and the complete decomposition, this method is free of measurement unit and is a decomposition of relative indicators. It has strong implications and application values in emission reduction and regional decarbonization policies.

The rest of the paper is organized as follows. Section 2 introduces the mathematical theory behind the electricity consumption carbon emission measurement model based on the OM factor, the LMDI decomposition model, and the decoupling model. Section 3 analyzes the results of the calculation and presents the corresponding perspectives on carbon emission reduction. Section 4 concludes the paper.

2 Methodologies and data descriptions

2.1 Electricity consumption carbon emission model

China's power generation structure comprises thermal power, hydropower, wind power, and so on, but carbon emissions are primarily generated by thermal power. Therefore, only the CO_2 emissions of thermal power need to be calculated as a proportion of power generation.

The carbon emissions from electricity consumption in a region can be expressed as

$$C_a = E_a \times \frac{F_{af}}{F_a} \times \frac{\sum_t (FC_{t,y} \times NCV_{t,y} \times EF_{CO_2,t,y})}{EG_y}, \tag{1}$$

where C_a and E_a represent the carbon emissions of electricity consumption and electricity consumption in provincial region a, respectively; F_a and F_{af} represent the total and the thermal power generation in provincial region a, respectively; EG_y represents the total net power generation of the power system in year y, i.e., the total power (MWh) supplied to the grid by all units except for the low-operating cost/must-operate units; $FC_{t,y}$ represents the total consumption (mass or volume unit) of fuel t by the above-mentioned unit in year y; $NCV_{t,y}$ represents the average low calorific value of fuel t in year y (GJ/mass or volume unit); $EF_{CO_2,t,y}$ represents the CO_2 emission factor of fuel t in year y (tCO_2/GJ); t represents the type of fossil fuel consumed by the power system for the power generation in year y; and year y denotes each of the most recent three years for which data were available at the time of the submission of the project design documents (pre-calculation).

Equation (1) can be rewritten as

$$C_a = E_a \times F_{afp} \times OM_a, \tag{2}$$

where F_{afp} and OM_a represent the proportion of thermal power in provincial region a to the total electricity generation, and carbon emission factor of OM power generation in provincial region a, respectively.

2.2 LMDI model

The LMDI model has advantages, such as path independence, absence of residuals, ability to deal with zero values, and aggregation consistency (Zhang and Da, 2015; Zhao et al., 2017; Chen et al., 2020; Liu et al., 2021). The LMDI model is used to decompose carbon emissions from electricity consumption. The total carbon emissions in year t can be expressed as

$$C_a^t = OM_a^t \times \frac{F_{af}^t}{F_a^t} \times \frac{E_a^t}{GDP_a^t} \times \frac{GDP_a^t}{P_a^t} \times \frac{P_a^t}{P^t} \times P^t, \tag{3}$$

where C_a^t, E_a^t, F_{af}^t, F_a^t, OM_a^t, GDP_a^t, and P_a^t represent the carbon emissions of electricity consumption, electricity consumption, thermal power generation, total power generation, carbon emission factor of OM power generation, GDP value, and population, respectively, of provincial region a in year t. Furthermore, P^t represents the population of the country in year t.

Therefore, by simplifying Eq. (3), we derive

$$C_a^t = OM_a^t \times F_{afp}^t \times EG_a^t \times GP_a^t \times PP_a^t \times P^t, \tag{4}$$

where F_{afp}^t, EG_a^t, GP_a^t, and PP_a^t represent the power generation structure, electricity consumption intensity, economic scale, and population structure, respectively, of provincial region a in year t.

The overall effects are expressed by ΔC_a^{0-t} and can be decomposed into

$$\begin{aligned}\Delta C_a^{0-t} &= C_a^t - C_a^0 \\ &= OM_a^t \times F_{afp}^t \times EG_a^t \times GP_a^t \times PP_a^t \times P^t \\ &\quad - OM_a^0 \times F_{afp}^0 \times EG_a^0 \times GP_a^0 \times PP_a^0 \times P^0 \\ &= \Delta OM_a^{0-t} + \Delta F_{afp}^{0-t} + \Delta EG_a^{0-t} + \Delta GP_a^{0-t} \\ &\quad + \Delta PP_a^{0-t} + \Delta P^{0-t},\end{aligned} \tag{5}$$

where

$$\Delta OM_a^{0-t} = \frac{C_a^t - C_a^0}{\ln C_a^t - \ln C_a^0} \times \ln\left(\frac{OM_a^t}{OM_a^0}\right), \tag{5.1}$$

$$\Delta F_{afp}^{0-t} = \frac{C_a^t - C_a^0}{\ln C_a^t - \ln C_a^0} \times \ln\left(\frac{F_{afp}^t}{F_{afp}^0}\right), \tag{5.2}$$

$$\Delta EG_a^{0-t} = \frac{C_a^t - C_a^0}{\ln C_a^t - \ln C_a^0} \times \ln\left(\frac{EG_a^t}{EG_a^0}\right), \tag{5.3}$$

$$\Delta GP_a^{0-t} = \frac{C_a^t - C_a^0}{\ln C_a^t - \ln C_a^0} \times \ln\left(\frac{GP_a^t}{GP_a^0}\right), \tag{5.4}$$

$$\Delta PP_a^{0-t} = \frac{C_a^t - C_a^0}{\ln C_a^t - \ln C_a^0} \times \ln\left(\frac{PP_a^t}{PP_a^0}\right), \tag{5.5}$$

$$\Delta P^{0-t} = \frac{C_a^t - C_a^0}{\ln C_a^t - \ln C_a^0} \times \ln\left(\frac{P^t}{P^0}\right). \tag{5.6}$$

2.3 Decoupling method

Tapio (2005) proposed the Tapio decoupling index to understand the relationship between the relative incremental values of carbon emissions and economic growth. The carbon emission decoupling model of each province and region in China is set as

$$T^t = \frac{\Delta CO_2/CO_2^0}{\Delta GDP/GDP^0} = \frac{GDP^0}{CO_2^0} \times \frac{\Delta CO_2}{\Delta GDP} = \frac{GDP^0}{CO_2^0} \times \frac{CO_2^t - CO_2^0}{GDP^t - GDP^0}, \tag{6}$$

where T^t denotes the decoupling index elasticity between carbon emissions and economic growth in year t for each province and region in China; CO_2^t and CO_2^0 represent the carbon emissions (million tons of CO_2) for each province and region in China in target year t and the base year, respectively; and GDP^t and GDP^0 are China's GDP (billion yuan) in target year t and the base year, respectively.

The Tapio model provides guidelines for evaluating eight decoupling/coupling states based on hook elasticity value T^t (Table 1); the evaluation thresholds of 0.8 and 1.2 in the guidelines are empirical values. Decoupling can be classified as weak, strong, and recessive. Negative decoupling can be classified as expansionary negative, strong negative, and weak negative. Coupling can be classified as expansionary and recessive. Among these, strong decoupling is the most desirable state for achieving low-carbon economic development; accordingly, strong negative decoupling is the most unfavorable state. When the total economic volume continues to grow ($\Delta GDP > 0$), the lower the GDP elasticity of energy carbon emissions is, the more significant the decoupling is, i.e., the higher the degree of decoupling is.

On the basis of the improved decomposition technique described above, decoupling elasticity was divided into six variables according to Eq. (5) and tested in this study to determine the contribution of the various influencing factors on the decoupling elasticity of carbon emissions from economic growth in each province and region of China. The specific change in the contribution of each variable can be calculated using

$$\begin{aligned} T^t &= \frac{\Delta CO_2/CO_2^0}{\Delta GDP/GDP^0} \\ &= \frac{GDP^0}{CO_2^0} \times \frac{\Delta OM_a^{0-t} + \Delta F_{afp}^{0-t} + \Delta EG_a^{0-t} + \Delta GP_a^{0-t} + \Delta PP_a^{0-t} + \Delta P^{0-t}}{\Delta GDP} \\ &= \frac{GDP^0}{CO_2^0} \times \frac{\Delta OM_a^{0-t}}{\Delta GDP} + \frac{GDP^0}{CO_2^0} \times \frac{\Delta F_{afp}^{0-t}}{\Delta GDP} + \frac{GDP^0}{CO_2^0} \times \frac{\Delta EG_a^{0-t}}{\Delta GDP} + \frac{GDP^0}{CO_2^0} \times \frac{\Delta GP_a^{0-t}}{\Delta GDP} \\ &\quad + \frac{GDP^0}{CO_2^0} \times \frac{\Delta PP_a^{0-t}}{\Delta GDP} + \frac{GDP^0}{CO_2^0} \times \frac{\Delta P^{0-t}}{\Delta GDP} \\ &= t_1 + t_2 + t_3 + t_4 + t_5 + t_6, \end{aligned} \tag{7}$$

where t_1, t_2, t_3, t_4, t_5 and t_6 represent the contribution of the provincial region's generation factor, generation structure, electricity consumption intensity, economy size, population structure, and population size to decoupling elasticity, respectively.

2.4 Data source

The OM factor data used in this study were derived from those published by the Ministry of Ecology and Environment of China in 2019; the factor part was excluded in

Table 1 Decoupling/Coupling states in the Tapio decoupling model

Categories	Status	ΔCO_2	ΔGDP	T^t	Practical implications
Negative decoupling	Expansionary negative decoupling	> 0	> 0	$T^t > 1.2$	Both GDP and CO_2 emissions are growing; the growth rate of GDP is slower than that of CO_2 emissions
	Weak negative decoupling	< 0	< 0	$0 \leqslant T^t < 0.8$	Both GDP and CO_2 emissions are declining; the decline rate of GDP is faster than that of CO_2 emissions
	Strong negative decoupling	> 0	< 0	$T^t < 0$	CO_2 emissions are growing, but GDP is declining
Decoupling	Recessive decoupling	< 0	< 0	$T^t > 1.2$	Both GDP and CO_2 emissions are declining; the decline rate of GDP is slower than that of CO_2 emissions
	Weak decoupling	> 0	> 0	$0 \leqslant T^t < 0.8$	Both GDP and CO_2 emissions are growing; the growth rate of GDP is faster than that of CO_2 emissions
	Strong decoupling	< 0	> 0	$T^t < 0$	CO_2 emissions are declining, but GDP is growing
Coupling	Expansionary coupling	> 0	> 0	$0.8 \leqslant T^t \leqslant 1.2$	CO_2 emissions and GDP are growing at similar rates
	Recessive coupling	< 0	< 0	$0.8 \leqslant T^t \leqslant 1.2$	CO_2 emissions and GDP are declining at similar rates

this study because of the small annual changes. The thermal power share data and electricity consumption data are provincial data from the *China Electric Power Statistical Yearbook 2015–2019*. The economic and population data are provincial data values from the *China Statistical Yearbook 2015–2019*.

3 Empirical results and analyses

3.1 Results of electricity consumption carbon emission data and thermal power generation data for each provincial-level region

As can be seen in Fig. 1, from a spatial perspective, the top five provinces with the highest electricity consumption carbon emissions in 2019 were Shandong, Jiangsu, Guangdong, Hebei, and Inner Mongolia with 493, 418, 337, 284, and 264 million tons of CO_2 emissions, respectively. Guangdong, Jiangsu, and Shandong were the top three provinces in terms of overall economic value added and secondary industry value added in 2019. Guangdong, Shandong, Jiangsu, and Hebei were among the top six provinces in the country in terms of population size. Although Inner Mongolia ranked in the middle in terms of overall economic value and population, it ranked fifth in terms of the electricity consumption of the secondary industry. Thermal power generation accounted for more than 80% of the total power generation in all regions, except for Guangdong. The overall economic value added of the secondary industry, population, and proportion of thermal power may explain the high carbon emissions of electricity consumption in the five provinces.

From a temporal perspective, the carbon emissions of electricity consumption in most of the regions showed an overall upward trend in 2015–2019, and Anhui, Shandong, Shaanxi, Zhejiang, and Jiangsu had the largest increases. The overall economic growth of Zhejiang, Jiangsu, and Anhui was at the forefront of the country, and the growth of Shaanxi and Shandong was at the middle. In addition, the overall electricity consumption of the five provinces (Shandong, Jiangsu, Guangdong, Hebei, and Inner Mongolia) and the secondary industry ranked high in terms of growth rate during the five years. North China and East China also showed large carbon emission increases in the five years (2015–2019); four of the above-mentioned provinces (Zhejiang, Anhui, Jiangsu, Shandong) belong to East China.

The estimated total carbon emissions from electricity consumption suggest that the total economic value added, the economic value added from the secondary industry, population, and the proportion of thermal power are the main contributors to the large carbon emissions of electricity consumption and the increase in emissions.

Figure 2 has showed an upward trend for the overall proportion of renewable energy in China. The proportion of renewable energy in each province and region after 5 years showed a change of about 5%. In 2019, China's thermal power accounted for an average of 67.1%, and 12 regions had values lower than the average, which are located mainly in the natural resource-rich regions of Southwest and Northwest China, implying that these regions generate more clean power. Except for Hainan, Fujian, and Guangdong, the 9 remaining regions are dominated by hydropower (more than 30%). Hainan, Fujian, and Guangdong have relatively low overall thermal power because of the high proportion of nuclear power, and their electricity consumption carbon emission ranks are in the middle and late stages. The overall electricity consumption of Sichuan Province ranks 9th in the country; however, in terms of the proportion of renewable energy, it ranks 4th. Therefore, it ranks 27th in carbon emissions of electricity consumption. Replacing thermal power generation with renewable energy generation could considerably reduce the overall carbon emissions of electricity consumption.

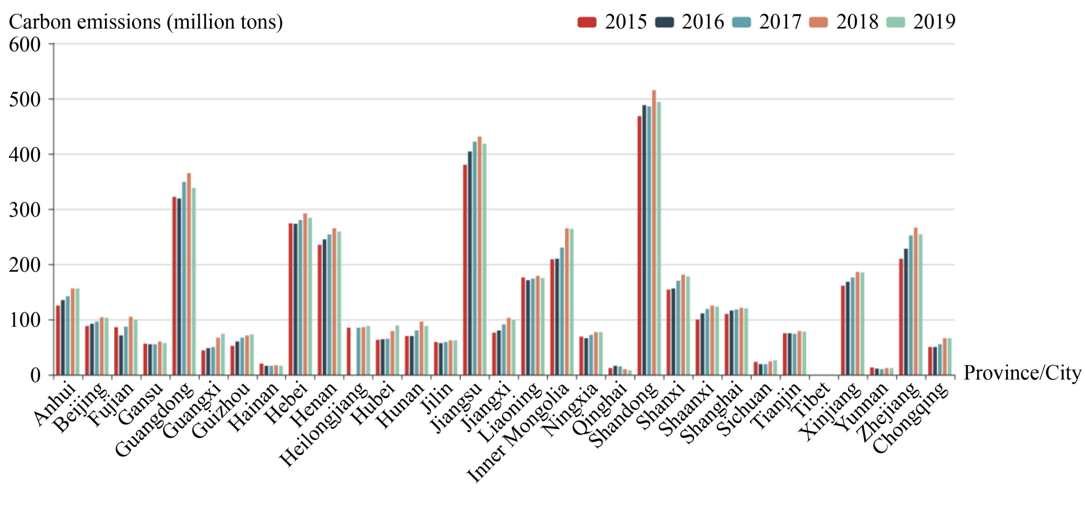

Fig. 1 2015–2019 overall electricity consumption carbon emission data.

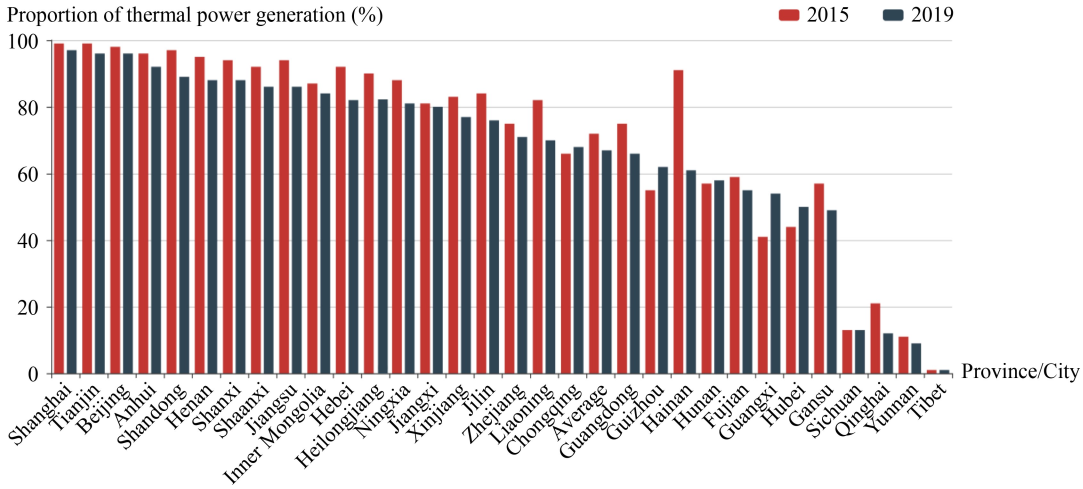

Fig. 2 Proportion of China's thermal power generation in 2015 and 2019, respectively.

3.2 LMDI decomposition results

3.2.1 China's overall LMDI results for 2015–2019

Figures 3 and 4 show the overall LMDI decomposition results of China's provincial-level regions from 2015 to 2019. From a holistic perspective, the power generation structure and consumption electricity intensity effects were the main factors that reduced carbon emissions from electricity consumption in most regions. The results for these five years suggest that most regions have achieved varying degrees of progress in terms of integrating renewable energy, leading to a considerable reduction in carbon emissions from electricity consumption. Electricity consumption intensity is an indicator of electricity consumption/economic value that reflects the amount of carbon emissions per unit of economic value. The five-year results suggest that electricity consumption intensity is one of the main reasons for suppressing carbon emissions. In most regions, the rate of economic growth is faster than that of electricity consumption, resulting in a decrease in electricity consumption per unit of economy. Most regions achieve economic growth along with electricity efficiency improvement partially from digitalization. Meanwhile, the agglomeration of urban industrialization is expected to transform electricity consumption patterns, which can help enterprises achieve highly efficient electricity consumption.

In the past five years, economic and population scales were the main factors contributing to an increase in carbon emissions from electricity use. The economic scale represents the value of carbon emissions analyzed per capita economic contribution; the rate of population change is slower than the rate of economic change given the growth of the population and economy in recent years. The GDP per capita and economic energy consumption per unit of population increase, which introduces a certain amount of carbon emissions related to electricity

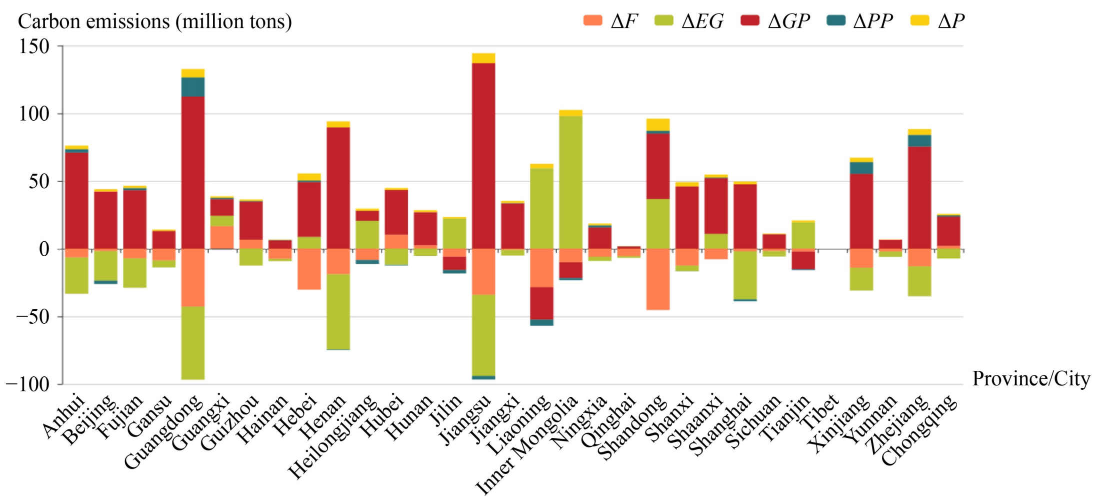

Fig. 3 Accumulation map of the contribution value of each provincial-level region for 2015–2019.

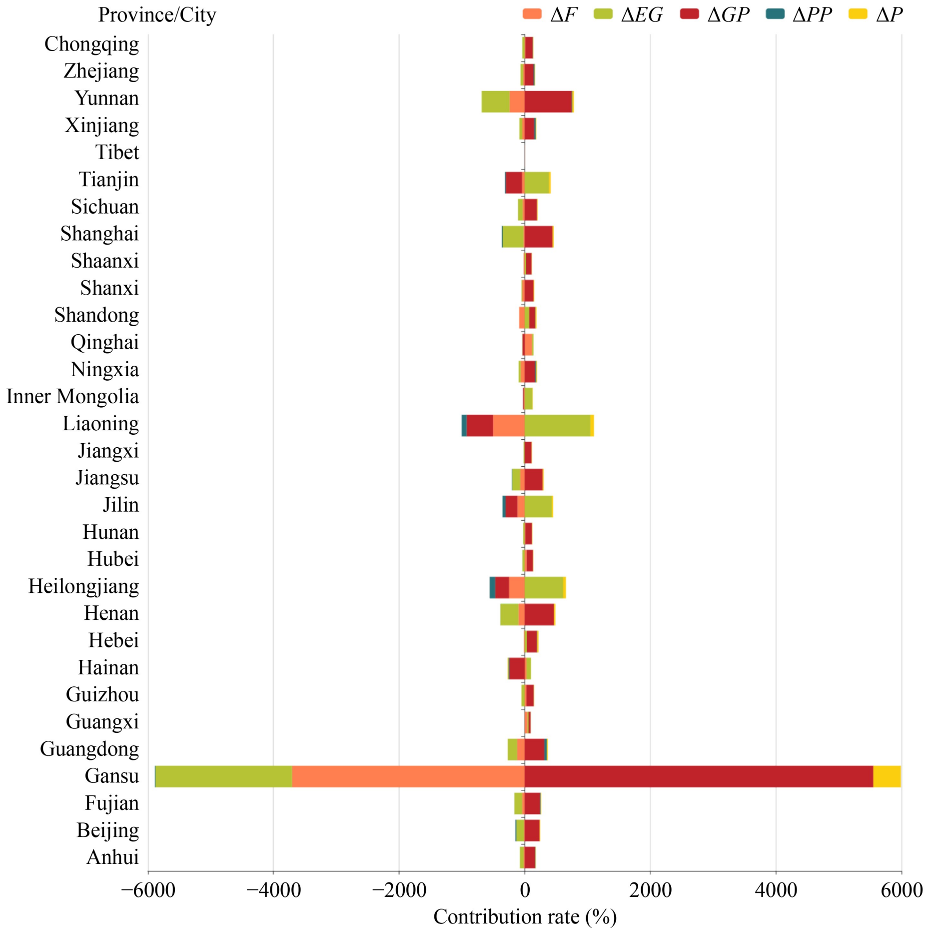

Fig. 4 Contribution rate of each provincial-level region in China from 2015 to 2019.

consumption. The population scale reflects the comprehensive effect of the nation's population on the carbon emissions from electricity consumption of a region. The increase in the population of the country in the past five years has resulted in a certain degree of pressure on the comprehensive carbon emissions from electricity consumption.

The population structure is a neutral indicator of the overall scenario of a country. Hainan and Qinghai Provinces showed a downward trend in the overall electricity consumption carbon emissions during the five-year period; however, the population structure showed a positive upward trend in carbon emissions, so it was classified as an indicator that drives electricity consumption to increase carbon emissions. As shown in Fig. 4, 14 regions showed an inhibitory effect in terms of population structure, and the remaining regions showed a driving effect.

3.2.2 2015–2019 LMDI results for various regions of China

From the value added part of Table 2, it can be seen that the carbon emissions from electricity consumption in Northeast region (Heilongjiang, Jilin, and Liaoning) showed an overall upward trend. The power generation structure was the main reason that helped curb the carbon emissions from 2015 to 2019. The non-thermal power generation in Liaoning Province, mainly nuclear and wind power, accounted for 30%. Liaoning is the greenest province in Northeast China.

Electricity consumption intensity, economic scale, and population scale are the main factors that increase the carbon emissions in Northeast China. However, the intensity of electricity consumption is a factor that inhibits carbon emissions in the country; this indicator reflects the amount of carbon emissions per unit of economic value, indicating that the three provinces of Northeast China consume high energy while realizing economic growth. This situation is related to the actual large-scale industries in the three provinces. Furthermore, a certain economic gap exists relative to the rest of the country due to the relatively stagnant development of the Northeast region in recent years. Only Liaoning Province showed that the indicator of electricity consumption intensity inhibited the growth of carbon emissions in the two periods of 2016–2017 and 2017–2018. Therefore, the three Northeast provinces need to accelerate their pace of energy

Table 2 2015–2019 LMDI decomposition results of some provincial-level regions in China

Province/City	Time period	Contribution value (million tons)						Contribution rate (%)				
		Value added	ΔF	ΔEG	ΔGP	ΔPP	ΔP	ΔF	ΔEG	ΔGP	ΔPP	ΔP
Heilongjiang	15–16	0.83	−1.83	0.97	1.98	−0.79	0.50	−219	117	237	−95	60
	16–17	0.64	−2.36	0.17	3.05	−0.68	0.46	−367	27	476	−106	71
	17–18	2.02	−2.12	1.67	2.84	−0.70	0.33	−104	82	140	−34	16
	18–19	−0.14	−2.08	18.12	−15.66	−0.81	0.29	1485	−12925	11173	576	−210
Jilin	15–16	−1.96	−3.33	−1.50	3.30	−0.77	0.34	171	77	−169	39	−17
	16–17	1.71	−1.29	2.34	1.00	−0.65	0.31	−76	138	59	−38	18
	17–18	3.04	−0.91	3.43	0.81	−0.52	0.23	−30	113	27	−17	8
	18–19	2.37	−0.08	18.31	−15.55	−0.52	0.21	−4	771	−655	−22	9
Liaoning	15–16	−5.34	−9.87	48.59	−43.90	−1.18	1.02	185	−911	823	22	−19
	16–17	3.08	−5.04	−0.67	9.14	−1.27	0.92	−164	−22	297	−41	30
	17–18	4.58	−8.68	−0.54	14.21	−1.08	0.67	−189	−12	310	−23	15
	18–19	3.34	−4.26	10.52	−2.63	−0.89	0.60	−127	315	−79	−27	18
Guizhou	15–16	7.45	4.31	−3.28	6.02	0.07	0.33	58	−44	81	1	4
	16–17	7.17	0.25	−1.93	8.40	0.11	0.34	4	−27	117	1	5
	17–18	4.13	−0.55	−1.48	5.78	0.12	0.26	−13	−36	140	3	6
	18–19	5.19	2.34	−6.32	8.70	0.22	0.25	45	−122	167	4	5
Sichuan	15–16	−4.20	−5.29	−0.80	1.75	0.02	0.12	126	19	−42	−1	−3
	16–17	0.10	−0.81	−1.26	2.08	−0.01	0.10	−824	−1289	2121	−9	102
	17–18	5.65	3.30	0.30	1.95	0.02	0.08	58	5	34	0	1
	18–19	3.88	2.05	−1.76	3.48	0.02	0.09	53	−46	90	0	2
Yunnan	15–16	−1.85	−1.62	−1.18	0.88	0.00	0.07	88	64	−48	0	−4
	16–17	−0.63	−1.52	−0.16	0.99	0.01	0.05	244	26	−159	−2	−9
	17–18	2.03	1.07	0.00	0.90	0.02	0.04	53	0	44	1	2
	18–19	1.32	0.35	−2.35	3.25	0.03	0.04	26	−179	247	2	3
Chongqing	15–16	0.59	−2.15	−3.29	5.52	0.22	0.29	−363	−556	933	37	49
	16–17	4.85	0.93	−0.84	4.30	0.18	0.28	19	−17	89	4	6
	17–18	10.80	3.83	4.13	2.31	0.30	0.23	36	38	21	3	2
	18–19	2.20	−0.23	−7.45	9.41	0.25	0.22	−10	−338	427	11	10
Tibet	15–16	/	/	/	/	/	/	/	/	/	/	/
	16–17	0.01	0.00	0.00	0.00	0.00	0.00	49	12	34	4	2
	17–18	0.06	0.05	0.00	0.01	0.00	0.00	82	5	11	2	0
	18–19	−0.01	−0.02	0.00	0.01	0.00	0.00	207	20	−109	−15	−3

transformation and improve the overall efficiency of their electricity consumption to minimize carbon emissions from electricity consumption.

Table 2 shows that the carbon emissions of electricity consumption in the Southwest region excluding Tibet (i.e., Guizhou, Sichuan, Yunnan, and Chongqing) are generally on the rise. The power generation structure from 2015 to 2019 showed that the four regions demonstrated increased carbon emissions from electricity consumption. The proportion of renewable energy power generation in the four regions is higher than the national average, and the renewable energy in the four regions is hydropower. The proportion of thermal power generation in Sichuan and Yunnan is around 10%, and the proportion of hydropower exceeds 80%. Thus, compared with other regions, the Southwest region has a higher proportion of renewable energy, and its sensitivity is greater than that of regions dominated by thermal power generation because of the unstable characteristics of hydropower availability.

The intensity of electricity consumption in the Southwest region curbed carbon emissions from electricity consumption. The economic scale, population structure, and population scale were manifested as the effect of driving electricity consumption on carbon emissions. The electricity consumption intensity, economic scale, and population scale were consistent with the overall scenario of the country. For the population structure of Chongqing and Sichuan, these two places drove the growth of carbon emissions from electricity consumption, indicating that the two places have attracted many migrant settlers. This result is in line with the actual scenario. With the agglomeration of Beijing, Shanghai, Guangzhou (Guangdong), and Shenzhen (Guangdong), an increasing number of people are migrating to new first-tier cities, leading to an increase in the number of permanent residents in areas such as Chengdu (Sichuan) and Chongqing. It has also caused an increase in carbon emissions from electricity consumption. Thus, new first-tier cities need to be aware of such a migration effect. The migrant population is expected to introduce a large amount of carbon emissions, and the future population inflow needs to be considered when formulating future emission reduction plans.

3.3 Decoupling model measurement results

The decoupling relationship between economic development and carbon emissions in each province and region was determined by obtaining the decoupling elasticity between carbon emissions and economic development in each province and region from 2015–2019. This task was achieved by dividing the average rate of change in GDP by the contribution of carbon emissions in each province and region based on previously calculated carbon emissions of 31 provincial-level regions in China from 2015 to 2019 (Fig. 5).

During 2015–2019, 19 regions, including Anhui, Beijing, and Fujian, showed a weak decoupling scenario wherein the economic growth increased in tandem with overall carbon emissions from electricity consumption; however, carbon emissions grew at a slower rate than economic growth. Heilongjiang, Jilin, Liaoning, Inner Mongolia, and Tianjin were strongly negatively decoupled, which is the most undesirable state where economic development shows a decreasing trend while carbon emissions are increasing. This phenomenon corresponds to the abovementioned LMDI decomposition, which indicates that the three Northeast provinces consume much energy while developing their economies; they are weaker than the developed provinces in various aspects, such as economy, talents, and digital technology. Hebei, Hunan, Jiangxi, Shandong, and Shaanxi are in expansionary coupling state, which indicates that economic and carbon emission growth remain relatively synchronized, so economic development and carbon emissions from electricity consumption in these regions are closely related. Guangxi and Tibet are expansionary-negatively decoupled, which implies that economic growth and carbon emissions are both increasing, and the growth rate of the economy is less than that of carbon emissions.

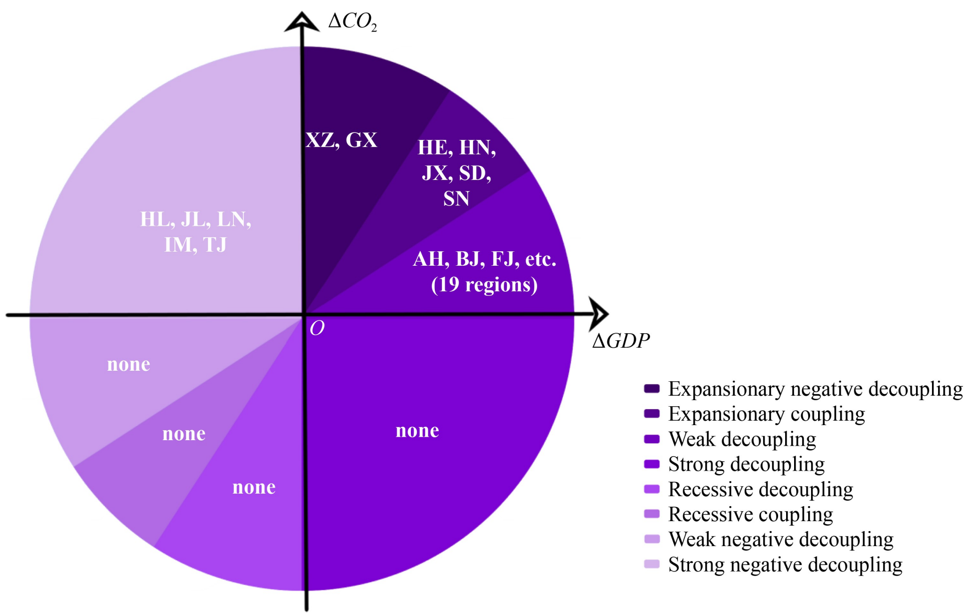

Fig. 5 Decoupling elasticity between carbon emissions and economic development by province and region (Notes: 1) BJ: Beijing, XZ: Tibet, GX: Guangxi, HE: Hebei, HN: Hunan, JX: Jiangxi, SD: Shandong, SN: Shaanxi, AH: Anhui, FJ: Fujian, HL: Heilongjiang, JL: Jilin, LN: Liaoning, IM: Inner Mongolia, TJ: Tianjin; 2) The formula $T^t = \frac{\Delta CO_2 / CO_2^0}{\Delta GDP / GDP^0}$ is used to calculate the decoupling status of carbon emissions and economic development in each region).

Equation (7) was applied to decompose carbon emissions in China's provinces and regions. The contribution values of the generation factor, generation structure, electricity consumption intensity, economic size, population structure, and population size in China's provinces and regions during the five years were calculated, and the contribution values were divided by the average rate of change in GDP in accordance with Eq. (7) to explore the relationship between carbon emissions and economic growth in China's provinces and regions during 2015–2019. We performed a causal chain decomposition to derive the decoupling elasticities of carbon emissions and economic growth for each province and region, as shown in Fig. 6.

Given that the rate of change of generation factor t_1 from 2015 to 2019 was 0, it had little impact on the decoupling elasticity indicator; therefore, it is not shown in the figure. Figures 6(a) and 6(b) show that most regions in China (e.g., Anhui, Beijing, and Fujian) showed strong decoupling between the elasticity of the generation structure and the elasticity of electricity consumption. This result implies that the economy is growing while the decomposed carbon emissions of electricity consumption in terms of generation structure and electricity consumption intensity are decreasing, which is the most ideal state for economic development and decarbonization. As the economy grows, most regions in China rely less on thermal power and focus on effective use of renewable energy and improvement of electricity efficiency. However, Heilongjiang, Liaoning, and Inner Mongolia presented a declining link between the structural elasticity of electricity generation and consumption (Fig. 6(a)). This result suggests that the reduction in economic development indicators and the reduction in carbon emissions in the three provinces remain relatively synchronized due to the relatively stagnant development of industries that are not energy-intensive in the Northeast region in recent years.

Figure 6(c) shows that the decoupling states between economic scale and economic growth are distributed in the first and third quadrants, with more than half of the cities/provinces, such as Anhui, Beijing, and Jiangsu, showing economic scale elasticities greater than 0.8 and being in an expansionary coupling state. This finding indicates that economic growth and the growth of carbon emissions remain relatively synchronized.

Figures 6(d) and 6(e) show that the population structure elasticity and population size elasticity of the vast majority of regions, such as Anhui, Fujian, and Guizhou, are less than 0.8; this result indicates that the economic development of most regions and the corresponding carbon emissions are weakly decoupled, implying further that China is currently in the process of transitioning from labor-intensive to technology-based manufacturing. The correlation between economic and population growth has weakened.

4 Conclusions

4.1 Summary

On the basis of the OM factor, this study estimated China's carbon emissions from electricity consumption from 2015 to 2019. It used the LMDI method to decompose the CO_2 emissions of electricity consumption and the changes in carbon emission intensity to determine the main influencing factors. Meanwhile, a decoupling index was introduced to analyze the decoupling relationship between CO_2 emissions and economic growth. The main conclusions of this study are as follows.

(1) The average carbon emissions of electricity consumption in North and East China were the largest, and the carbon emissions of electricity consumption in most regions in China showed an overall upward trend. The overall electricity consumption carbon emissions suggested that the overall economic value added, secondary industry economic value added, population, and proportion of thermal power were the main factors that contributed to the high carbon emissions and increments in emissions from electricity consumption.

(2) The changes in the power generation structure and power consumption intensity were the main factors that reduced carbon emissions from electricity consumption in most regions. The main reason was that the increase in the amount of electricity generated by renewable energy led to a considerable decrease in carbon emissions from electricity consumption. In most regions, the rate of economic growth was faster than that of electricity consumption, resulting in a decrease in electricity consumption per unit of economy. Economic and population scales were the main factors that increased carbon emissions from electricity consumption. The population structure was a neutral indicator in the overall scenario of the country.

(3) The changes in carbon emissions and GDP in China's provinces and regions were generally positive, and they continued to grow. The decoupling relationship between carbon emissions and economic growth in each province and region showed four states: Weak decoupling, expansionary negative decoupling, expansionary coupling, and strong negative decoupling. Weak decoupling was the dominant state.

4.2 Policy implications

(1) According to the results on population, economic value added, and secondary industry value added, China is currently at a critical stage of industrialization and urbanization. In terms of the future economic and population growth, increased amounts of electricity will be inevitably consumed, which will lead to increased CO_2 emissions. Although economic growth and electricity

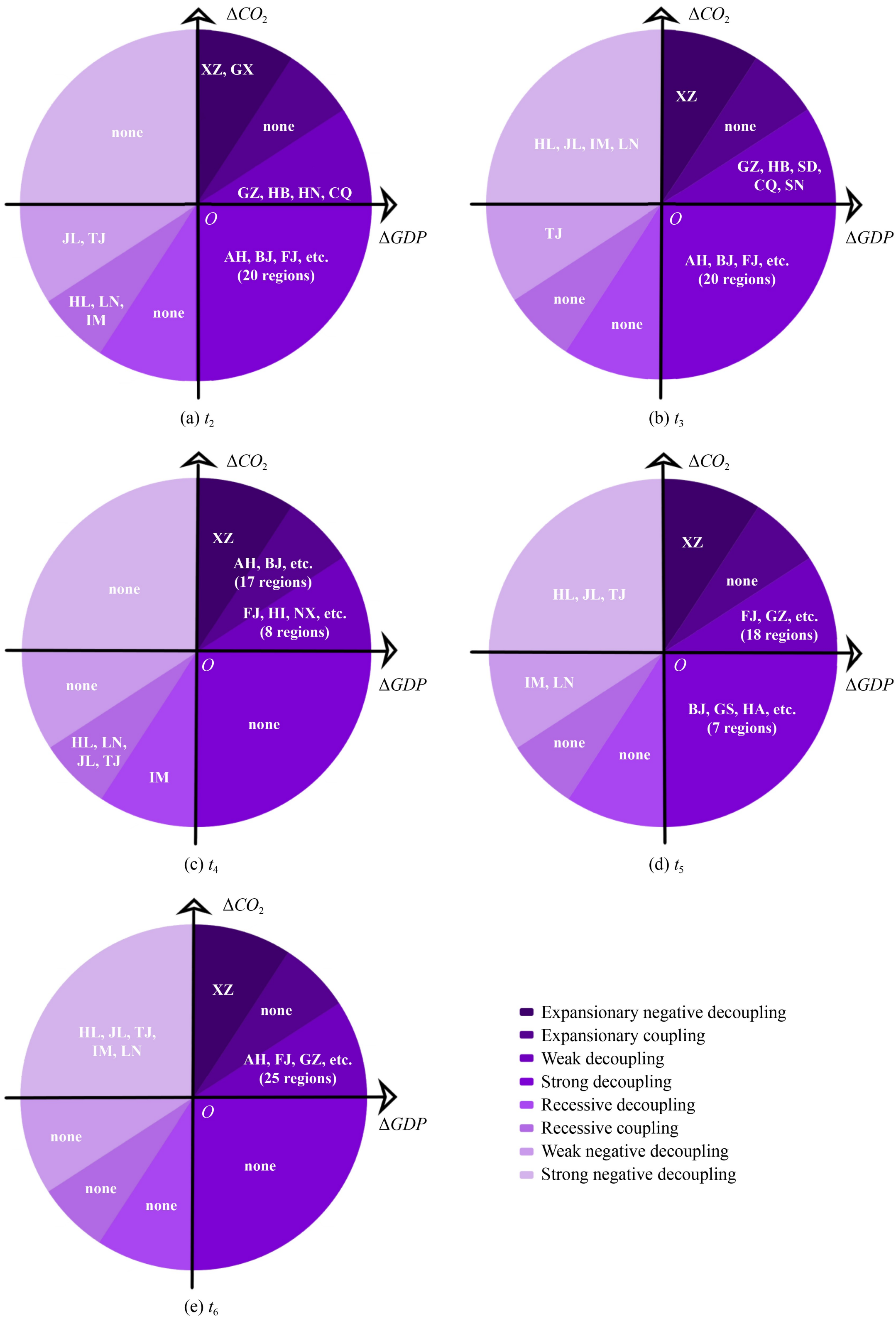

Fig. 6 Decoupling elasticity of carbon emissions and economic growth and its decomposition for each province and region in China (Notes: BJ: Beijing, XZ: Tibet, GX: Guangxi, HN: Hunan, SD: Shandong, SN: Shaanxi, GZ: Guizhou, HB: Hubei, CQ: Chongqing, AH: Anhui, FJ: Fujian, HL: Heilongjiang, JL: Jilin, LN: Liaoning, IM: Inner Mongolia, TJ: Tianjin, HI: Hainan, NX: Ningxia, HA: Henan, GS: Gansu).

consumption carbon emissions in most regions showed a weak decoupling relationship in this study, a certain correlation still exists between the two. The current economic growth remains inseparable from energy-intensive industries. We must not slow down the pace of the economy to ensure stable and sustained economic growth while achieving the goal of carbon neutrality. Regions with abundant renewable energy should be preferred locations for energy-intensive industries. Regions with relatively low proportion of renewable energy should learn from the development mode of regions with high penetrations of renewable energy, study their transitioning plans, consider own regional conditions, and select a well-informed transitioning path that suits themselves. For example, regions with increased electricity density, such as Heilongjiang and Jilin, can improve their unit economic electricity consumption efficiency and adopt a more energy-saving means to increase the economic value. Coastal regions can refer to Guangdong, Fujian, and Hainan and appropriately develop nuclear and wind energy to increase renewable energy generation.

(2) The relatively stagnant development of the Northeast region in recent years, the serious brain drain, and other reasons have led to a certain economic gap with the other regions in China; the level of digital technology is also relatively weaker than that of economically developed regions. The Northeast region should therefore increase the introduction of talents, accelerate the pace of energy transformation and digital transformation, and improve the overall efficiency of electricity consumption to reduce the carbon emissions of electricity consumption effectively.

(3) To formulate a carbon neutral policy, the government should consider not only the carbon emissions per unit of GDP, but also the population carbon emissions. According to the results in Table 2, new first-tier cities need to focus on population migration. The populations of second- and third-tier cities are gradually flowing to new first-tier cities, such as Hangzhou (Zhejiang) and other places aside from Beijing, Shanghai, Guangzhou, and Shenzhen, and the migrating population is expected to bring about a large amount of carbon emissions, and the future population inflow needs to be considered when formulating future emission reduction plans. The carbon-neutral route of new first-tier cities needs to consider the additional power load growth and carbon emissions brought about by these migrating populations. New first-tier cities in regions with developed renewable energy, such as Chengdu, should devise numerous population inflow plans. Moreover, the development of digital technology can maximize the flexibility of these incremental loads and improve the cooperation with renewable-energy-abundant regions to eliminate the impact of electricity consumption carbon emissions caused by population migration. The government should vigorously support industrial development and appropriately give preferential treatment to new first-tier cities with developed renewable energy in order to attract foreign population inflows. Doing so will minimize the impact of carbon emissions from population influx.

References

Abokyi E, Appiah-Konadu P, Tangato K F, Abokyi F (2021). Electricity consumption and carbon dioxide emissions: The role of trade openness and manufacturing sub-sector output in Ghana. Energy and Climate Change, 2: 100026

Andersson F, Karpestam P (2013). CO_2 emissions and economic activity: Short- and long-run economic determinants of scale, energy intensity and carbon intensity. Energy Policy, 61: 1285–1294

Andreoni V, Galmarini S (2012). Decoupling economic growth from carbon dioxide emissions: A decomposition analysis of Italian energy consumption. Energy, 44(1): 682–691

Chen G (2011). Trends in US carbon intensity indicator and enlightenment to China. Sino-Global Energy, 16(2): 17–22 (in Chinese)

Chen L, Cai W, Ma M (2020). Decoupling or delusion? Mapping carbon emission per capita based on the human development index in Southwest China. Science of the Total Environment, 741: 138722

Feng K, Davis S J, Sun L, Li X, Guan D, Liu W, Liu Z, Hubacek K (2013). Outsourcing CO_2 within China. Proceedings of the National Academy of Sciences of the United States of America, 110(28): 11654–11659

Howard B, Waite M, Modi V (2017). Current and near-term GHG emissions factors from electricity production for New York State and New York City. Applied Energy, 187: 255–271

Jiang Q, Khattak S I, Rahman Z U (2021). Measuring the simultaneous effects of electricity consumption and production on carbon dioxide emissions (CO_2e) in China: New evidence from an EKC-based assessment. Energy, 229: 120616

Kucukvar M, Cansev B, Egilmez G, Onat N C, Samadi H (2016). Energy–climate–manufacturing nexus: New insights from the regional and global supply chains of manufacturing industries. Applied Energy, 184: 889–904

Lin J, Pan D, Davis S J, Zhang Q, He K, Wang C, Streets D G, Wuebbles D J, Guan D (2014). China's international trade and air pollution in the United States. Proceedings of the National Academy of Sciences of the United States of America, 111(5): 1736–1741

Liu M, Zhang X, Zhang M, Feng Y, Liu L, Wen J, Liu L (2021). Influencing factors of carbon emissions in transportation industry based on C–D function and LMDI decomposition model: China as an example. Environmental Impact Assessment Review, 90: 106623

Liu Z, Feng K, Hubacek K, Liang S, Anadon L D, Zhang C, Guan D (2015a). Four system boundaries for carbon accounts. Ecological Modelling, 318: 118–125

Liu Z, Guan D, Wei W, Davis S J, Ciais P, Bai J, Peng S, Zhang Q, Hubacek K, Marland G, Andres R J, Crawford-Brown D, Lin J, Zhao H, Hong C, Boden T A, Feng K, Peters G P, Xi F, Liu J, Li Y, Zhao Y, Zeng N, He K (2015b). Reduced carbon emission estimates from fossil fuel combustion and cement production in China. Nature, 524(7565): 335–338

Lu Q, Yang H, Huang X, Chuai X, Wu C (2015). Multi-sectoral decomposition in decoupling industrial growth from carbon emissions in the developed Jiangsu Province, China. Energy, 82: 414–425

Ma M, Cai W (2019). Do commercial building sector-derived carbon emissions decouple from the economic growth in tertiary industry? A case study of four municipalities in China. Science of the Total Environment, 650(Part 1): 822–834

Mi Z, Meng J, Zheng H, Shan Y, Wei Y M, Guan D (2018). A multi-regional input–output table mapping China's economic outputs and interdependencies in 2012. Scientific Data, 5(1): 180155

Quick J C (2014). Carbon dioxide emission tallies for 210 US coal-fired power plants: A comparison of two accounting methods. Journal of the Air & Waste Management Association, 64(1): 73–79

Shan Y, Liu J, Liu Z, Xu X, Shao S, Wang P, Guan D (2016). New provincial CO_2 emission inventories in China based on apparent energy consumption data and updated emission factors. Applied Energy, 184: 742–750

Tapio P (2005). Towards a theory of decoupling: Degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. Transport Policy, 12(2): 137–151

Wang Q, Hang Y, Zhou P, Wang Y (2016). Decoupling and attribution analysis of industrial carbon emissions in Taiwan. Energy, 113: 728–738

Xi X, Han F, Xie Y, Yang L, Yan H, Luo C, Sun L (2021). The key factors influencing the decline of carbon emission intensity in low-carbon cities and countermeasure research: A case of Fuzhou, Jiangxi. IOP Conference Series: Earth and Environmental Science, 769(2): 022040

Yousuf I, Ghumman A R, Hashmi H N, Kamal M A (2014). Carbon emissions from power sector in Pakistan and opportunities to mitigate those. Renewable & Sustainable Energy Reviews, 34: 71–77

Zhang X, Jiang Q, Khattak S I, Ahmad M, Rahman Z U (2021). Achieving sustainability and energy efficiency goals: Assessing the impact of hydroelectric and renewable electricity generation on carbon dioxide emission in China. Energy Policy, 155: 112332

Zhang X, Zhang H, Zhao C, Yuan J (2019). Carbon emission intensity of electricity generation in Belt and Road Initiative countries: A benchmarking analysis. Environmental Science and Pollution Research International, 26(15): 15057–15068

Zhang Y J, Da Y B (2015). The decomposition of energy-related carbon emission and its decoupling with economic growth in China. Renewable & Sustainable Energy Reviews, 41: 1255–1266

Zhao Y, Li H, Zhang Z, Zhang Y, Wang S, Liu Y (2017). Decomposition and scenario analysis of CO_2 emissions in China's power industry: Based on LMDI method. Natural Hazards, 86(2): 645–668

Zhou Z, Liu J, Zeng H, Xu M, Li S (2022). Carbon performance evaluation model from the perspective of circular economy — The case of Chinese thermal power enterprise. Frontiers of Engineering Management, 9(2): 297–311