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Original Research

Exploring Carbon Neutrality in Power Industry Based on Electric Carbon Productivity: a Multi-Dimensional Decomposition from the Perspective of Production and Consumption

Peiyan Li[1]*, Wei Sun[1], Ziyun Cheng[2], Wenting Wang[3], Yujun He[4]

[1]School of Economics and Management, North China Electric Power University, Baoding 071003, China
[2]Division of Development, Gansu Electric Power Corporation, State Grid (Research Institute of Economy and Technology), Lanzhou 730050, China
[3]School of Electrical Engineering and Information Engineering, Lanzhou University of Technology, Lanzhou 730050, China
[4]School of Electrical and Electronic Engineering, North China Electric Power University, Baoding 071003, China

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Abstract

Achieving carbon-neutrality 2060 target is a solemn commitment made by China to the world. In the process of advancing carbon neutrality goals, power industry is an important starting point for addressing climate change. This study employs China's electric carbon productivity (ECP) to efficiently integrate economy and environment to explore carbon neutrality in power industry. Based on the electricity, economy, and population-related data of 30 provinces and municipalities in China from 2007 to 2017, the LMDI method is used to decompose ECP on the power production and consumption side, while considering regional and industrial dimensions. Furthermore, it is divided into six drivers respectively. The results show that: 1) From the production perspective, the regional ECP and reciprocal of standard coal consumption for power supply are the dominating drivers to improve China's ECP. 2) From the consumption perspective, the per capita GDP and reciprocal of provincial industrial electricity consumption intensity are primary drivers in the rise of ECP. 3) The regional decomposition indicates that electricity utilization efficiency and economic development mode are the main reasons why Xinjiang's ECP level is lower than that of Guangdong and Jiangsu. Finally, some conclusions that may be helpful to the government and enterprises are drawn.

Keywords: electric carbon productivity, production and consumption-based decomposition, power industry, carbon neutrality, Logarithmic Mean Divisia Index (LMDI) decomposition

*e-mail: 953132937@qq.com

Introduction

The world's durative electrification makes the power industry the central role in global energy system [1]. This is the case in China. Electricity, the primary energy, is the backbone for China's economy, since the continuous electricity production and supply is required to match the rapid continuous economic development. In 2020, the elasticity coefficient of electricity consumption reached 1.35, which means the resilient and vigorous gross domestic product (GDP) with the growth rate of 2.3% is supported by the total electricity consumption with the growth rate of 3.1% [2]. Still dominated by fossil fuel-based power plants, China's power industry accounts for 30.03% of the national total carbon dioxide (CO_2) emissions in 2019 [3]. Apparently, the power industry plays a vital role in realizing the goal of peaking the carbon emissions around 2030 and reaching carbon neutrality by 2060, proposed in the 75th session of the UN General Assembly in 2020. The concept of carbon neutrality is based on the theory of net-zero emissions, which means that the amount of CO_2 emission and absorption in the system are equal [4]. The kernel of applying carbon neutrality to the power industry is carbon abatement. Under such severe situation, more attention has been drawn by the central and local governments to balance the steady economic development and the CO_2 emissions from the power industry [5-6]. Therefore, carbon productivity enhancement would be the fundamental means to achieve carbon neutrality.

Carbon productivity, coined by Kaya and Yobobori (1999), is defined as the amount of economic output per CO_2 emission [7]. It is an integrated indicator to evaluate the coordination of emission reduction and the sustainable steady economic growth, which can also evaluate certain country's or industry's low-carbon development level [8-9]. By applying carbon productivity to the power industry, electric carbon productivity is very appropriate to assess the contribution to the national emission reduction [10-11]. Meanwhile, the ECP improvement is a pivotal measure to decrease the cost of power industry emission reduction and realize the coordination of maintaining acceptable economic development supported by the power industry.

Recently, a number of scholars have paid more and more attention to the carbon productivity. The study of carbon productivity has devoted to expanding the research of coordination between economy and environment from different aspects. Certain relevant references mainly focused the trend analysis, such as the growth trend, the convergence trend, the spillover effect, etc. which involves national, industrial or regional aspect. He and Su (2009) [12] mainly made a theoretical analysis of the annual growth rate of carbon productivity and the key factors of enhancing carbon productivity in order to assess the effort to echo the climate change. Yu et al. (2017) [13] provided a novel index to measure the carbon productivity growth for the stated- and non-state-owned power plants, which could assess the heterogeneities and technological progress on the productivity. Yu et al. (2017) [14] proposed a new method to quantify the carbon productivity for regional transport industry and explored the dynamic change across different geographic regions. Bai et al. (2019) [15] applied the log t regression method and the club convergence theory to test the carbon productivity convergence trend for eighty-eight countries and regions for the period of 1975-2013. Ding et al. (2019) [16] combined the cross efficiency and Malmquist productivity index to explore the time effect of energy and economy on the provincial productivity, and investigate the dynamic change of carbon efficiency for China's 30 provinces. Hu et al. (2020) [17] investigated the spatial correlation between different regions' carbon productivity to find out the threshold of the environmental regulation on the carbon productivity based on the spatial spillover effect. Pan et al. (2011) [18] employed Theil index, decoupling technique and clustering theory to analyze the provincial difference of carbon productivity, and provided the targeted measures for abating carbon emission.

A vast body of research work has investigated the driving indicators of carbon productivity or the influential mechanism of certain factor on carbon productivity by entities at national scale or different provincial or industrial scale. There are two main research branches. One branch focused on the driving factors investigation of carbon productivity from nation-, industrial-, or provincial aspect, showing as follows. Hu and Liu (2016) [19] applied the LMDI decomposition technique to explore the potential drivers of machinery and equipment net capital stock, construction work done and other representative indicators on carbon productivity in Australian construction industry. Long et al. (2016) [20] employed the Moran's I index and spatial panel data model to explore the influence of space-time characteristics and main drivers such as industrial energy efficiency on industrial carbon productivity from 2005 to 2012 for 30 provinces. Li and Wang (2019) [21] applied the spatial econometric model and the STIRPAT decomposition technique to assess the impact of socioeconomic indicator on the country's carbon productivity. Yang et al. (2021) [22] applied the production-theoretical decomposition technique to investigate the main influencing factors such as industrial added value, capital and labor at the provincial and sectoral levels and the regional disparities. The other research branch focuses on the influential mechanism of one factor or several factors, such as: foreign trade, technology, technological progress, etc, showing as follows. Zhang et al. (2018) [23] concluded that China's carbon productivity will be boosted mainly by export-import, especially import. Du et al. (2019) [24] argued that green technology innovations could only be effective in increasing carbon productivity in high-income economies and encouraged worldwide green technology corporation. Pan et al. (2020) [25] found that outward foreign direct investment promoted total factor carbon productivity by enhancing regional technology capabilities. Long et al. (2020) [26] concluded that local Foreign Direct Investment could boosted local carbon productivity due to structural effect, while surroundings areas Foreign Direct Investment reduced local carbon productivity. Fan et al. (2021) [27] came to a conclusion that the progress of capital-embodied technology and neutral technology indirectly affected carbon productivity (CP) through the progress of energy technology and carbon technology respectively, which were beneficial to improve CP.

Given the aforementioned, though the power industry plays a crucial role in national carbon neutrality goal and the future sustainable development of power industry, the researches on carbon productivity of electric power industry are limited. Especially to the author's knowledge, the study that investigates the drivers from the production and consumption aspects simultaneously is scarce. The production side and consumption side are linked by electric transmission network, which is inseparable from electricity supply. Therefore, it is necessary to analyze the effect of possible production-side driving factors and the consumption-side factors on electric carbon productivity.

In this paper, we attempt to investigate the time series characteristics of ECP and decompose the ECP from multi-dimensions which involve provincial-, industrial- aspects and production-side, consumption-side to explore the comprehensive influential factors. The contributions of our work lie in three aspects. First, the research data were extended to 30 provinces as well as the industrial scale. Second, the time series characteristics of influential factors' contribution rate on ECP were explored in our work. Third, from the multi-dimensions involving production-, consumption -side, and provincial-, industrial perspective, an in-depth comprehensive investigation of drivers of ECP was carried out through using the LMDI technique, so as to provide theoretical support for carbon neutrality in power industry.

The paper is organized as follows. The definition of electric carbon productivity and the LMDI decomposition method based on production and consumption are given in Section 2. Section 3 describes the data part in detail. And then, Section 4 elaborates the decomposition results and discusses the empirical results. The conclusions of this paper and some policy recommendations for the government and enterprises are drawn in Section 5.

Methodology and Data Sources

Concept of Electric Carbon Productivity

According to the original concept of carbon productivity, advanced by Kaya and Yobobori [7], ECP is defined as the ration of the economic output to the amount of CO_2 emissions from power industry due to the electricity generation or terminal consumption, shown as Eq. (1).

$$P = {}^{G}\!/\!{}_{C} \tag{1}$$

where G represents the economic output; C represents the amount of CO_2 emissions from power industry, which can be calculated through Eq. (2).

$$C = T \quad S \quad 2.6308 tonCO_2 / tce \tag{2}$$

where T is the amount of thermal power generation, S is the standard coal consumption per unit power generation, 2.6306 $ton\text{CO}_2/tce$ is the CO_2 emission coefficient per unit standard coal, recommended by the National Development and Reform Commission (NDRC) Energy Research Institute (ERI) [28].

Production-Side Based Decomposition for ECP

LMDI, provided by Ang B.W. in 1998, is a commonly used decomposition technique, which has been used to investigate the drivers on certain parameter with perfect decomposition character and no decomposition residuals [29]. In our work, the LMDI decomposition technique is adopted to analyze drivers of ECP change from production-side and consumption-side, and with considering provincial and industrial dimensions. The production-side based and consumption-side decomposition for ECP are described in detail in the next sections.

Based on LMDI decomposition technique, ECP is decomposed as Eq. (3) to analyze drivers of ECP change from power generation perspective, shown as follows.

$$\begin{aligned} P &= \frac{G}{C} = \frac{\sum_{i=1}^{n} G_i}{C} = \frac{\sum_{i=1}^{n} \frac{G_i}{ECE_i} \times \frac{ECE_i}{THPG_i} \times \frac{THPG_i}{TPG_i} \times \frac{TPG_i}{TPS_i} \times \frac{TPS_i}{SCC_i} \times \frac{SCC_i}{NSC_i} \times NSC_i}{C} \\ &= \sum_{i=1}^{n} P_i \times TCI_i \times PGS_i \times PUR_i \times PSC_i \times RSC_i \times CEF \end{aligned} \tag{3}$$

Where G_i is the GDP of province i (i = 1, 2……, n), ECE_i represents CO_2 emissions from power industry of province i, $THPG_i$ represents thermal power generation of province i, TPG_i represents total power generation of province i, TPS_i represents total power supply of province i, SCC_i represents total standard coal consumption of province i, and NSC_i represents national standard coal consumption. Moreover, P_i is the ECP of province i, TCI_i denotes the CO_2 emissions per unit thermal power generation, *i.e.* the CO_2 emission intensity of power generation, PGS_i represents the proportion of thermal power generation in total power generation of province i, PUR_i denotes the ration of power generation to power supply of province i, PSC_i is the reciprocal of standard coal consumption rate per unit power supply province i, RSC_i denotes the proportion of standard coal consumption in province i to national standard coal consumption, CEF is the reciprocal to carbon emission factor of national standard coal.

Consumption-Side Based Decomposition for ECP

From the consumption side, the ECP could be decomposed as Eq. (4)

$$P=\frac{G}{C}=\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}G_{ij}}{C}=\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\frac{G_{ij}}{E_{ij}}\times\frac{E_{ij}}{E_i}\times\frac{E_i}{G_i}\times\frac{G_i}{POP_i}\times\frac{POP_i}{POP}\times POP}{C}$$
$$=\sum_{i=1}^{n}\sum_{j=1}^{m}RECI_{ij}\times IEC_{ij}\times ECI_i\times PCG_i\times PR_i\times PC \tag{4}$$

where G_{ij} is the GDP added value of industrial sector j in province i, E_{ij} is the power consumption of industrial sector j in province i, E_i indicates the total power consumption of province i, POP_i denotes the population of province i, POP represents the national population. In addition, $RECI_{ij}$ is the reciprocal of industrial electricity consumption intensity of province i, IEC_{ij} is the proportion of industrial power consumption to provincial total power consumption, ECI_i is the electricity consumption intensity of province i, PCG_i denotes per capital GDP of province i, PR_i represents the ration of provincial population to the total amount, *i.e.* the population scale of province i, PC is the ratio of total population to total CO_2 emissions from power industry, *i.e.* the reciprocal of CO_2 emissions per capita.

Additive Decomposition Method

Analysis of Production Side

In order to analyze the effect of drivers on ECP, the addictive decomposition technique of LMDI [29] is adopted in our work.

First, Eq. (3) is differentiated about time t to yield Eq. (5).

$$\begin{aligned}\frac{dP_t}{dt}=&\frac{dP_{it}}{dt}\cdot TCI_{it}\cdot PGS_{it}\cdot PUR_{it}\cdot PSC_{it}\cdot RSC_{it}\cdot CEF_t\\&+\frac{dTCI_{it}}{dt}\cdot P_{it}\cdot PGS_{it}\cdot PUR_{it}\cdot PSC_{it}\cdot RSC_{it}\cdot CEF_t\\&+\frac{dPGS_{it}}{dt}\cdot P_{it}\cdot TCI_{it}\cdot PUR_{it}\cdot PSC_{it}\cdot RSC_{it}\cdot CEF_t\\&+\frac{dPUR_{it}}{dt}\cdot P_{it}\cdot TCI_{it}\cdot PGS_{it}\cdot PSC_{it}\cdot RSC_{it}\cdot CEF_t\\&+\frac{dPSC_{it}}{dt}\cdot P_{it}\cdot TCI_{it}\cdot PGS_{it}\cdot PUR_{it}\cdot RSC_{it}\cdot CEF_t\\&+\frac{dRSC_{it}}{dt}\cdot P_{it}\cdot TCI_{it}\cdot PGS_{it}\cdot PUR_{it}\cdot PSC_{it}\cdot CEF_t\\&+\frac{dCEF_t}{dt}\cdot P_{it}\cdot TCI_{it}\cdot PGS_{it}\cdot PUR_{it}\cdot PSC_{it}\cdot RSC_{it}\end{aligned} \tag{5}$$

Through calculating the definite integral of Eq. (5) over the time interval [t_1, t_2], where t_1 and t_2 are the benchmark year and the target year respectively ($t_2>t_1$), Eq. (6) can be obtained as follows.

$$\begin{aligned}\Delta P=&P_{t_2}-P_{t_1}\\=&\int_{t_1}^{t_2}\left(\frac{dRECI_{ijt}}{dt}\cdot IEC_{ijt}\cdot ECI_{it}\cdot PCG_{it}\cdot PR_{it}\cdot PC_t\right)\\&+\int_{t_1}^{t_2}\left(\frac{dIEC_{ijt}}{dt}\cdot RECI_{ijt}\cdot ECI_{it}\cdot PCG_{it}\cdot PR_{it}\cdot PC_t\right)\\&+\int_{t_1}^{t_2}\left(\frac{dECI_{it}}{dt}\cdot RECI_{ijt}\cdot IEC_{ijt}\cdot PCG_{it}\cdot PR_{it}\cdot PC_t\right)\\&+\int_{t_1}^{t_2}\left(\frac{dPCG_{it}}{dt}\cdot RECI_{ijt}\cdot IEC_{ijt}\cdot ECI_{it}\cdot PR_{it}\cdot PC_t\right)\\&+\int_{t_1}^{t_2}\left(\frac{dPR_{it}}{dt}\cdot RECI_{ijt}\cdot IEC_{ijt}\cdot ECI_{it}\cdot PCG_{it}\cdot PC_t\right)\\&+\int_{t_1}^{t_2}\left(\frac{dPC_t}{dt}\cdot RECI_{ijt}\cdot IEC_{ijt}\cdot ECI_{it}\cdot PCG_{it}\cdot PR_{it}\right)\end{aligned} \tag{6}$$

Eq. (6) is difficult to calculate the weight function including the time term. Consequently, Vartia [30] and Sato [31] introduced refinements of the weights to eliminate the influence of t. Furthermore, Vartia defined weight function $L(x,y)$, which denotes the 'logarithmic average' with Vartia Indices I and II [32].

$$L(x,y)=\begin{cases}\dfrac{x-y}{\ln x-\ln y} & x\neq y\\ x & x=y\end{cases} \tag{7}$$

In additive decomposition, the change in ECP for the period of t_1 to t_2 can be decomposed into seven factors: regional effect ΔP_{Pi}, CO_2 emission intensity of thermal power generation effect ΔP_{TCIi}, power generation structure effect ΔP_{PGSi}, import-export effect ΔP_{PURi}, standard coal consumption for power supply effect ΔP_{PSCi}, standard coal structure effect ΔP_{RSCi}, emission-factor effect ΔP_{CEF}, shown as Eq. (8).

$$\Delta P = P_{t_2} - P_{t_1} = \Delta P_{P_i} + \Delta P_{TCI_i} + \Delta P_{PGS_i} + \Delta P_{PUR_i} + \Delta P_{PSC_i} + \Delta P_{RSC_i} + \Delta P_{CEF} \quad (8)$$

Therefore, the contribution of each effect on ECP could be obtained through Eqs (9)-(15), respectively.

$$\Delta P_{P_i} = \sum_i f\left(\frac{G_i^{t_2}}{C^{t_2}}, \frac{G_i^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{P_i^{t_2}}{P_i^{t_1}}\right) = \sum_i \frac{G_i^{t_2}/C^{t_2} - G_i^{t_1}/C^{t_1}}{\ln G_i^{t_2}/C^{t_2} - \ln G_i^{t_1}/C^{t_1}} \cdot \ln\left(\frac{P_i^{t_2}}{P_i^{t_1}}\right) \quad (9)$$

$$\Delta P_{TCI_i} = \sum_i f\left(\frac{G_i^{t_2}}{C^{t_2}}, \frac{G_i^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{TCI_i^{t_2}}{TCI_i^{t_1}}\right) = \sum_i \frac{G_i^{t_2}/C^{t_2} - G_i^{t_1}/C^{t_1}}{\ln G_i^{t_2}/C^{t_2} - \ln G_i^{t_1}/C^{t_1}} \cdot \ln\left(\frac{TCI_i^{t_2}}{TCI_i^{t_1}}\right) \quad (10)$$

$$\Delta P_{PGS_i} = \sum_i f\left(\frac{G_i^{t_2}}{C^{t_2}}, \frac{G_i^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{PGS_i^{t_2}}{PGS_i^{t_1}}\right) = \sum_i \frac{G_i^{t_2}/C^{t_2} - G_i^{t_1}/C^{t_1}}{\ln G_i^{t_2}/C^{t_2} - \ln G_i^{t_1}/C^{t_1}} \cdot \ln\left(\frac{PGS_i^{t_2}}{PGS_i^{t_1}}\right) \quad (11)$$

$$\Delta P_{PUR_i} = \sum_i f\left(\frac{G_i^{t_2}}{C^{t_2}}, \frac{G_i^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{PUR_i^{t_2}}{PUR_i^{t_1}}\right) = \sum_i \frac{G_i^{t_2}/C^{t_2} - G_i^{t_1}/C^{t_1}}{\ln G_i^{t_2}/C^{t_2} - \ln G_i^{t_1}/C^{t_1}} \cdot \ln\left(\frac{PUR_i^{t_2}}{PUR_i^{t_1}}\right) \quad (12)$$

$$\Delta P_{PSC_i} = \sum_i f\left(\frac{G_i^{t_2}}{C^{t_2}}, \frac{G_i^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{PSC_i^{t_2}}{PSC_i^{t_1}}\right) = \sum_i \frac{G_i^{t_2}/C^{t_2} - G_i^{t_1}/C^{t_1}}{\ln G_i^{t_2}/C^{t_2} - \ln G_i^{t_1}/C^{t_1}} \cdot \ln\left(\frac{PSC_i^{t_2}}{PSC_i^{t_1}}\right) \quad (13)$$

$$\Delta P_{RSC_i} = \sum_i f\left(\frac{G_i^{t_2}}{C^{t_2}}, \frac{G_i^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{RSC_i^{t_2}}{RSC_i^{t_1}}\right) = \sum_i \frac{G_i^{t_2}/C^{t_2} - G_i^{t_1}/C^{t_1}}{\ln G_i^{t_2}/C^{t_2} - \ln G_i^{t_1}/C^{t_1}} \cdot \ln\left(\frac{RSC_i^{t_2}}{RSC_i^{t_1}}\right) \quad (14)$$

$$\Delta P_{CEF} = \sum_i f\left(\frac{G_i^{t_2}}{C^{t_2}}, \frac{G_i^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{CEF^{t_2}}{CEF^{t_1}}\right) = \sum_i \frac{G_i^{t_2}/C^{t_2} - G_i^{t_1}/C^{t_1}}{\ln G_i^{t_2}/C^{t_2} - \ln G_i^{t_1}/C^{t_1}} \cdot \ln\left(\frac{CEF^{t_2}}{CEF^{t_1}}\right) \quad (15)$$

Analysis of Consumption Side

Based on Eq. (4), the change of ECP for the same research period can be decomposed from the consumption side, shown as Eq. (16).

$$\Delta P = P_{t_2} - P_{t_1} = \Delta P_{RECI_{ij}} + \Delta P_{IEC_{ij}} + \Delta P_{ECI_i} + \Delta P_{PCG_i} + \Delta P_{PR_i} + \Delta P_{PC} \quad (16)$$

where ΔP_{RECIij} denotes the provincial industrial electricity intensity effect, ΔP_{IECij} denotes the electricity consumption structure effect of provincial industry, ΔP_{ECIi} denotes the provincial electricity consumption intensity effect, ΔP_{PCGi} denotes the provincial per capita GDP effect, ΔP_{PRi} denotes the population scale effect, ΔP_{PC} denotes the CO_2 emissions per capita effect. The terms in Eq. (6) can be calculated as Eqs. (17) -(22), respectively.

$$\Delta P_{RECI_{ij}} = \sum_i \sum_j f\left(\frac{G_{ij}^{t_2}}{C^{t_2}}, \frac{G_{ij}^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{RECI_{ij}^{t_2}}{RECI_{ij}^{t_1}}\right) = \sum_i \sum_j \frac{G_{ij}^{t_2}/C^{t_2} - G_{ij}^{t_1}/C^{t_1}}{\ln G_{ij}^{t_2}/C^{t_2} - \ln G_{ij}^{t_1}/C^{t_1}} \cdot \ln\left(\frac{RECI_{ij}^{t_2}}{RECI_{ij}^{t_1}}\right) \quad (17)$$

$$\Delta P_{IEC_{ij}} = \sum_i \sum_j f\left(\frac{G_{ij}^{t_2}}{C^{t_2}}, \frac{G_{ij}^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{IEC_{ij}^{t_2}}{IEC_{ij}^{t_1}}\right) = \sum_i \sum_j \frac{G_{ij}^{t_2}/C^{t_2} - G_{ij}^{t_1}/C^{t_1}}{\ln G_{ij}^{t_2}/C^{t_2} - \ln G_{ij}^{t_1}/C^{t_1}} \cdot \ln\left(\frac{IEC_{ij}^{t_2}}{IEC_{ij}^{t_1}}\right) \quad (18)$$

$$\Delta P_{ECI_i} = \sum_i \sum_j f\left(\frac{G_{ij}^{t_2}}{C^{t_2}}, \frac{G_{ij}^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{ECI_i^{t_2}}{ECI_i^{t_1}}\right) = \sum_i \sum_j \frac{G_{ij}^{t_2}/C^{t_2} - G_{ij}^{t_1}/C^{t_1}}{\ln G_{ij}^{t_2}/C^{t_2} - \ln G_{ij}^{t_1}/C^{t_1}} \cdot \ln\left(\frac{ECI_i^{t_2}}{ECI_i^{t_1}}\right) \quad (19)$$

$$\Delta P_{PCG_i} = \sum_i \sum_j f\left(\frac{G_{ij}^{t_2}}{C^{t_2}}, \frac{G_{ij}^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{PCG_i^{t_2}}{PCG_i^{t_1}}\right) = \sum_i \sum_j \frac{G_{ij}^{t_2}/C^{t_2} - G_{ij}^{t_1}/C^{t_1}}{\ln G_{ij}^{t_2}/C^{t_2} - \ln G_{ij}^{t_1}/C^{t_1}} \cdot \ln\left(\frac{PCG_i^{t_2}}{PCG_i^{t_1}}\right) \quad (20)$$

$$\Delta P_{PR_i} = \sum_i \sum_j f\left(\frac{G_{ij}^{t_2}}{C^{t_2}}, \frac{G_{ij}^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{PR_i^{t_2}}{PR_i^{t_1}}\right) = \sum_i \sum_j \frac{G_{ij}^{t_2}/C^{t_2} - G_{ij}^{t_1}/C^{t_1}}{\ln G_{ij}^{t_2}/C^{t_2} - \ln G_{ij}^{t_1}/C^{t_1}} \cdot \ln\left(\frac{PR_i^{t_2}}{PR_i^{t_1}}\right) \quad (21)$$

$$\Delta P_{PC} = \sum_i \sum_j f\left(\frac{G_{ij}^{t_2}}{C^{t_2}}, \frac{G_{ij}^{t_1}}{C^{t_1}}\right) \cdot \ln\left(\frac{PC^{t_2}}{PC^{t_1}}\right)$$

$$= \sum_i \sum_j \frac{G_{ij}^{t_2}/C^{t_2} - G_{ij}^{t_1}/C^{t_1}}{\ln G_{ij}^{t_2}/C^{t_2} - \ln G_{ij}^{t_1}/C^{t_1}} \cdot \ln\left(\frac{PC^{t_2}}{PC^{t_1}}\right) \tag{22}$$

Data Sources

In this paper, 2007 was chosen as the base year of the research period because China had become the world's largest carbon emitter since 2007. For the research period of 2007-2017, data from 30 provinces (including province-level municipalities i = 1,2,…,30) are collected in our work, in that Tibet, Macao, Hong Kong and Taiwan are not considered due to the lack of data availability.

On the production side, provincial G_i (100 million Yuan) data are collected from National Bureau of Statistics (NBS) and provincial ECE_i data are calculated by Eq. (2). Provincial $THPG_i$ (billion kWh), TPG_i (billion kWh), the auxiliary power consumption rate (%) and standard coal consumption of power generation (g/kWh) data are collected from Chinese Electric Power Yearbook (CEPY) of corresponding year [33]. Provincial TPS_i (billion kWh) data are calculated according to provincial $THPG_i$ and the auxiliary power consumption rate, provincial SCC_i (100 tons) and NSC_i (100 tons) data are calculated by the standard coal consumption of power generation and provincial TPG_i. On the consumption side, power consumption was considered from three industrial sectors (j = 1,2,3). According to China Energy Statistical Yearbook of corresponding year (CESY) [34], the primary industry includes agriculture, forestry, animal husbandry, fishing and water conservation. The secondary industry consists of industry and construction. The tertiary industry contains transport, storage, post, wholesale, retail trade and other services. Provincial industrial G_{ij} (100 million Yuan) and population (ten thousand persons) data come from NBS, and E_{ij} (billion kWh) data come from CESY.

Results and Discussion

Fig. 1 plots the provincial ECP (100 million Yuan/ten thousand tonnes) series from 2007-2017. On the one hand, the provincial ECP exhibits a fluctuating increasing trend, and notably, it shows significant improvement. On the other hand, the growth rate of provincial ECP shows remarkable regional differences. Compared with 2007, ECP in Yunnan has increased by 633.66% in 2017, the fastest growth among all the provinces. Sichuan and Guizhou increase 431.26% and

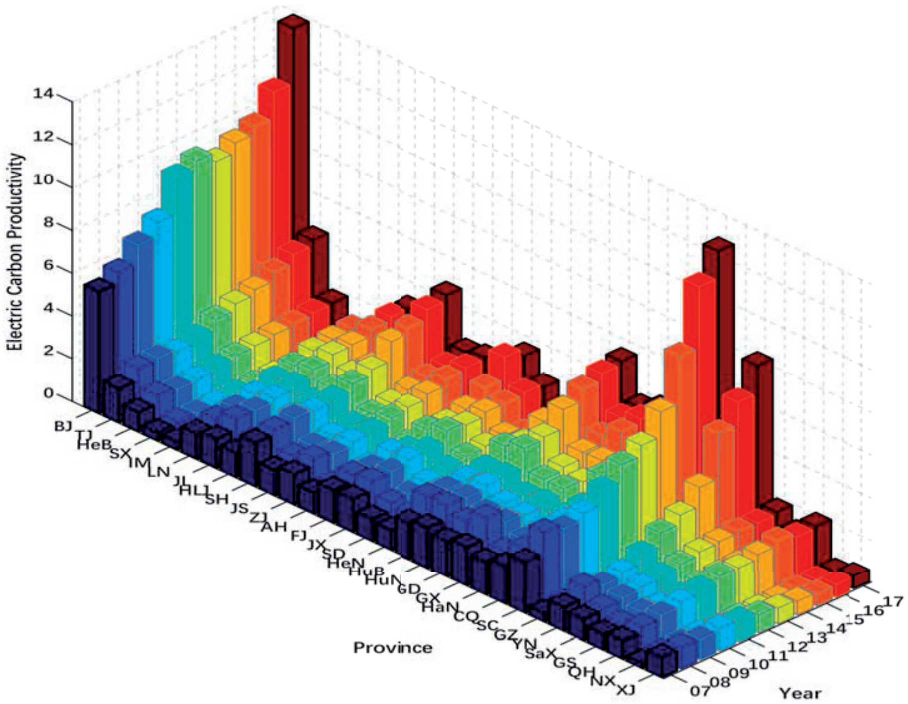


Fig. 1. Provincial ECP series (100 million Yuan/ten thousand tonnes) for the period of 2007-2017.
Note: The abscissa letters represent the abbreviations of 30 provinces, the details are as follows: BJ = Beijing, TJ = Tianjin, HeB = Hebei, SX = Shanxi, IM = Inner Mongolia, LN = Liaoning, JL = Jilin, HLJ = Heilongjiang, SH = Shanghai, JS = Jiangsu, ZJ = Zhejiang, AH = Anhui, FJ = Fujian, JX = Jiangxi, SD = Shandong, HeN = Henan, HuB = Hubei, HuN = Hunan, GD = Guangdong, GX = Guangxi, HaN = Hainan, CQ = Chongqing, SC = Sichuan, GZ = Guizhou, YN = Yunnan, SaX = Shaanxi, GS = Gansu, QH = Qinghai, NX = Ningxia, XJ = Xinjiang.

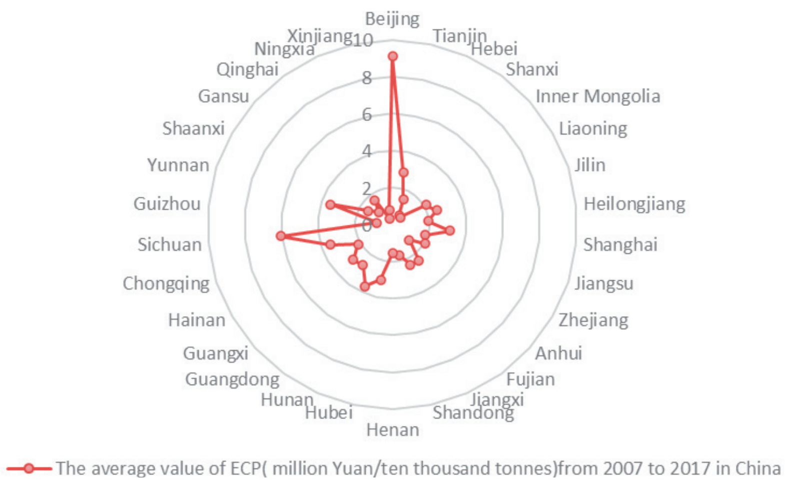


Fig. 2. The average value of ECP in China, 2007-2017.

251.26% respectively. ECP in Xinjiang has decreased by 36.03% in 2017, which is the only province to show negative growth.

ECP in China shows significant regional differences in time series. For the sake of comparison, Fig. 2 presents the ECP of China's provincial average level from 2007 to 2017. Totally, Beijing ranks the first with the highest ECP level of 9.112 and Ningxia shows the lowest ECP level of 0.327. Specifically, the four provinces with lower ECP average value are Inner Mongolia, Shanxi, Xinjiang and Guizhou, while the two provinces with higher ECP average value are Beijing and Sichuan. Analyzing ECP for each province-level municipalities requires more actual considerations. Further decomposition results need to be explored considering various industry sector and regional factor based on production side and consumption side into account.

Time Decomposition Analysis Based on the Production Side

As shown in Table 1, the contribution rate of each driver of ECP in China is defined as the relative proportion of the change of each driver to the total change in ECP value. P_i and PSC_i have a positive impact on ECP with the average contribution rates of 168.7% and 29.2% to national ECP. PGS_i, TCI_i, RSC_i and PUR_i play major roles in the decline of ECP, with the average contribution rates of -50.3%, -22.6%, -22% and -3.1%, respectively.

Raising P_i will distinctly improve the national ECP. PSC_i is the reciprocal of the standard coal consumption for power supply. Accordingly, the standard coal consumption for power supply has negative contribution of Chinese ECP. The standard coal consumption for power supply is defined as the average standard coal consumption per one kWh

Table 1. Contribution rates of each driver for Chinese ECP from the production side.

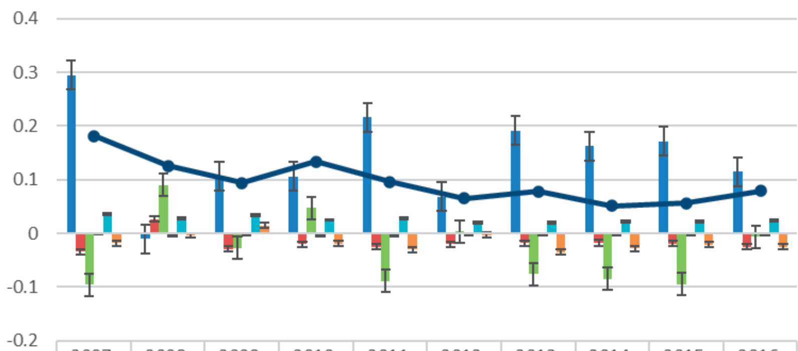
Year	$\Delta P_{P\text{-}i}$	$\Delta P_{TCI\text{-}i}$	$\Delta P_{PGS\text{-}i}$	$\Delta P_{PUR\text{-}i}$	$\Delta P_{PSC\text{-}i}$	$\Delta P_{RSC\text{-}i}$
2007-2008	1.626	-0.191	-0.529	-0.001	0.198	-0.104
2008-2009	-0.083	0.211	0.716	-0.029	0.218	-0.033
2009-2010	1.120	-0.310	-0.294	-0.022	0.357	0.150
2010-2011	0.793	-0.153	0.351	-0.031	0.187	-0.147
2011-2012	2.262	-0.263	-0.928	-0.041	0.288	-0.318
2012-2013	1.037	-0.310	0.060	-0.044	0.307	-0.049
2013-2014	2.442	-0.239	-0.974	-0.037	0.262	-0.453
2014-2015	3.177	-0.347	-1.659	-0.041	0.423	-0.554
2015-2016	3.048	-0.343	-1.682	-0.041	0.391	-0.373
2016-2017	1.451	-0.319	-0.086	-0.020	0.293	-0.320
2007-2017 (Average)	1.687	-0.226	-0.503	-0.031	0.292	-0.220

of power supply in coal-fired power plants, and it is also one of the important assessment indicators for thermal power plants. Cutting-edge clean coal technology can reduce the standard coal consumption of power supply by improving power supply efficiency, such as 700ºC ultra-supercritical power generation technology [35].

Obviously, PGS_i is a driver with the largest contribution rate among the negative factors. According to CESY, the share of clean energy generation (including hydropower, nuclear power, wind power and solar power) increased from 16.66% in 2007 to 37.82% in 2017, while the share of thermal power generation decreased from 83.34 % to 62.18 %. However, thermal power generation is still the main source of CO_2 emissions in China [36], and China needs to reduce the proportion of thermal power generation to accelerate carbon neutrality. TCI_i as a whole has a negative impact, which was actually related to the power generation technology and the fuel structure of generator units [37]. It is effective to boost ECP by improving the technical level and optimizing the fuel consumption structure. To some extent, RSC_i reflects the electricity consumption proportion of each province to the national amount. The decomposition results show that coal has maintained a fundamental position in China's energy structure for a long time. Although the proportion of coal in primary energy production decreased from 81.6% in 2007 to 76.6% in 2017, coal is still the most important primary energy source. Therefore, in the long run, it is necessary to vigorously develop clean energy to reduce the dependence on coal resources, which may be the first target to achieve carbon neutrality. PUR_i shows the least negative contribution to ECP in China. In fact, PURi is related to the auxiliary power consumption rate. Reducing the auxiliary power consumption rate requires optimizing operation technology, improving equipment maintenance and using independent innovation to implement energy-saving technological transformation.

Fig. 3 explicitly displays the time series decomposition results of each driver of ECP increments from the production side. In general, ECP has shown annual growth trend since 2007. The policy of "suppressing the small thermal power units with high energy consumption and heavy pollution" was implemented in 2007, which had a significant impact on energy conservation and emission reduction. During the period of the 11th Five-Year Plan, a total of 72.1 million kilowatts of small thermal power units have been shut down. The measure reduced CO_2 emissions by 124 million tons per year [38].

ECP has five stages of significant change. From 2007 to 2010, the increment in ECP along the timeline was 0.1814, 0.126, and 0.0944. China's GDP had been affected by the global financial crisis and its economic performance had declined. In 2008, 2009 and 2010, the GDP growth rates were 9.7%, 9.4% and 10.6%, respectively, which were down from 14.2% in 2007. Furthermore, the economic crisis had led to a reduction in economic activities and power consumption, thereby reducing electricity CO_2 emissions. CO_2 emissions in power industry dropped from 2379.34MT in 2007 to 2303.21MT in 2008, with the growth rate of -3.20%, which was the lowest value during the research period (Fig. 4). From 2009 to 2010, what restrained ECP was the power generation structure and CO_2 emission intensity of thermal power generation. It is due to the weakening of the adjustment measures for high energy-



	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017
ΔP_P-i	0.295	-0.0105	0.1057	0.1058	0.216	0.0678	0.1912	0.163	0.1716	0.1152
ΔP_TCI-i	-0.0347	0.0266	-0.0293	-0.0204	-0.0251	-0.0203	-0.0187	-0.0178	-0.0193	-0.0253
ΔP_PGS-i	-0.096	0.0902	-0.0278	0.0469	-0.0886	0.0039	-0.0763	-0.0851	-0.0947	-0.0068
ΔP_PUR-i	-0.0001	-0.0037	-0.0021	-0.0041	-0.0039	-0.0029	-0.0029	-0.0021	-0.0023	-0.0016
ΔP_PSC-i	0.036	0.0275	0.0337	0.0249	0.0275	0.0201	0.0205	0.0217	0.022	0.0233
ΔP_RSC-i	-0.0188	-0.0041	0.0142	-0.0196	-0.0304	-0.0032	-0.0355	-0.0284	-0.021	-0.0254
ΔP	0.1814	0.126	0.0944	0.1335	0.0955	0.0654	0.0783	0.0513	0.0563	0.0794

Fig. 3. Effects of drivers for Chinese ECP increment from the production side.

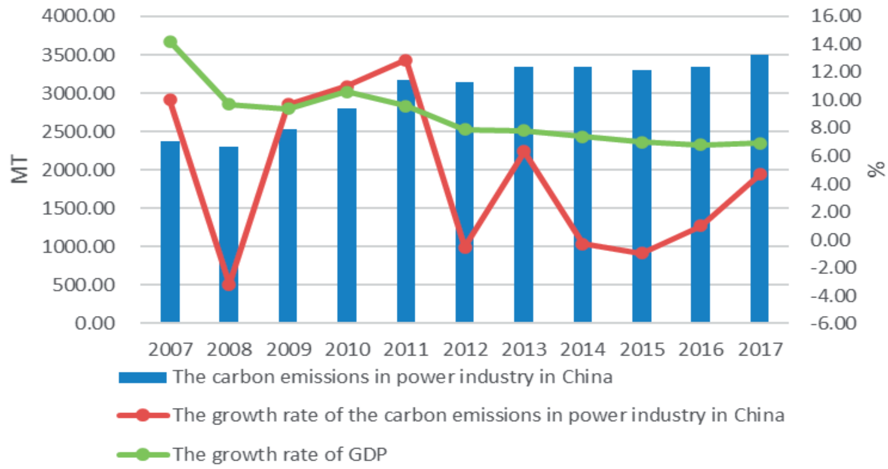


Fig. 4. Chinese electricity CO_2 emissions and GDP growth rate, 2007-2017.

intensive industries during this period, which led to a 10.99% growth rate of electricity CO_2 emissions. In 2010-2011, ECP increment reached the second highest value of 0.1335. China's four trillion USD investment plan in response to the economic crisis had partly stimulated infrastructure construction and heavy industries, such as the emission-intensive power sector, which were slowly recovering from the recession [39]. This led to a rapid increase in power consumption and therefore electricity CO_2 emissions increased by 12.87% in 2011 (Fig. 4), the highest value in the research period. In 2014-2015, the ECP increment was 0.0513, the lowest value during the research period. It was in line with the fact that local governments focused on economic growth and led to the emergence of energy-intensive projects rebound at the end of the 12th Five-Year Plan period. From 2015 to 2017, the increment of ECP were 0.0563 and 0.0794 along the timeline, showing an upward trend. China's power generation structure has been further optimized. The proportion of clean energy power generation in 2015-2017 was 26.30%, 28.15% and 37.82%, respectively, compared to only 16.67% in 2007.

In-Depth Analysis of the Provinces Based on Production Side

In this part, the decomposition results of ECP are displayed in the form of provinces (Table 2). Regional ECP ($\Delta Pp\text{-}i$) shows significant differences. Only the contribution value in Xinjiang is negative. Specifically, the GDP in Xinjiang increased by 208.87% from 2007 to 2017; CO_2 emissions increased by 382.82% from 2007 to 2017. It can be seen that the economic growth is an expansive negative decoupling relationship with electricity CO_2 emissions. Although the contribution values of Ningxia, Qinghai, Hainan and Inner Mongolia show a positive effect, the values are minor. At the same time, Guangdong, Jiangsu, and Sichuan have the highest contribution values. Guangdong and Jiangsu are more developed regions with strict environmental standards. They need to import electricity from other regions to meet power shortages. The inflow of electricity helps reduce local CO_2 emissions based on electricity production. In Sichuan, the improvement of energy efficiency and the substitution of non-fossil fuels have led to a decrease in electricity CO_2 emissions, dropped from 43.67MT in 2007 to 36.74MT in 2017, with a growth rate of -34.10%. It can be inferred that clean energy power generation (including hydropower, solar PV, wind energy, etc) is essential to reduce electricity CO_2 emissions based on production side. For standard coal structure effect ($\Delta P_{RSC\text{-}i}$), the decomposition results also reflect that each provincial energy use proportion is obvious unbalanced due to the different regional resources endowment. The contribution value in Sichuan is the lowest due to abundant water resources. The contribution values in Xinjiang, Anhui, Jiangxi and Shanxi are relatively high, indicating that these four provinces are over-reliant on coal resources. Therefore, in order to improve the ECP level of provinces, in the short term, coal production and utilization should be planned reasonably; in the long term, clean energy sources must be exploited and utilized to realize the transformation of economic development pattern. The regional differences in other parameters are not obvious.

Time Decomposition Analysis Based on the Consumption Side

Table 3 shows the contribution rates of each driving factor of ECP from the consumption side. It should be noted that the data of $\Delta P_{PCG\text{-}i}$, $\Delta P_{PR\text{-}i}$ and ΔP_{PC} in 2008-2009 are abnormal, so they are deleted when calculating the average value. $\Delta P_{PCG\text{-}i}$, $\Delta P_{RECI\text{-}ij}$ and $\Delta P_{PR\text{-}i}$ show positive impacts, with the average contribution rates of 120.34%, 64.32% and 2.18%, respectively. ΔP_{PC}, $\Delta P_{ECI\text{-}i}$ and $\Delta P_{IEC\text{-}ij}$ play key roles in

Table 2. Drivers for Chinese provincial ECP (100 million Yuan*10^{-3}/ten thousand tonnes) from the production side in 2007-2017.

Province	ΔP_{P-i}	ΔP_{TCI-i}	ΔP_{PGS-i}	ΔP_{PUR-i}	ΔP_{PSC-i}	ΔP_{RSC-i}
Beijing	52.854	-20.992	-1.764	-3.079	24.459	-13.995
Tianjin	39.233	-6.393	-0.338	-0.246	6.870	-8.168
Hebei	53.48	-10.200	-11.093	-0.541	10.407	-13.226
Shanxi	23.885	-4.268	-2.952	-0.263	4.501	-4.723
Inner Mongolia	9.600	-3.503	-8.489	-0.252	3.736	9.513
Liaoning	40.681	-9.777	-17.945	-0.434	10.204	-20.534
Jilin	28.233	-6.095	-3.004	-0.353	6.390	-7.629
Heilongjiang	29.526	-6.487	-4.756	-0.365	7.001	-13.826
Shanghai	57.822	-5.811	-1.137	-0.134	5.728	-22.594
Jiangsu	131.040	-20.656	-1.994	-2.048	22.81	5.596
Zhejiang	70.135	-11.187	-0.849	-1.027	12.497	-0.653
Anhui	25.099	-6.981	-3.331	-0.610	7.816	21.375
Fujian	56.054	-3.621	-22.233	-1.129	4.644	-2.728
Jiangxi	16.796	-5.386	-0.416	-0.899	6.255	16.147
Shandong	92.030	-23.963	-12.741	-1.189	25.511	7.699
Henan	82.794	-10.893	-4.074	-1.419	12.681	-18.261
Hubei	60.134	-7.578	-0.565	-1.056	8.591	2.285
Hunan	70.997	-9.320	-7.517	-0.604	10.437	-13.539
Guangdong	147.647	-25.442	-20.448	-2.051	24.099	-24.245
Guangxi	33.655	-4.792	-9.318	-0.309	5.256	-5.058
Hainan	6.563	-0.582	-3.795	-0.024	0.532	0.950
Chongqing	36.624	-5.013	-6.064	-0.811	5.516	-0.630
Sichuan	127.346	-10.445	-106.487	-3.489	12.706	-65.797
Guizhou	28.133	-1.927	-4.097	0.459	1.686	-1.462
Yunnan	67.863	-2.197	-64.381	0.416	1.886	-41.010
Shannxi	26.433	-3.451	-5.419	0.230	3.421	12.109
Gansu	10.419	-1.609	-4.847	-0.159	1.759	-0.403
Qinghai	4.475	-0.849	-0.948	-0.059	0.927	-0.305
Ningxia	2.755	-0.702	-1.273	0.047	0.665	3.247
Xinjiang	-11.485	-7.476	-2.020	-0.168	8.147	27.853

the decline in ECP, with the average contribution rates of -55.30%, -28.34% and -6.29%, respectively.

ΔP_{PCG-i} is the most obvious driver in the increment of ECP. GDP per capita can represent the level of economic development of a country. Accordingly, economic development will help boost the ECP. $\Delta P_{RECI-ij}$ has a notable positive impact on the ECP, and the key to increasing the provincial industrial electricity consumption intensity is to improve the electricity utilization efficiency. ΔP_{PR-i} shows limited impact on ECP. Overall, the provincial population scale has not yet reached the most conducive to promoting carbon neutrality, so there is still room for improvement.

ΔP_{PC} is the driver with the greatest negative impact, reflecting the fact that the growth rate of electricity CO_2 emissions is significantly higher than the population growth rate. ΔP_{ECI-i} can manifest the use of electricity in economic activities. From the international aspect, China's electricity consumption intensity is still higher than the major developed countries, which is about 2.9 times that of the United States [40], because the proportion of the tertiary industry and the level of

Table 3. Contribution rates of each driver for China's ECP from the consumption side.

Year	$\Delta P_{RECI-ij}$	ΔP_{IEC-ij}	ΔP_{ECI-i}	ΔP_{PCG-i}	ΔP_{PR-i}	$\Delta P_{P}C$
2007-2008	0.6608	0.0705	-0.3238	0.4689	0.0168	0.1069
2008-2009	-0.4121	-1.0192	2.3874	-7.2380	-0.5465	7.8284
2009-2010	0.8549	-0.1305	-0.5744	1.8893	0.0937	-1.1330
2010-2011	1.1603	0.0157	-1.3339	3.5622	0.0273	-2.4317
2011-2012	0.6125	0.0171	-0.2930	0.5894	0.0086	0.0654
2012-2013	1.3025	-0.0599	-1.2910	2.7637	0.0302	-1.7454
2013-2014	0.6435	0.0132	-0.3001	0.5703	0.0065	0.0666
2014-2015	0.5672	0.1035	-0.2390	0.4301	0.0102	0.1280
2015-2016	0.5142	0.1516	-0.1918	0.5565	0.0032	-0.0338
2016-2017	0.5281	0.2093	-0.6742	1.9400	0.0208	-1.0240
2007-2017 (Average)	0.6432	-0.0629	-0.2834	1.2034	0.0218	-0.5530

energy-saving technologies in the United States is higher than that in China. To analyze the reasons for high industrial electricity consumption intensity, on the one hand, some provinces have developed rapidly in high energy-intensive industries, which have a more obvious promotion effect on electricity, but the economic development is out of sync. On the other hand, the growth of non-productive power consumption is faster, such as household power consumption does not directly increase GDP, but only directly waste electricity. In consequence, the improvement of China's electricity utilization efficiency in the future is still a larger space. For the sake of analysis ΔP_{IEC-ij}, Fig. 5 shows the power consumption of three industrial sectors. The secondary industry shows the highest power consumption, of which the high energy-intensive industries have a long-term high proportion in the secondary industry, but the contribution rate of the secondary industry to GDP is declining, from 50.1% in 2007 to 34.2% in 2017. With China stepping into the middle and late stage of industrialization, the supporting role of the tertiary industry for economic development has become more and more obvious. The proportion of the tertiary industry is increasing, but it is still lower than the world average. In 2007, the proportion of the tertiary industry in China was 52.68%, and the global average of the proportion of the tertiary industry was 65.9% [41]. What's more, increasing the proportion of the tertiary industry will reduce electricity consumption intensity, but it will improve energy efficiency. Hence, increasing investment in tertiary industries with low energy consumption and high output, and relatively reducing investment in high energy-intensive secondary industries can promote industrial upgrading and improve the level of ECP.

In Fig. 6, ECP has four periods of distinct changes along the timeline. The change in ECP from 2008 to 2009 was -0.0162, which was the only period that

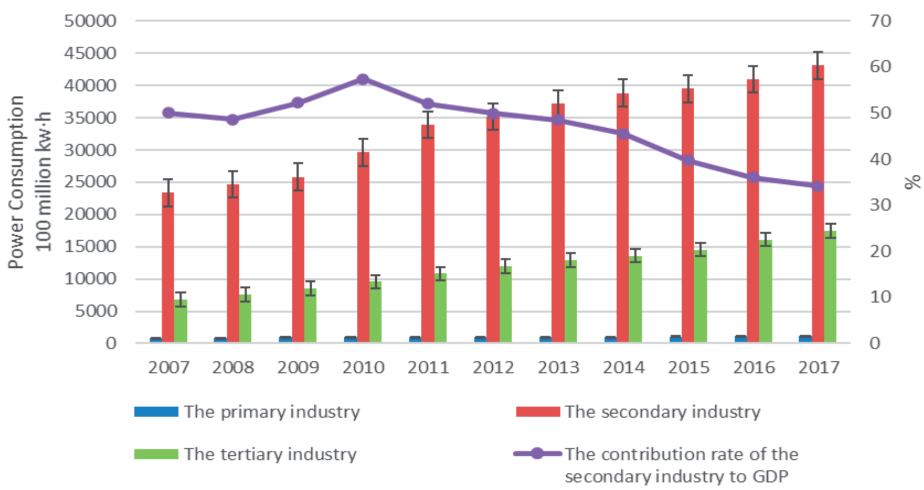


Fig. 5. Power consumption of three industrial sectors in China, 2007-2017.

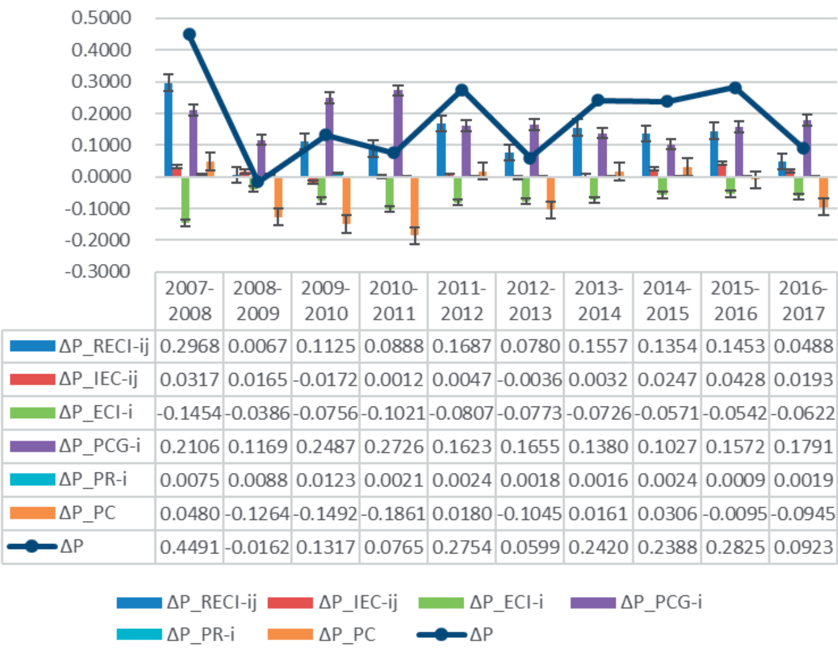


Fig. 6. Effects of drivers for Chinese ECP increment from the consumption side.

Table 4. Drivers for Chinese provincial ECP (100 million Yuan*10^{-3}/ten thousand tonnes) from the consumption side in 2007-2017.

Province	$\Delta P_{RECI\text{-}ij}$	$\Delta P_{IEC\text{-}ij}$	$\Delta P_{ECI\text{-}i}$	$\Delta P_{PCG\text{-}i}$	$\Delta P_{PR\text{-}i}$	ΔP_{PC}
Beijing	38.760	4.353	-33.588	46.663	10.050	-18.069
Tianjin	30.989	4.629	-26.859	33.018	9.845	-11.909
Hebei	40.124	2.616	-25.732	63.601	2.222	-25.636
Shanxi	19.104	5.600	-18.127	29.357	1.035	-11.391
Inner Mongolia	19.052	1.653	5.512	34.192	-0.579	-14.553
Liaoning	20.047	3.557	-14.930	45.005	-2.663	-22.258
Jilin	20.542	1.041	-20.548	33.739	-2.288	-11.054
Heilongjiang	15.637	6.469	-16.307	31.015	-2.408	-12.857
Shanghai	63.792	6.774	-35.556	48.725	5.521	-22.244
Jiangsu	136.303	28.423	-85.949	192.111	-2.443	-53.311
Zhejiang	69.279	11.981	-38.520	99.803	4.354	-34.810
Anhui	46.356	0.175	-18.590	61.581	-0.776	-15.816
Fujian	53.196	5.134	-29.783	70.455	1.869	-19.163
Jiangxi	32.856	-3.185	-10.569	44.986	0.061	-12.308
Shandong	99.454	-1.836	-30.141	146.938	2.499	-49.932
Henan	64.361	10.034	-51.504	96.432	-2.608	-29.379
Hubei	19.637	-4.181	-40.926	81.996	-0.792	-19.847
Hunan	57.316	18.527	-57.553	76.658	1.479	-20.902
Guangdong	123.073	11.624	-86.635	164.878	16.629	-58.549
Guangxi	28.516	3.293	-15.389	41.411	-0.681	-12.309
Hainan	7.495	0.675	-2.212	9.826	0.418	-2.682
Chongqing	40.996	0.368	-20.688	43.430	1.308	-10.590

Table 4. Continued.

Sichuan	61.400	1.164	-46.429	85.509	-1.710	-22.448
Guizhou	26.616	3.640	-18.002	34.042	-0.887	-6.500
Yunnan	26.789	2.476	-17.504	36.144	0.257	-9.686
Shannxi	38.451	2.018	-15.130	52.366	-0.686	-13.257
Gansu	9.977	0.709	-6.029	15.562	-0.320	-5.253
Qinghai	4.158	1.088	-1.921	5.723	0.156	-1.746
Ningxia	5.988	0.775	-3.012	7.757	0.421	-2.190
Xinjiang	16.324	-6.261	16.802	20.724	2.495	-6.922

showed negative value. Affected by the economic crisis, the contribution rate of per capita GDP to ECP reached -723.8% (Table 2). Since 2009, ECP increments have been positive. In 2011-2012, the ECP increment reached a high value. As China's residential electricity used step tariff at the end of 2011, rational use of electricity through economic means will help increase ECP values and promote carbon neutrality. From 2013 to 2016, ECP increased year by year, because China promulgated a series of energy conservation, emission reduction and industrial energy price adjustment policies. Especially carbon abatement of thermal power generation, so the transformation of thermal power generation to energy conservation and emission reduction had entered a stage of high-speed and high-quality development. In 2016-2017, the increment in ECP decreased to 0.0923. In 2017, due to the pressure of assessment, the construction of energy-intensive projects increased, resulting in a large increase in the power consumption of the secondary industry.

In-depth Analysis of the Provinces Based on Consumption Side

Table 4 shows the contribution values of the electricity consumption structure effect of provincial industry (ΔP_{IEC-ij}) in Xinjiang, Jiangxi, Hubei, and Shandong are negative, indicating that the proportion of industrial power consumption in the provinces is declining, and the proportion of non-productive power consumption is increasing. The contributions of the provincial electricity consumption intensity effect (ΔP_{ECI-i}) in Xinjiang and Inner Mongolia are positive, indicating that the electricity consumption intensity of the two provinces is increasing. For example, Xinjiang has undertaken the transfer of high energy-intensive industries such as electrolytic aluminum, and the electricity utilization efficiency is low. The population scale effect (ΔP_{PR-i}) has subtle influence on ECP, which means that the population growth of other provinces except Guangdong, Beijing, Tianjin and Zhejiang is similar to that of the whole country. Specifically, from the regional perspective, the population scale of Guangdong, Beijing, Tianjin, and Zhejiang has a greater impact on ECP than other regions, and these provinces are the main areas of net population inflow. Similarly, regional differences in other parameters are not obvious.

Conclusions

This study explores the carbon neutrality of the power industry through the study of the ECP in 30 provinces in China during the period 2007-2017, effectively combining the economy and the environment. Based on the LMDI method, the ECP is decomposed on the power production and consumption side, while considering the regional and industrial dimensions. Finally, it is decomposed into six driving factors respectively, and the following main conclusions are drawn:

From the perspective of production, first, the provincial ECP and the reciprocal of standard coal consumption for power supply are the main driving factors for improving China's ECP. Raising regional ECP is the top priority. With regard to reducing coal consumption for power supply, China has listed clean and efficient use of coal as Science and Technology Innovation 2030 Major Project. In addition, the power generation structure, the CO_2 emission intensity of power generation and standard coal structure effect are negative factors for ECP growth. In the context of China's announcement that it plans to achieve carbon neutrality by 2060 and peak coal consumption by 2025, the development of clean energy should be accelerated. Second, in-depth analysis of the provinces, the ECP of each province shows significant regional differences. Xinjiang's ECP level is the lowest because Xinjiang's economic growth relies to a large extent on the support of high investment and high energy-intensive, following an extensive economic development path. Guangdong, Jiangsu and Sichuan have the highest levels of ECP. In Guangdong and Jiangsu, the inflow of electricity has resulted in low local electricity production-based CO_2 emissions; in Sichuan, on the one hand, low-carbon energy reduces local electricity CO_2 emissions; on the other hand, as China's economy has entered the 'New Normal' era, the slowdown in economic growth has accelerated the decarbonization of Sichuan's power industry. Third, according to the timeline analysis of ECP changes, the continuous growth of ECP from 2007 to 2017 benefited from economic development and optimization of the power generation structure.

From the perspective of consumption, first, the provincial per capita GDP and the reciprocal provincial industrial electricity consumption intensity are the main positive factors for ECP growth. ECP can be enhanced by improving electricity utilization efficiency and economic development, but it is more critical to master the balance between ECP and economic development. If a higher level of ECP is to be achieved, the economy will be sacrificed up to a point. In addition, the CO_2 emissions per capita and the provincial electricity consumption intensity are the main negative factors. On the one hand, technological transformation can improve electricity utilization efficiency and realize energy conservation and emission reduction; on the other hand, it can promote industrial upgrading. Second, for in-depth analysis of the provinces, low electricity utilization efficiency is the reason why ECP in Xinjiang, Inner Mongolia and other places is lower than that in Jiangsu and Guangdong. Third, for the analysis of change in the ECP according to the timeline, ECP only declined in 2008-2009 due to the negative impact of the financial crisis.

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Conflict of Interest

The authors declare no conflict of interest.

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