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O Comparisons of CO_2 emission performance between secondary and service industries in Yangtze River Delta cities

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Abstract

To put the brakes on global climate change, China, the world's top emitter, has established ambitious CO_2 emissions reduction targets. Industry-level emissions analysis can help policymakers determine better ways to achieve mitigation targets. This study is the first to target the total-factor carbon emission performance (TCPI) of secondary and service industries. We first compile industry-level CO_2 emission inventories of 25 Yangtze River Delta cities during 2007-2016. The TCPI of secondary and service industries is then estimated by the non-radial directional distance function. We then compare the TCPI of the two industries across levels, dynamics, and inequalities using a global metafrontier approach. The results show the TCPI of the service industry (0.563 in 2016) was significantly higher than that of secondary industry (0.256 in 2016), suggesting that the service industry was more carbon-friendly. The TCPI gap between the secondary and service industries narrowed over the study period. The TCPI of secondary industry showed a promising increase during 2007-2016 with an annual growth rate of 2.30%, reflecting the positive effects of the government's reforms and environmental regulations. By contrast, the service industry saw a downward trend in TCPI, decreasing by 1.68% annually, primarily because it is a newcomer to low-carbon development. TCPI inequality in secondary industry was much larger than in the service industry, suggesting that significant heterogeneity exists in secondary industry. Therefore, policymakers should implement targeted mitigation policies for secondary industry, and place decarbonising the service industry on the agenda to reverse its decreasing TCPI.

Keywords: Carbon emission performance; Non-radial directional distance function; Secondary industry; Service industry; Inequality

1. Introduction

As the world's largest CO_2 producer, China contributed 27.9% of global CO_2 emissions in 2017, an amount greater than the sum of the USA (15.2%) and Europe (12.4%) (BP, 2018). China has erected ambitious CO_2 emissions mitigation targets to put the brakes on global climate change: carbon intensity will decrease by 60 to 65% compared to 2005 levels by 2030 (Chinese Government, 2015a). Considering that China has entered into a new normal characterised by slowing economic activities, it is important to achieve its CO_2 mitigation targets while maintaining its current economic growth. Single-factor indexes, such as carbon intensity, are widely adopted to calculate environmental performance (Ang, 1999; Sinton et al., 1998). However, in the single-factor analysis framework, indicators consider only outputs and ignore input factors, implying that they achieve a partial-factor carbon emission performances analysis (Ang, 1999; Ang and Goh, 2018; Farajzadeh and Nematollahi, 2018). Partial-factor indicators ignore substitution or complementary effects among input factors. Data envelopment analysis (DEA) is a useful technique for measuring total-factor carbon emission performance (TCPI) because it uses a multiple input-output framework to compute environmental performance, overcoming the limitations of a single-factor index (Hu and Wang, 2006; Zhou et al., 2007; Zhou and Ang, 2008). Therefore, improvement in TCPI has attracted increasing attention in planning for sustainable development.

Most studies regarding TCPI focus on the national (Liou and Wu, 2011; Zhang et al., 2018; Zhou et al., 2010), regional (Wang et al., 2012; Yao et al., 2015), or provincial levels (Guo et al., 2011; Wang et al., 2013). However, the future achievement of the intensity targets will increasingly depend on industry-level emissions mitigation schemes (Shan et al., 2018). For example, the Emission Trading Scheme, which covers the electricity sector, was launched nationwide in 2017 (Chinese Government, 2017). Industry-level research can help policymakers to identify better ways to reach mitigation targets compared than studies of economic entities as a whole. Another motivation for targeting industry-level TCPI is that many cities are facing the challenge of industrial restructuring and upgrading from an energy-intensive to a service-based economy (Chinese Government, 2015b). Determining how to reduce CO_2 emissions at the industry level during the transitional period is a crucial issue. However, this issue has received little attention, and the TCPI of the secondary and service industries remains unknown.

To address this gap, we conduct an empirical study on the TCPI of the secondary and service industries of the Yangtze River Delta cities. The Yangtze River Delta has become one of the three most developed metropolitan circles in China because of its high urbanisation rate and industrialisation level. The Yangtze River

Delta's GDP accounted for 20.53% of China in 2016 (NBS, 2017). However, rapid economic development inevitably consumes a considerable amount of energy and produces large quantities of CO_2. The Yangtze River Delta contributed a considerable amount of CO_2, at 1284.17 million tons (Mt) in 2016, representing approximately 13.4% of China's CO_2 emissions (Fig.1).

The Secondary industry of the Yangtze River Delta cities contributed large quantities of CO_2 emissions in 2016, representing 83.96% of the total CO_2 emissions (Figure 1). This is mainly because secondary industry carry out a large number of high energy consuming and high emission production activities (Xu et al., 2018). Thus, determining better ways to reduce energy consumption and CO_2 emissions in secondary industry is crucial to promoting low-carbon economy. As the largest CO_2 emitting industry, however, the TCPI of secondary industry remains unclear. Several studies have focused on the TCPI of industrial sectors (Cheng et al., 2018; Wang and Wei, 2014; Yao et al., 2016; Zhang et al., 2016b). Zhang et al. (2016) measured the TCPI of China's manufacturing sectors. He et al. (2013) and Wei et al. (2007) evaluated the energy efficiency of China's iron and steel industry. Zhang and Choi (2013) measured the TCPI of China's fossil fuel power plants. Even though these studies provide valuable information for policymakers who seek to mitigate carbon emissions, the environmental performance of secondary industry as a whole is unclear because the process-related emissions (e.g., cement) and emissions from certain subsectors (e.g. the construction sector) are neglected (Rehan and Nehdi, 2005; Shan et al., 2016b).

Service industry plays an increasingly significant role when a country has reached a certain level of industrialization, based on the experience of countries with developed market economies. Services accounted for 65.08% of global GDP in 2016 (The World Bank, 2017), while the figure for the Yangtze River Delta cities was 53.95% (NBS, 2017). Thus, there is enormous space for the growth of this region's service industry. However, the environmental impacts of service industry such as tourism (Bakhat and Rosselló, 2011; Kelly and Williams, 2007; Kuo and Chen, 2009), transportation (Chang et al., 2013; Paravantis and Georgakellos, 2007) and accommodation (Becken et al., 2001) should not be underestimated. Despite this, the environmental performance of the service industry is poorly researched, although numerous studies examine its economic implications. Some causes for this neglect may be the underestimation of its negative impacts on climate change and the problem of data unavailability (Pardo Martínez and Silveira, 2012).

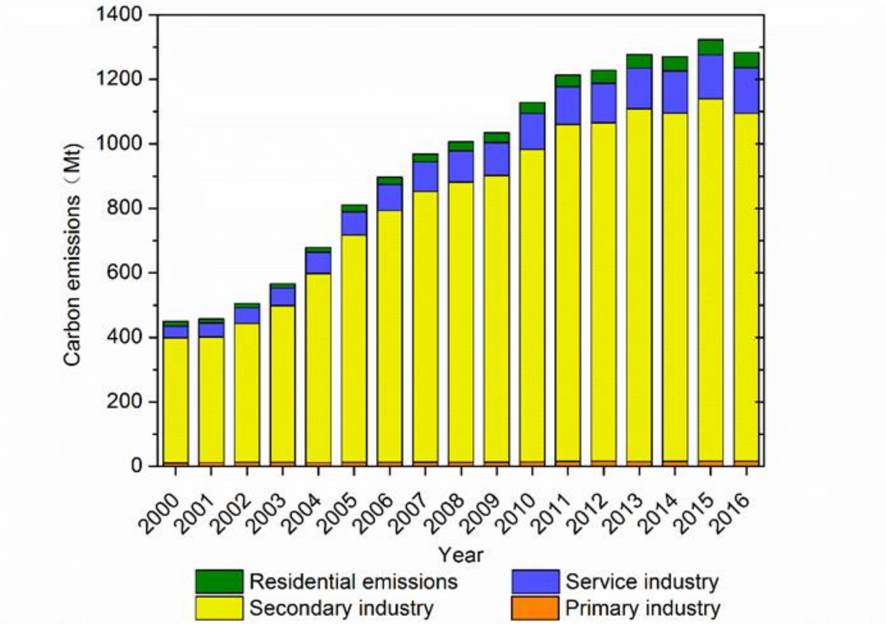

Figure 1. CO_2 emissions in the Yangtze River Delta by sector, 2000-2016.[1]

Baumol Fuchs Hypothesis suggested that the productivity growth in the service industry is lower than that in manufacturing sectors (Baumol, 1967; Fuchs, 1968). This hypothesis and Baumol's cost disease have been tested and confirmed by many scholars (Bates and Santerre, 2013; Inklaar et al., 2008; Last and Wetzel, 2011). However, to the best of our knowledge, efficiency in terms of CO_2 emissions between service industry and secondary industry has not been compared. Though the service industry produces lower CO_2 emissions (Guan et al., 2018; Liu et al., 2016; Zhang et al., 2014), whether it will be more efficient or carbon-friendly than secondary industry? How large is the TCPI gap between the two industries? What have been the changes in their TCPI in the last decade? Finally, what are the differences in TCPI inequality between the two industries? To examine these questions, we further compare the TCPI of secondary and service industries considering their levels, dynamics, and inequalities. Our results will increase understanding of the differences between the secondary and service industries and provide a scientific basis for policymakers to mitigate CO_2 emissions at the industry-level more effectively.

This study first compiles the CO_2 emission inventories of secondary and service industries for 25 Yangtze River Delta cities in China during 2007-2016. Their TCPI is then estimated using the non-radial directional

[1] The calculation method for CO_2 emissions inventory is based on Shan et al. (2018). Data are collected from provincial statistical yearbooks from 2001 to 2017.

distance function. Last, the TCPI of secondary and service industries is compared in terms of levels, dynamics, and inequalities using a global metafrontier approach. The contributions of this study are threefold. This study is the first to target the TCPI of secondary and service industries, while most previous studies regarding TCPI focused on the national, regional, or provincial levels. Second, carbon emission performance analysis in most previous research was static or single objective. This analysis includes TCPI comparisons between the secondary and service industries across levels, dynamics, and inequalities using a newly developed DEA method which has improved comparability. Therefore, its results may yield richer insights. Last, our study analyses industry-level TCPI for cities instead of a province. Study of a whole province may lead to biased results because there is great heterogeneity across cities. Moreover, the cooperation of city-level governments can help to achieve CO_2 emissions mitigation targets more effectively because they are the implementers of mitigation policies.

2. Data and Methodology

2.1. Data

We estimate the energy inventories of secondary and service industries of 25 Yangtze River Delta cities from 2007 to 2016. In this study, 47 socioeconomic sectors are divided into four main categories, namely primary industry, secondary industry, service industry, and households (Table S1). Energy consumption includes 17 types of energy from 47 socioeconomic sectors, transformed into standard coal equivalents. Energy consumption data are collected from the energy balance tables and industrial sectoral energy consumption tables of city-level statistical yearbooks. Because of the incomplete data problem, the energy balance table is only available for Shanghai. This study obtains the other cities' energy balance tables by scaling down their respective provincial tables following Shan et al. (2017). The data used for scaling, namely sectoral GDP, the gross value of industrial output, and urban/rural population, are derived from cities' and their corresponding province's statistical yearbooks.

We further construct the CO_2 emission inventories of secondary and service industries of these cities between 2007 and 2016. Since the CO_2 emissions inventory construction method adopted in this study was presented in our previous study (Shan et al., 2017), only significant calculation processes are shown in this paper. This paper follows the IPCC, (2006) sectoral approach to measure CO_2 emissions. The CO_2 emissions inventory contains two components, namely energy-related and process-related emissions.

Energy-related CO_2 emissions are obtained as follows:

$$\mathrm{C}E_{ij} = \sum_{i=1}^{17} \sum_{j=1}^{47} AD_{ij} \times NCV_i \times CC_i \times O_{ij} \tag{1}$$

In Equation (1), *i* and *j* represent fuel types and socioeconomic sectors, respectively. CE_{ij} represents CO_2 emissions from fossil fuel *i* and sector *j*. AD_{ij}, NCV_i and $\mathrm{CC_i}$ indicate the amount of fossil fuel consumption, net caloric value, and carbon content per calorie, respectively. O_{ij} denotes the carbon oxidation ratio for different sectors and fuel types. We adopt the newly measured emissions factors, which are collected based on the estimation of 602 coal samples from China's 100 largest coal-mining areas, from Liu et al. (2015). These factors have been widely used by many scholars because they are more representative of Chinese fuels (Li et al., 2019; Shan et al., 2016a; Xiao et al., 2019; Zhou et al., 2018).

Process-related CO_2 emissions are obtained as follows:

$$CE_{process} = \sum_{t=1}^{9} AD_t \times EF_t \tag{2}$$

where t refers to industrial process t. $CE_{process}$ is CO_2 emissions from industrial processes, and AD_t is the activity data. EF_t is the emissions factor, derived from Liu et al. (2015).

The number of employees and GDP of secondary and service industries are obtained from the China City Statistical Yearbooks. GDP is converted into 2007 constant prices using an industry-level GDP index. Considering that capital stock data cannot directly be collected from official sources, we calculate it using the perpetual inventory method, as in Eq. (3).

$$K_t = I_t + (1-\delta)K_{t-1} \tag{3}$$

where *t* indicates period t. K_t, I_t, and δ indicate the capital stock, investment in fixed assets, and depreciation rate, respectively. The investment in fixed assets data of secondary and service industries are obtained from city-level statistical yearbooks, and we use the depreciation rate given in Shan (2008). Capital stock is also converted into 2007 constant prices. The descriptive statistics of the data set are given in Table 1.

Table 1. Descriptive statistics, 2007-2016.

Variables	Unit	Obs	Mean	Std.Dev.	Min	Max
			Secondary industry			
K	100 million yuan	250	4623.83	3120.76	411.82	16720.45
L	10 thousand person	250	58.29	54.24	4.08	273.47
E	1 million tce	250	26.67	27.43	1.16	119.33
Y	100 million yuan	250	1923.39	1767.49	179.00	9214.46
C	1 million tons	250	64.28	61.88	3.36	258.77
			Service industry			
K	100 million yuan	250	4637.13	5833.52	211.96	32788.84

L	10 thousand person	250	43.09	63.73	7.02	471.33
E	1 million tce	250	2.92	5.84	0.28	35.99
Y	100 million yuan	250	1686.40	2262.50	171.91	15996.54
C	1 million tons	250	4.66	10.15	0.39	61.41

2.2 Global Meta-Frontier Non-Radial Directional Distance Function

In this study, we adopt a global meta-frontier non-radial directional distance function (GMNDDF), which envelops all DMUs and all periods, to measure the TCPI of secondary and service industries (Zhang et al., 2016a). The GMNDDF approach is capable of improving the discrimination power and comparing DMUs across different periods and different industry groups using the same benchmark (Zhang et al., 2016a).

Assume that *K, L, E* are respectively capital stock, labour force and energy consumption, which represent production process inputs. *Y* and *C* denote GDP (good output) and CO_2 emissions (bad output), respectively. The joint production technology can be expressed as

$$T = \{(K, L, E, Y, C): (K, L, E) \text{ can produce } (Y, C)\} \tag{4}$$

Inputs and good outputs are assumed to be strongly disposable, and environmental production technology is considered to be a closed and bounded set (Färe and Grosskopf, 2004). Considering that a production technology can generate good and bad outputs simultaneously, the weak disposability and null-jointness assumptions are also considered in this framework (Färe et al., 1989).

The NDDF can be defined as (Zhou et al., 2012):

$$\overrightarrow{ND}(K, L, E, Y, C; g) = \sup\{w^T\beta: \left(K, L, E, Y, C + g \times \text{diag}(\beta)\right) \in T\} \tag{5}$$

where $w = (w_K, w_L, w_E, w_Y, w_c)^T$ is the normalized weight vector. We set it as (1/9, 1/9, 1/9, 1/3, 1/3) to estimate the inefficiency of inputs and outputs. $g = (-g_K, -g_L, -g_E, g_Y - g_C)$ indicates the directional vector. The symbol *diag* represents the diagonal matrices, and $\beta = \left(\beta_K^G, \beta_L^G, \beta_E^G, \beta_Y^G, \beta_C^G\right) \geq 0$ is the scaling factor used to describe the inefficiency. The effects of all the factors are considered to calculate the TCPI of a DMU. If

$\overrightarrow{ND}(K, L, E, Y, C; G) = 0$, it implies that the DMU is the most efficient under the technology production technology in 'g' direction.

Based on Oh (2010) and Tulkens and Vanden Eeckaut, (1995), this study describes the contemporaneous environmental production technology of an industry as $T_i^C = \{(K_i^t, L_i^t, E_i^t, Y_i^t, C_i^t): (K_i^t, L_i^t, E_i^t \; can \; produce \; (Y_i^t, C_i^t)\}$, where *i* =2, 3 and *t* = 1, 2 …, T. *i*=2 and *i*=3 indicate secondary industry or the service industry, respectively. Further, the global production technology of *i* industry can be expressed as $T_i^G = T_i^1 \cup T_i^2 \cup \ldots \cup T_i^T$. This technology covers the entire study period for *i* industry. Last, the global meta-frontier production technology can be expressed as $T^{GM} = T_2^G \cup T_3^G$. This global meta-frontier technology covers the global production technology of both secondary industry and service industry. We denote the value of GMNDDF of a specific DMU as $\overrightarrow{ND^{GM}}(K, L, E, Y, C; g)$. We obtain the value for $\overrightarrow{ND^{GM}}(K, L, E, Y, C; g)$ by calculating the DEA model in Eq. (6), where superscript *GM* represents the global meta-frontier production technology.

$$\overrightarrow{ND^{GM}}(K, L, E, Y, C; g) = sup\{w^T \beta^{GM}: (K, L, E, Y, C + g \times diag(\beta^{GM})) \in T^{GM}\},$$

$$s.t. \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{i=2}^{3} z_{ni}^t K_{ni}^t \leq K_{ni'} - \beta_K^{GM} g_K ,$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{i=2}^{3} z_{ni}^t L_{ni}^t \leq L_{ni'} - \beta_L^{GM} g_L ,$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{i=2}^{3} z_{ni}^t E_{ni}^t \leq E_{ni'} - \beta_E^{GM} g_E , \tag{6}$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{i=2}^{3} z_{ni}^t Y_{ni}^t \geq \mathrm{Y}_{ni'} + \beta_Y^{GM} g_Y ,$$

$$\textstyle\sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{i=2}^{3} z_{ni}^t C_{ni}^t = C_{ni'} - \beta_C^{GM} g_C , z_{in}^s \geq 0,\; \sum z_n^t = 1,\; \beta^{GI} \geq 0,\; \mathrm{t} = 1,2, \ldots \mathrm{T},\; n = 1,2, \ldots, \mathrm{N},\; \mathrm{i} = 2 \text{ and } 3.$$

where K_{ni}^t indicates capital stock of *i* industry of *n* city in *t* period. $i = 2$ and $i = 3$ mean secondary and service industries, respectively. $\sum z_n^t = 1$ denotes variable returns to scale.

TCPI can be expressed as the potential target carbon intensity divided by the actual carbon intensity (Zhou et al., 2012):

$$\text{TCPI} = \frac{(C - \beta_C^* C)/(Y + \beta_Y^* Y)}{C/Y} = \frac{1 - \beta_C^*}{1 + \beta_Y^*} \tag{7}$$

$TCPI$ indicates the potential to decrease carbon intensity. $TCPI$ ranges from zero to unity. If $TCPI$ equals 1, the DMU is considered to have the best TCPI. According to the values of GMNDDF obtained in Eq. (6), we have:

$$\text{TCPI}^{GM}(\text{K, L, E, Y, C}) = \frac{(C - \beta_C^{GM^*} C)/(Y + \beta_Y^{GM^*} Y)}{C/Y} = \frac{1 - \beta_C^{GM^*}}{1 + \beta_Y^{GM^*}} \tag{8}$$

where $TCPI^{GM}$ can be used to estimate TCPI for a DMU under global meta-frontier production technology.

2.3. Inequality

The Theil index, which was proposed by Theil, (1967), has been widely used to evaluate economic inequality. As a weighted entropy index, it is capable of decomposing inequality into two components, namely within-group inequality and between-group inequality (Conceicao and Ferreira, 2000; Theil, 1967). Many scholars have applied the Theil index to environmental analysis (Clarke-Sather et al., 2011; Lin and Fei, 2015; Padilla and Duro, 2013). Here, we use the Theil index to measure the inequality in the TCPIs of 25 cities' secondary and service industries. We can formulate the Theil Index as

$$\text{T} = \sum_{i=1}^{N} (y_i) \log \left(\frac{y_i}{x_i}\right) \tag{9}$$

In Eq. (9), y_i is the ratio of TCPI of *i* sample to the total TCPI of all samples and x_i equals one divided by the number of all samples. The decomposition equation of the Theil Index can be expressed as follows:

$$\text{T} = T_{bi} + T_{wi} \tag{10}$$

where T_{bi} and T_{wi} indicate between industry inequality and within industry inequality, respectively. T_{bi} can be calculated through the following equation:

$$T_{bi} = \sum_{r=1}^{N} (y_r) \log \left(\frac{y_r}{x_r}\right) \tag{11}$$

where y_r means the ratio of total TCPI of the *r* industry to the total TCPI of all industries. x_r indicates the share of the number of samples in the *r* industry to the number of all samples.

T_{wi} can be measured as

$$T_{wi} = \sum_{r=1}^{N} (w_r) \left[\sum_{i} (y_{i(r)}) \log \left(\frac{y_{i(r)}}{x_{i(r)}}\right) \right] \tag{12}$$

In Eq. (12), w_r is a weighting factor, indicating the share of total TCPI of *r* industry to the total TCPI of all industries. $y_{i(r)}$ is the share of TCPI of the *i* sample in the *r* industry. $x_{i(r)}$ is equal to one divided by the number of samples in *r* industry.

3. Empirical results

3.1. Total-factor carbon emission performance

Table 2 reports results of the TCPI of secondary industry of 25 Yangtze River Delta cities between 2007 and 2016. The mean values of secondary industry are well below one during 2007-2016 (Table 2), suggesting a great potential to increase TCPI to bring the secondary industry up to the best-practice global meta-frontier. In 2016, the average TCPI of secondary industry is 0.256, indicating that the proportion of target carbon intensity to actual carbon intensity is 0.256 and that secondary industry had the potential to increase its performance by 74.4% (Table 2). Considering specific cities, in 2016, the TCPI of the secondary industry of Shanghai, Wuxi, Hangzhou, and Lishui equals 1, showing that they have the best-practice TCPI under the global meta-frontier technology (Table 2). Among the laggards in 2016, Huzhou (0.047), Huaian (0.043), Jiaxing (0.036), Xuzhou (0.034), Nanjing (0.032), and Zhoushan (0.031) show significant potential to improve their TCPI (Table 2). Noticeably, the TCPI of secondary industry in Nanjing, the capital city of Jiangsu Province, is a mere 0.032 in 2016 (Table 2), which is primarily because Nanjing has four major industrial zones. In these zones, there are many high-energy-consumption and high-emission enterprises, such as Baosteel Group, the Nanjing Nangang Iron & Steel Group Corporation, and Nanjing Chemical Construction Co., LTD (Nanjing City

Government, 2015, 2014). Therefore, improvement in the TCPI of Nanjing's secondary industry should be highlighted. Moreover, well known as an old industrial base and a coal city, Xuzhou has many high-energy-intensive industries (Xuzhou Government, 2017). Therefore, the TCPI of secondary industry of Xuzhou is the third lowest in 2016 (Table 2). Noticeably, Zhoushan has the lowest TCPI in 2016 not only for secondary industry (0.031) but for its service industry as well (0.256) (Tables 2, 3). This is mainly because Zhoushan benefiteds greatly from the Zhoushan fishing grounds and became one of the designated State-level New Areas in 2011 because of its developed marine fishery (Chinese Government, 2011). However, the development of secondary and service industries of Zhoushan is far from sufficient, sluggish and end in low efficiency.

Table 2. Total-factor carbon emission performance of the secondary industry of 25 Yangtze River Delta cities, 2007-2016.

Province	City	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Shanghai	Shanghai	0.056	0.073	0.136	0.199	0.281	0.402	0.514	0.706	0.797	1.000	0.416
Jiangsu	Nanjing	0.071	0.024	0.061	0.098	0.107	0.029	0.183	0.181	0.036	0.032	0.082
	Wuxi	0.042	0.057	0.114	0.171	0.215	0.360	0.216	0.211	0.233	1.000	0.262
	Xuzhou	0.014	0.016	0.020	0.025	0.021	0.021	0.061	0.059	0.055	0.034	0.033
	Changzhou	0.076	0.085	0.093	0.101	0.060	0.079	0.051	0.056	0.064	0.063	0.073
	Suzhou	0.173	0.212	0.313	0.413	0.834	1.000	0.264	0.273	0.264	0.408	0.415
	Nantong	0.055	0.060	0.063	0.065	0.069	0.074	0.085	0.067	0.076	0.081	0.070
	Lianyungang	0.100	0.102	0.098	0.094	0.086	0.086	0.052	0.054	0.062	0.062	0.080
	Huaian	0.059	0.055	0.059	0.063	0.063	0.061	0.028	0.030	0.043	0.043	0.050
	Yancheng	0.075	0.068	0.093	0.118	0.132	0.136	0.068	0.073	0.088	0.097	0.095
	Yangzhou	0.059	0.063	0.067	0.072	0.069	0.092	0.045	0.056	0.068	0.067	0.066
	Zhenjiang	0.070	0.067	0.073	0.080	0.069	0.070	0.053	0.043	0.066	0.067	0.066
	Taizhou	0.146	0.139	0.135	0.130	0.116	0.125	0.060	0.068	0.066	0.053	0.104
	Suqian	0.416	0.530	0.537	0.544	0.488	0.238	0.097	0.095	0.101	0.113	0.316
Zhejiang	Hangzhou	0.170	0.191	0.237	0.282	0.306	0.364	0.415	0.440	0.501	1.000	0.391

	Ningbo	0.077	0.093	0.106	0.119	0.127	0.139	0.152	0.158	0.103	0.155	0.123
	Wenzhou	1.000	0.949	0.974	1.000	1.000	0.475	0.264	0.247	0.255	0.449	0.661
	Jiaxing	0.104	0.134	0.082	0.030	0.029	0.029	0.031	0.032	0.034	0.036	0.054
	Huzhou	0.022	0.032	0.035	0.038	0.049	0.061	0.052	0.044	0.044	0.047	0.042
	Shaoxing	0.046	0.052	0.052	0.052	0.053	0.057	0.054	0.055	0.057	0.122	0.060
	Jinhua	0.222	1.000	0.566	0.132	0.128	0.080	0.080	0.085	0.085	0.210	0.259
	Quzhou	0.113	0.137	0.135	0.133	0.134	0.140	0.121	0.123	0.134	0.150	0.132
	Zhoushan	1.000	0.817	0.614	0.411	0.209	0.252	0.257	0.032	0.033	0.031	0.366
	Taizhou	0.043	0.043	0.044	0.044	0.043	0.054	0.056	0.063	0.067	0.070	0.053
	Lishui	1.000	0.911	0.849	0.788	0.898	0.740	0.778	0.910	1.000	1.000	0.887
Average		0.208	0.236	0.222	0.208	0.224	0.207	0.161	0.166	0.173	0.256	0.206

Table 3 presents results of the TCPI of service industry of 25 cities during 2007-2016. The average TCPI of the service industry is 0.563 in 2016, which is much higher than the secondary industry TCPI of 0.256 (Table 3). This implies that the carbon intensity of the service industry can be reduced by 43.7% if it is on the global meta-frontier. For specific cities, in 2016, the TCPI of the service industry of Shanghai, Wuxi, and Suzhou is 1, indicating that these cities are the most efficient under the global meta-frontier technology (Table 3). Shanghai's service industry is well-developed and the share of service industry is the third highest among China's cities (NBS, 2018), which helps explain why Shanghai is one of the most efficient cities in CO2 emissions. By contrast, the TCPI of Ningbo (0.310), Xuzhou (0.306), and Zhoushan (0.256) is the lowest in 2016 (Table 3), representing that 69.0%, 69.4%, and 74.4% improvement space can be achieved to reach the global meta-frontier, respectively.

Table 3. Total-factor carbon emission performance of the service industry of 25 Yangtze River Delta cities, 2007-2016.

Province	City	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
Shanghai	Shanghai	0.235	0.322	0.414	0.446	0.541	0.628	0.730	0.831	0.947	1.000	0.609

Jiangsu	Nanjing	0.449	0.494	0.549	0.546	0.503	0.536	0.559	0.701	0.754	0.910	0.600
	Wuxi	0.655	0.928	1.000	0.978	0.919	1.000	0.898	0.860	0.951	1.000	0.919
	Xuzhou	0.218	0.211	0.242	0.255	0.269	0.267	0.259	0.244	0.250	0.306	0.252
	Changzhou	0.503	0.480	0.548	0.570	0.670	0.472	0.465	0.478	0.502	0.559	0.525
	Suzhou	0.995	1.000	1.000	1.000	1.000	1.000	0.846	0.832	0.903	1.000	0.958
	Nantong	0.987	1.000	0.816	0.753	0.682	0.631	0.579	0.530	0.500	0.538	0.702
	Lianyungang	0.491	0.518	0.510	0.487	0.491	0.499	0.496	0.495	0.466	0.485	0.494
	Huaian	0.527	0.513	0.592	0.547	0.553	0.540	0.545	0.498	0.482	0.506	0.530
	Yancheng	0.551	0.512	0.510	0.491	0.521	0.538	0.538	0.501	0.483	0.527	0.517
	Yangzhou	0.971	0.671	0.687	0.627	0.640	0.621	0.593	0.521	0.523	0.568	0.642
	Zhenjiang	1.000	1.000	1.000	1.000	0.958	1.000	0.633	0.644	0.586	0.655	0.848
	Taizhou	0.384	0.395	0.407	0.404	0.414	0.416	0.415	0.386	0.367	0.395	0.398
	Suqian	1.000	1.000	1.000	0.733	0.551	0.532	0.496	0.515	0.508	0.472	0.681
Zhejiang	Hangzhou	0.512	0.517	0.543	0.571	0.584	0.550	0.552	0.485	0.606	0.758	0.568
	Ningbo	0.365	0.323	0.362	0.356	0.360	0.337	0.384	0.293	0.300	0.310	0.339
	Wenzhou	1.000	0.967	0.893	1.000	0.729	0.586	0.548	0.406	0.404	0.419	0.695
	Jiaxing	0.394	0.399	0.492	0.487	0.476	0.433	0.430	0.400	0.364	0.383	0.426
	Huzhou	0.488	0.464	0.472	0.467	0.460	0.477	0.454	0.460	0.428	0.407	0.458
	Shaoxing	0.503	0.495	0.538	0.508	0.469	0.455	0.434	0.411	0.401	0.408	0.462
	Jinhua	0.603	0.621	0.668	0.685	0.703	0.698	0.743	0.693	0.588	0.596	0.660
	Quzhou	1.000	0.819	0.675	0.687	0.583	0.535	0.586	0.579	0.577	0.599	0.664
	Zhoushan	1.000	0.828	0.362	0.313	0.324	0.277	0.284	0.248	0.233	0.256	0.412
	Taizhou	0.553	0.565	0.616	0.643	0.608	0.519	0.521	0.497	0.464	0.455	0.544
	Lishui	1.000	0.934	0.684	0.645	0.637	0.634	0.654	0.588	0.522	0.556	0.685
Average		0.655	0.639	0.623	0.608	0.586	0.567	0.546	0.524	0.524	0.563	0.584

3.2. Level analysis

Figure 2 shows the spatial distribution of 25 Yangtze River Delta cities and the mean TCPI of their secondary and service industries during 2007-2016. The overall TCPI of the service industry (0.584) is higher than that of secondary industry (0.205) (Fig. 2, Tables 2 and 3), likely because secondary industry include many energy-intensive sectors that produce more CO_2 emissions. Therefore, the production process of the service industry is more low-carbon than that of secondary industry. There are three shades of green for the secondary industry in Fig. 2 (A) and five shades of green for the service industry in Fig. 2 (B), which suggests that the value range of the TCPI of secondary industry is larger than that of the service industry. Specifically, the TCPI of secondary industry ranges from 0.041(Xuzhou) to 0.805 (Lishui) (Table 2), while the figure for the service industry ranges from 0.252 (Xuzhou) to 0.96 (Suzhou) (Table 3). Therefore, a preliminary estimate shows that the inequality in TCPI of secondary industry is larger than that of the service industry, which can be further confirmed based on Figure 5.

The TCPI gap between secondary industry and the service industry shrank during 2007-2016, decreasing from 0.447 in 2007 to 0.307 in 2016 (Tables 2 and 3), because of their opposite dynamic changes. The TCPI of secondary industry exhibited a promising upward trend during 2007-2016 (Table 2), while the service industry saw a decrease during 2007-2015 (Table 3). For specific cities, the gap in TCPI between the two industries during 2007-2016 for Zhenjiang is the largest, followed by Wuxi, Nantong, and Suzhou. The corresponding TCPI of secondary industry of these cities is 0.070, 0.258, 0.077, and 0.392 during 2007-2016, respectively, while the figures for the service industry are 0.848, 0.919, 0.702, and 0.958 (Table 3). By contrast, Lishui has the smallest gap in TCPI between these two industries, followed by Zhoushan, Wenzhou, and Shanghai (Table 3). The TCPI of the secondary industry of Lishui, Zhoushan, Wenzhou, and Shanghai is 0.805, 0.314, 0.576 and 0.413, respectively, while the TCPI for their respective service industries is 0.685, 0.412, 0.695, and 0.609 (Table 3). Lishui is the only city whose TCPI of secondary industry is higher than that of its service industry (Tables 2 and 3).

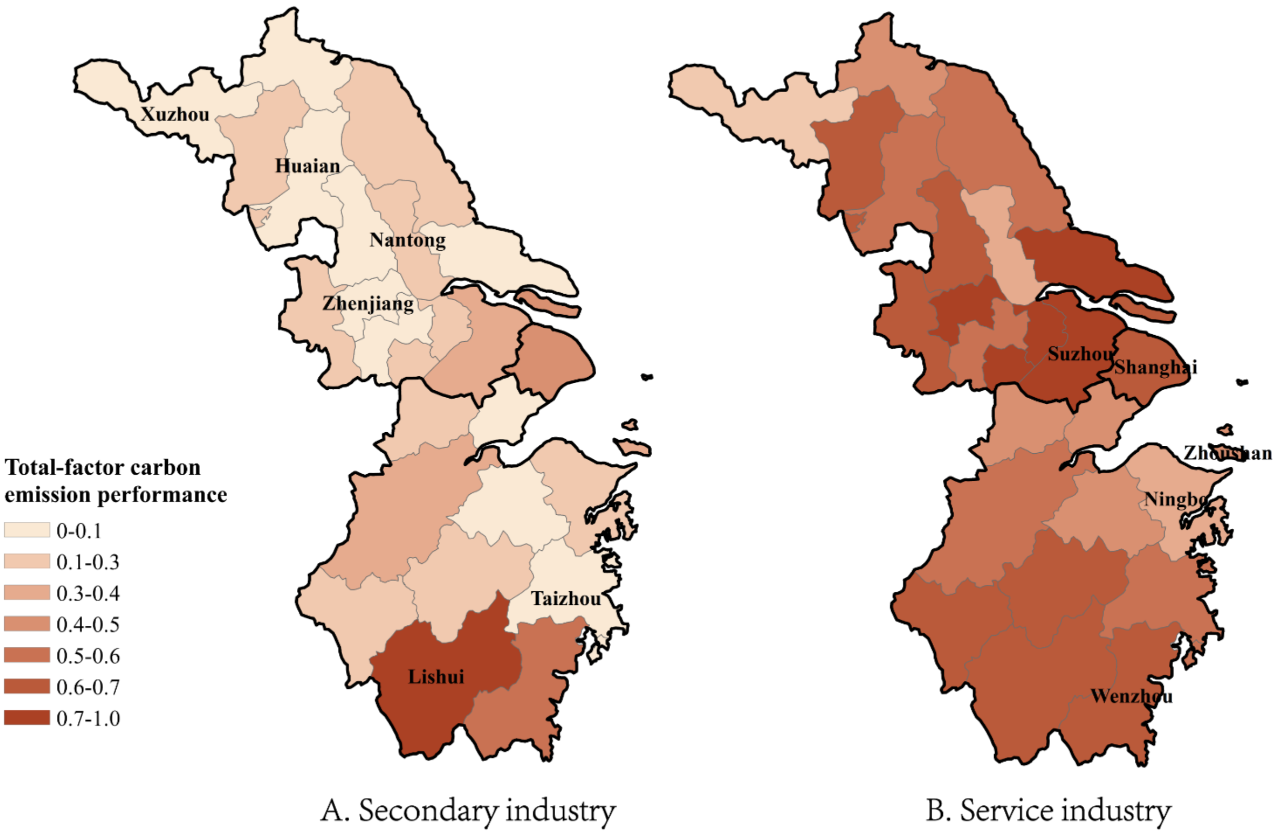

Figure 2. Spatial distribution and average carbon emission performance of the secondary industry (A) and service industries (B) of 25 Yangtze River Delta cities, 2007-2016.

3.3. Dynamic change analysis

According to Figure 3, thirteen cities experienced an increase in the TCPI of their secondary industry between 2007 and 2016, indicating that the annual growth rate of TCPI is positive, while the figure for the service industry is a mere eight cities. For secondary industry, Wuxi (42.2%), Shanghai (37.8%) and Hangzhou (21.8%) exhibited the largest annual growth rate in TCPI, while Jianxing (-11.1%), Suqian (-13.5%) and Zhoushan (-31.9%) saw the greatest drop (Fig. 3a). For the service industry, Shanghai (17.4%), Nanjing (8.2%), and Wuxi (4.8%) experienced the largest improvement in TCPI, while Suqian (-8.0%), Wenzhou (-9.2%), and Zhoushan (-14%) saw the most severe decrease (Fig. 3b).

In general, there was a promising upward trend in the TCPI of the 25 cities' secondary industry during 2007-2016, with an average annual growth rate of 2.30% (Table 2, Fig. 3a), showing the positive effects of the government's reforms and environmental regulations, such as energy structure optimization and reductions in coal production, steel processing, and cement (Guan et al., 2018; NBS, 2017). However, there was a downward trend, -1.68% annually, in the TCPI of the 25 cities' service industries during 2007-2016 (Table 3, Fig. 3b). Because service industry development is based on a certain level of industrialization, and the infant service industry's low-carbon development characteristics hinder improvement in TCPI. Service industries in the Yangtze River Delta cities experienced a remarkable growth of 4.97% annually from 2007 to 2016, whereas the average annual growth rate for secondary industry was a mere 2.82% (Fig. 1), showing that service industries were in their infancy at the beginning of the period.

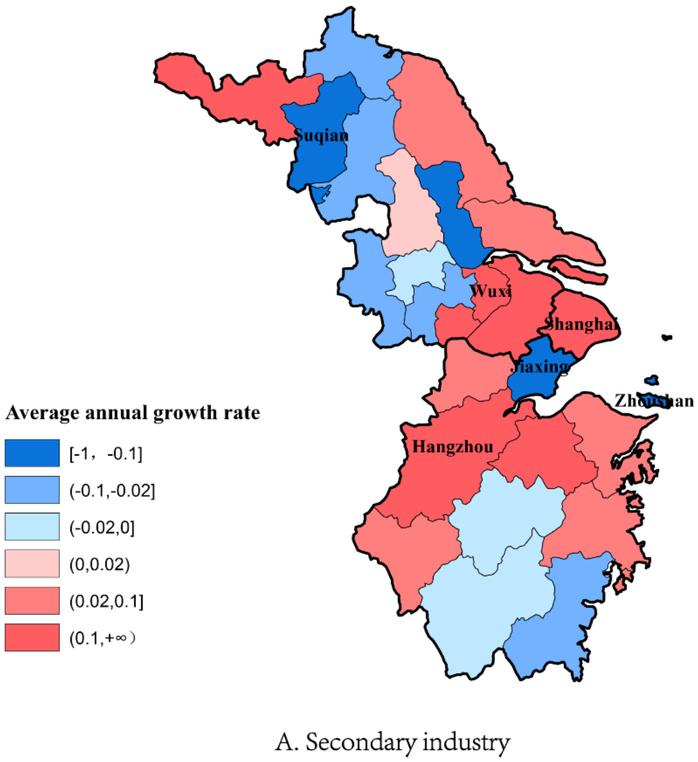

Figure 3. Spatial distribution and the average annual growth rate of the carbon emission performance of secondary industry (A) and service industries (B) of the 25 Yangtze River Delta cities, 2007-2016.

3.4. Inequality analysis

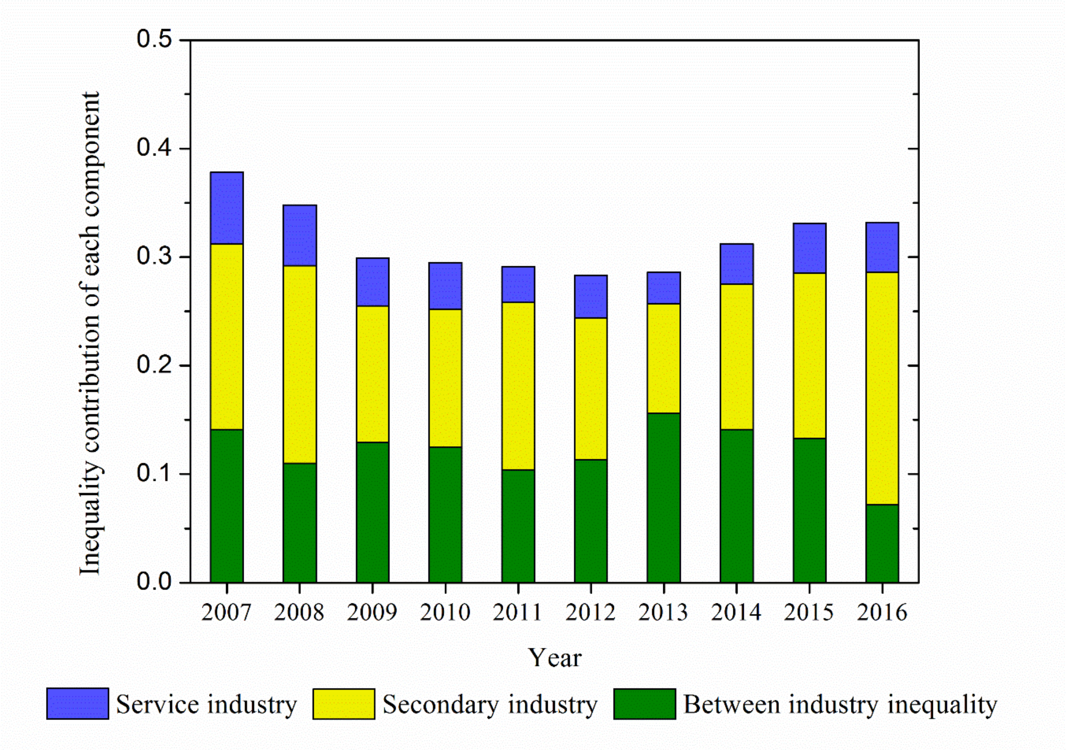

Figure 4. Contribution of each component to total inequality by the Theil index, 2007-2016.

Figure 4 illustrates the contribution of each component to the industry-level TCPI inequality over the study period using the Theil index. Total inequality is the sum of between industry inequality and within industry inequality, where the latter may be further decomposed into secondary and service industry inequalities. Total inequality experiences a sharp decrease from 0.379 in 2007 to 0.299 in 2009, a gradual decline to 0.285 in 2013 and then an increase to 0.332 in 2016 (Fig. 4). Between industry inequality fluctuated between 0.104 and 0.156 during 2007-2013, then fell continuously to 0.072 in 2016 (Figs. 4 and 5). The likely explanation for the recent decrease is that the improvement in the TCPI of secondary industry and the retrograde TCPI of the service industry bridges the inequality gap between these two industries (Tables 2 and 3). Compared to between industry inequality, within industry inequality is the primary contributor to total inequality, except for 2013 (Figs. 4 and 5). Within industry inequality experiences a decrease from 0.238 in 2007 to 0.156 in 2013 and rises to 0.260 in 2016 (Figs. 4 and 5). Among the three components, secondary industry inequality constitutes the largest proportion of the total Theil index (47.1%) over the study period, followed by between industry inequality (39.2%) and service industry inequality (13.7%) (Table 4).

Table 4. Share of components' TCPI inequalities in total inequality using the Theil index, 2007-2016.

Year	Between industry inequality (%)	secondary industry inequality (%)	Service industry inequality (%)
2007	37.1	45.3	17.5
2008	31.6	52.4	16.0
2009	43.0	42.3	14.7
2010	42.5	43.1	14.4
2011	35.7	53.0	11.3
2012	39.9	46.3	13.8
2013	54.6	35.3	10.0
2014	45.2	43.0	11.8
2015	40.0	46.0	13.9
2016	21.7	64.4	13.9
Average	39.2	47.1	13.7

The bar charts in Fig. 5 show the inequalities of secondary and service industries. It is noteworthy that the contribution inequalities of secondary and service industries in Fig. 4 are different from the bar chart values of the corresponding industry in Fig. 5 because the contribution values are calculated through a weighted equation, Eq. (12). Therefore, the inequality in the secondary industry and service industry in Fig.5 should be weighted to make them equal to the corresponding industry inequality in Fig. 4. The bar charts in Fig. 5 show that secondary industry inequality is significantly higher than service industry inequality, indicating that there is greater heterogeneity in secondary industry. This is mainly because secondary industry includes a vast range of subsectors, such as ‘coal mining and dressing’, ‘ordinary machinery’ and ‘construction’ (Table S1), which have various production technologies and energy utilization methods. Therefore, the TCPI of the secondary industry for each city differs significantly, resulting in high inequality in TCPI. Secondary industry inequality experiences a decrease from 0.711 in 2007 to 0.441 in 2013, and a significant increase to 0.685 in 2016 (Fig. 5). Service industry inequality fluctuates at a low level, between 0.037 and 0.088 during 2007-2016 (Fig. 5).

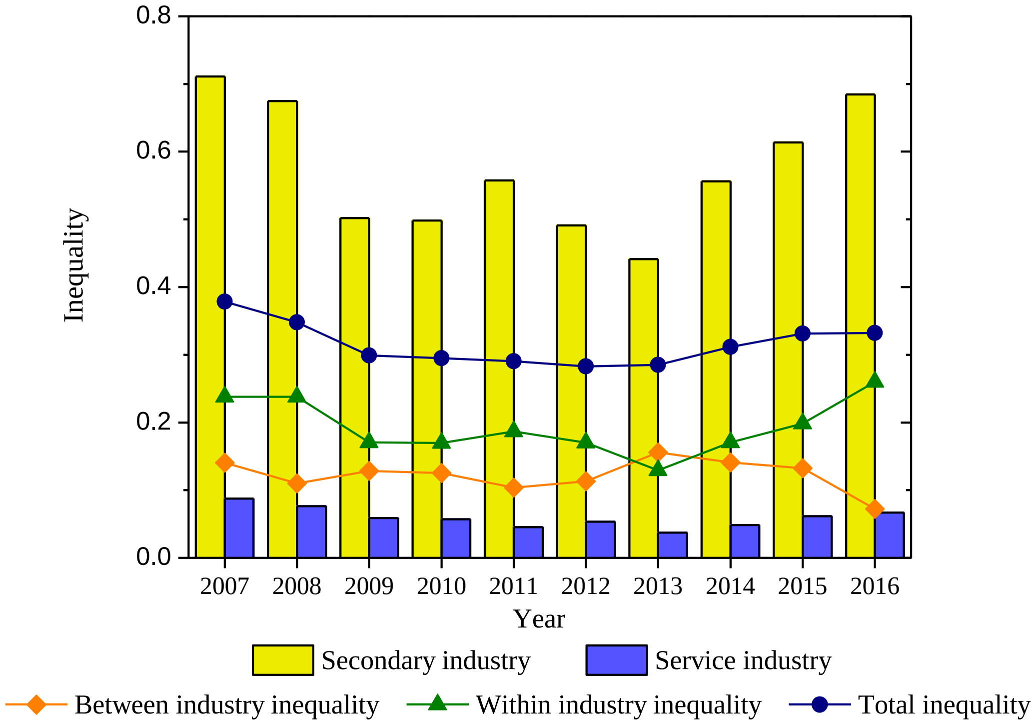

Figure 5. Carbon emission performance inequality for the whole industry, secondary, and service industries using the Theil index, 2007-2016.

4. Conclusion

To offer a scientific basis for governments to implement CO_2 emissions mitigation policies at the industry level and promote industrial transformation and upgrading, we target the TCPI of the secondary and service industries. This study first compiles industry-level CO_2 emission inventories of 25 Yangtze River Delta cities during 2007-2016. TCPI is then estimated using the non-radial directional distance function. Last, levels, dynamics and inequalities of TCPI between the secondary and service industries are compared.

We found that the TCPI of service industry was overall higher than that of secondary industry, suggesting that the service industry was more carbon-friendly. This is primarily because secondary industry have a large number of high energy consuming and high emission production activities. The TCPI of the secondary industry of the Yangtze River Delta cities was 0.205 in 2016, indicating a 79.5% improvement could be made. By contrast, the TCPI of the service industry of the Yangtze River Delta cities was 0.563 in 2016. Noticeably, Zhoushan had the lowest TCPI in 2016 not only for the secondary industry (0.031) but for the service industry as well (0.256).

Second, the gap in TCPI between secondary industry and service industry was narrowing, decreasing from 0.447 in 2007 to 0.307 in 2016. The TCPI of secondary industry exhibited a promising increasing trend during 2007-2016, improving by 2.30% annually, showing the positive effects of the government's reforms and environmental regulations. However, the service industry saw a decrease in TCPI during 2007-2015, with an annual growth rate of -1.68%. The retrograde TCPI of the service industry is likely because the service industry is in the early stages of low-carbon development.

Third, secondary industry inequality in TCPI was much higher than that of service industry, suggesting a greater TCPI heterogeneity in secondary industry. This is primarily because the secondary industry includes a large variety of sectors, such as textiles and coal mining which have widely varying production and energy utilization systems.

Further progress in mitigating CO_2 emissions will increasingly depend on the CO_2 abatement targets and policies that differ according to industry, especially during the transitional period. We offer several suggestions for policy-makers. First, policymakers should trade-off between the speed and quality of industry transformation and upgrading. Decarbonising service industry should also be placed on the agenda to reverse its declining TCPI. Promoting the service industry's green technology development and boosting recycling and renewable energy can help to abbreviate the path towards a low-carbon economy. Second, although the secondary industry saw a promising upward trend in TCPI in the last decade, it still has great potential to mitigate CO_2 emissions to reach global meta-frontier. Further progress should be made in reducing the TCPI of secondary industry by optimizing their energy mix and upgrading industrial process. Additionally, given that there is significant heterogeneity in the secondary industry, targeted mitigation goals and policies should be implemented for different cities' secondary industry instead of one-size-fits-all solutions

This study has several limitations. First, the emissions inventory was counted based on electricity consumption instead of by production, though the latter can help to mitigate CO_2 emissions more effectively. In this study, CO_2 emissions produced from the electricity generation process are all allocated to secondary industry, which may lead to underestimation of the carbon emission performance of secondary industry. Therefore, further research will focus on the calculation of CO_2 emissions derived from electricity generation using the consumption-based approach. Second, only one undesirable output (CO_2) is incorporated into the empirical study. Future work should take a wider range of undesirable outputs into consideration to better measure industry-level carbon emission performance.

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CO_2 emission inventories of the Yangtze River Delta cities can be download freely from China Emission Accounts and Datasets (CEADs) at http://www.ceads.net. This work was supported by the National Key Research and Development of China (2018YFC0213600), the National Natural Science Foundation of China (71822402, 91746112, 71704029), Research Center on Low-carbon Economy for Guangzhou Region, the Natural Science Foundation of Guangdong (No. 2016A030313091), Humanities and Social Science Foundation in Ministry of Education of China (16YJCZH162).

Summary declaration of interest statement

Declarations of interest: The authors declare no competing interests.

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Appendix. Supplementary tables

Table S1. Socioeconomic sectors division.

Table S2. Average annual growth rate of total-factor carbon emission performance, 2007-2016.

Table S3. Contribution of each component to total inequality using the Theil index, 2007-2016.

Table S4. Carbon emission performance inequality for the whole industry, secondary, and service industries using the Theil index, 2007-2016.

Table S1. Socioeconomic sectors division.

No.	Socioeconomic sectors
	Primary industry
1	Farming, Forestry, Animal Husbandry, Fishery and Water Conservancy
	secondary industry
2	Coal Mining and Dressing
3	Petroleum and Natural Gas Extraction
4	Ferrous Metals Mining and Dressing
5	Nonferrous Metals Mining and Dressing
6	Nonmetal Minerals Mining and Dressing
7	Other Minerals Mining and Dressing
8	Petroleum Processing and Coking
9	Production and Supply of Electric Power, Steam and Hot Water
10	Production and Supply of Gas
11	Raw Chemical Materials and Chemical Products
12	Chemical Fiber
13	Rubber Products
14	Plastic Products
15	Nonmetal Mineral Products
16	Smelting and Pressing of Ferrous Metals
17	Smelting and Pressing of Nonferrous Metals
18	Metal Products
19	Ordinary Machinery
20	Equipment for Special Purposes
21	Transportation Equipment
22	Production and Supply of Tap Water
23	Logging and Transport of Wood and Bamboo

24	Medical and Pharmaceutical Products
25	Food Processing
26	Food Production
27	Beverage Production
28	Tobacco Processing
29	Textile Industry
30	Garments and Other Fiber Products
31	Leather, Furs, Down and Related Products
32	Timber Processing, Bamboo, Cane, Palm Fiber & Straw Products
33	Furniture Manufacturing
34	Papermaking and Paper Products
35	Printing and Record Medium Reproduction
36	Cultural, Educational and Sports Articles
37	Electric Equipment and Machinery
38	Electronic and Telecommunications Equipment
39	Instruments, Meters, Cultural and Office Machinery
40	Other Manufacturing Industry
41	Scrap and waste
42	Construction
Service industry	
43	Transportation, Storage, Post and Telecommunication Services
44	Wholesale, Retail Trade and Catering Services
45	Others
Household consumption	
46	Urban Resident Energy Usage
47	Rural Resident Energy Usage

Table S2. Average annual growth rate of total-factor carbon emission performance, 2007-2016.

City	Province	Secondary industry (%)	Service industry (%)
Shanghai	Shanghai	37.76	17.44
Nanjing	Jiangsu	-8.25	8.17
Wuxi	Jiangsu	42.24	4.81
Xuzhou	Jiangsu	10.53	3.81
Changzhou	Jiangsu	-2.08	1.19
Suzhou	Jiangsu	10.03	0.06
Nantong	Jiangsu	4.28	-6.52
Lianyungang	Jiangsu	-5.24	-0.13
Huaian	Jiangsu	-3.64	-0.45
Yancheng	Jiangsu	2.88	-0.48
Yangzhou	Jiangsu	1.54	-5.78
Zhenjiang	Jiangsu	-0.47	-4.59
Taizhou	Jiangsu	-10.63	0.31
Suqian	Jiangsu	-13.52	-8.00
Hangzhou	Zhejiang	21.75	4.45
Ningbo	Zhejiang	8.04	-1.78
Wenzhou	Zhejiang	-8.52	-9.21
Jiaxing	Zhejiang	-11.15	-0.32
Huzhou	Zhejiang	8.89	-1.99
Shaoxing	Zhejiang	11.56	-2.30
Jinhua	Zhejiang	-0.63	-0.14
Quzhou	Zhejiang	3.18	-5.53
Zhoushan	Zhejiang	-31.92	-14.04
Taizhou	Zhejiang	5.65	-2.14
Lishui	Zhejiang	0.00	-6.32

Table S3. Contribution of each component to total inequality using the Theil index, 2007-2016.

	Inequality components

Year	Between industry inequality	Secondary industry inequality	Service industry inequality
2007	0.141	0.171	0.066
2008	0.110	0.182	0.056
2009	0.129	0.126	0.044
2010	0.125	0.127	0.043
2011	0.104	0.154	0.033
2012	0.113	0.131	0.039
2013	0.156	0.101	0.029
2014	0.141	0.134	0.037
2015	0.133	0.152	0.046
2016	0.072	0.214	0.046

Table S4. Carbon emission performance inequality for the whole industry, secondary, and service industries using the Theil index, 2007-2016.

Year	Total inequality	Between industry inequality	Within industry inequality	secondary industry inequality	Service industry inequality
2007	0.3785	0.1406	0.2379	0.7110	0.0875
2008	0.3477	0.1099	0.2379	0.6747	0.0763
2009	0.2990	0.1285	0.1704	0.5018	0.0587
2010	0.2950	0.1254	0.1696	0.4984	0.0571
2011	0.2906	0.1039	0.1867	0.5578	0.0452
2012	0.2830	0.1130	0.1701	0.4910	0.0532
2013	0.2852	0.1559	0.1294	0.4412	0.0371
2014	0.3115	0.1408	0.1708	0.5561	0.0483
2015	0.3311	0.1326	0.1985	0.6137	0.0613
2016	0.3322	0.0722	0.2600	0.6847	0.0671
Average	0.3154	0.1223	0.1931	0.5730	0.0592