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Research article

Emission drivers of cities at different industrialization phases in China

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ABSTRACT

As cities are the center of human activity and the basic unit of policy design, they have become the focus of carbon dioxide reduction, especially metropolitan areas that are high energy consumers and carbon dioxide emitters in countries such as China. The fact cities differ in their levels of development and stages of industrialization points to the need for tailor-made low-carbon policies. This study is the first to consider cities' different phases of industrialization when analyzing city-level emission patterns and drivers, as well as the decoupling statuses between economic growth and their emission levels in China. The results of 15 representative cities at different phases of industrialization show that various decoupling statuses, driving factors and decoupling efforts exist among cities, and that heterogeneity among these factors also exists among cities at the same industrialization phase. For further decomposition, energy intensity contributed the most to emissions reduction during the period 2005 to 2010, especially for cities with more heavy manufacturing industries, whereas industrial structure was a stronger negative emission driver during the period 2010 to 2015. Based on those findings, we suggest putting into practice a diversified carbon-mitigation policy portfolio according to each city's industrialization phase rather than a single policy that focuses on one specific driving factor. This paper sets an example on emissions-reduction experience for other cities undergoing different industrialization phases in China; it also sheds light on policy initiatives that could be applied to other cities around the world.

1. Introduction

With their high concentration of people, industries and infrastructure, worldwide cities contribute almost 70% of the anthropogenic greenhouse gas (GHG) emissions (Hebbert, 2012). More than 360 cities from different countries declared commitments on the 2015 Paris Climate Conference of making a collective contribution to at least half of the world's urban GHG emissions reductions by the year 2020 (International Energy Agency (IEA), 2008; UN-Habitat, 2011). Being one of the biggest energy consumers and CO_2 emitters in the world, China has pledged to peak its carbon dioxide emissions by 2030 (INDC, 2015). China has also focused its CO_2 emissions-reduction policies at the city level. With rapid economic growth and urbanization since its opening-up policy, the industrial structure of Chinese cities has also undergone extensive changes (Jiang and Lin, 2012; Wanfu et al., 2019). Different phases of urbanization or industrialization may exert a different impact on the economic and environmental relationship (Wang et al., 2018a; Xu and Lin, 2015), either in the short-run or the long-run (Wang and Su, 2019), or in coastal or inland areas (Qi et al., 2013). Considering the unbalanced development and different industrialization stages of cities in China and around the world, various low-carbon policies may be needed due to the different resource endowments, geographical locations, industrial focuses and functional orientations of the cities.

The driving factors of CO_2 emissions mainly includes energy intensity, energy structure, industrial structure, GDP per capita and population (Liu et al., 2013; Tan et al., 2011). The case of Turkish manufacturing industries shows that industrial activity and its consequent energy intensity are the driving factors influencing changes in carbon dioxide emissions. In Turkey, the largest CO_2 emitting sectors are industries supported by coal-based fuel structures (such as steel and iron-related industries) (Akbostancı et al., 2011). Research on South Korea's manufacturing industries indicates that the main driving factors of CO_2 emissions may change dynamically, including not only energy intensity, but also industrial structure (Jeong and Kim, 2013). Evidence also shows that CO_2 emissions in China decline largely due to changes in industrial and energy structure and decreasing energy intensity (Guan et al., 2018). However, some researchers use the "rebound effect" to explain the stimulating effect of reduced energy intensity on CO_2 emissions in heavy-manufacturing cities, indicating that improving

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Table 1
Tapio decoupling classification index (Tapio, 2005).

Tapio Decoupling Classification		Relevant factors		Tapio decoupling elasticity coefficient
Grade I index	Grade II indexes	ΔCO_2	ΔGDP	
Negative decoupling	Expansive negative decoupling	> 0	> 0	DI > 1.2
	Strong negative decoupling	> 0	< 0	DI < 0
	Weak negative decoupling	< 0	< 0	0 < DI < 0.8
Decoupling	Recessive decoupling	< 0	< 0	DI > 1.2
	Strong decoupling	< 0	> 0	DI < 0
	Weak decoupling	> 0	> 0	0 < DI < 0.8
Coupling	Recessive coupling	< 0	< 0	0.8 < DI < 1.2
	Expansive coupling	> 0	> 0	0.8 < DI < 1.2

energy efficiency will reduce the cost of energy-related products and services, and thereby expand energy demand, and finally lead to increasing CO_2 emissions (Lin and Li, 2014; Wang et al., 2012). Among the relevant literature, some studies explore the driving factors of CO_2 emissions at province or city level in China. Studies on Shanghai (Zhao et al., 2010), Beijing (Wei et al., 2017), Inner Mongolia (Wang et al., 2014), Tianjin (Wang et al., 2015), and Nanchang (Jia et al., 2018) show that growth in GDP mainly contributes to increases in CO_2 emissions while a decline in energy intensity significantly drives emission reductions. This mechanism is particularly significant in cities with heavy manufacturing industries (Jeong and Kim, 2013; Lin and Liu, 2017). Economic growth and changes in industrial structure have contributed to significant increasing CO_2 emissions in Beijing, a city with its emissions dominated by metal and nonmetal mining, construction, and utilities - electricity, natural gas and water (Wei et al., 2017). The research based on Shanghai indicates that for a service-oriented city, it is more critical to further reduce energy intensity and to adjust the industrial structure rather than its energy structure (Zhao et al., 2010). The research based on Nanchang identified the main industries that dominate this city's CO_2 emissions, including not only the traditional ferrous metal smelting and processing industry but also the communications equipment and electronic equipment manufacturing industries (Jia et al., 2018).

Different approaches have been used in CO_2 emissions research at the city level; these include the structural decomposition analysis (SDA) method based on input-output data, and the index decomposition analysis (IDA) method based on sector-aggregated data. As input-output tables are unavailable for most of the cities, the SDA method is less applicable to research on urban-level decomposition. Many research prefer the Logarithmic Mean Divisia Index (LMDI) decomposition method, an extended form of the IDA method, to identify the driving factors behind changes in CO_2 emissions, due to its easy access and extensive adaptability (Ang, 2004; Fernández González et al., 2014; Meng et al., 2016; Ren et al., 2014). In addition, the Tapio Decoupling Classification Index is often conducted along with the LMDI method to measure whether economic growth is disconnected from resource consumption or environmental pollution (Diakoulaki and Mandaraka, 2007). Apart from these, the Tapio Decoupling Effort Index, based on the LMDI results, is widely applied to evaluate cities' degree of efforts in realizing economic growth with less energy or environmental resources. A combination of these two methods can not only reveal the driving factors of decoupling in a more specific way but also target detailed industrial segments that contribute to CO_2 emissions (de Freitas and Kaneko, 2011).

Despite the above findings, the existing literature show research gaps in several ways. Most of the literature focuses on city clusters in geographically agglomerated zones, such as the Beijing-Tianjin-Hebei region (Yu et al., 2019), the Yangtze River Delta region (Zhu et al., 2017) and the Pearl River Delta region (Wang et al., 2018b), or on megacities such as Beijing and Shanghai (Shao et al., 2016; Shi et al., 2019; Wang et al., 2019); however, these studies lack the level of research that would take city classifications into consideration throughout the different stages of urban industrial development. In addition, few researchers have used the LMDI method and/or Decoupling Analysis to carry out thorough, detailed industrial segment-level studies on cities, especially research that is based on cities' changing fossil fuel structure, even though using these methods makes in-depth research feasible and practical.

In this paper, 15 representative cities in China are selected for detailed CO_2 emission decomposition and decoupling analyses. This paper contributes to the existing literature in three distinctive ways: **(i)** firstly, different city classifications are taken into consideration to better reflect the real unbalanced industrialization and urbanization development statuses among cities in China; **(ii)** secondly, detailed data of fossil energy types and industrial classifications that span the period from 2005 to 2015 are applied so as to better analyze the evolution of the sample cities' CO_2 emissions; and **(iii)** thirdly, an extended LMDI decomposition model is constructed, along with the Tapio Decoupling Classification Index and the Tapio Decoupling Effort Index, to study the driving factors behind changes of CO_2 emissions during different development stages of each of the 15 representative cities. The results indicate that decoupling does not only occur in cities that are leaders in high-tech or service industries but also in energy-producing cities and cities where heavy manufacturing is prevalent, and which are constrained by resource endowment or geographical location. However, to achieve this, coordinating efforts in improving energy structure, energy efficiency and industrial structure are required, and these would set examples for other similar cities and shed light on practical policymaking directions for the future.

2. Methodology

2.1. Emission accounts

The CO_2 emissions are calculated in the Intergovernmental Panel on Climate Change (IPCC) territorial administrative scope, based on the representative cities' energy balance tables (Shan et al., 2017). The inventories cover 47 socioeconomic sectors and 17 fossil fuels, which are consistent with national and provincial emission accounts of China (Shan et al., 2016, 2018a, 2018b). The emission levels are derived from activity data (fossil fuel consumption) multiplied by emission factors (IPCC, 2006), see Equation (1):

$$\mathrm{CE}_{energy} = \sum_i \sum_j CE_{ij} = \sum_i \sum_j Activity_{ij} \times NCV_{ij} \times EF_{ij} \times O_{ij},\ i \in [1{,}17],\ j \in [1.47] \quad 1$$

where CE_{ij} represents the CO_2 emissions from fossil fuel i combusted in sector j; $Activity_{ij}$ is the consumption of fossil fuels; NCV_i represents the net caloric value; EF_{ij} represents the emission factors; while O_{ij} represents the oxygenation efficiency. These three emission parameters (NCV_i, EF_{ij} and O_{ij}) are obtained from Liu et al. (2015). The residential consumption data is excluded.

2.2. Tapio Decoupling Classification Index

The Tapio Decoupling Classification Index measures the change in the economic growth and pollutant emissions in the form of an elasticity coefficient, and the range of the results is divided into three categories of first-level indicators and eight categories of second-level indicators, measuring different decoupling states (as shown in Table 1); the formula is shown in Equation (2). Among the results, strong decoupling indicates the ideal state of low-carbon economic development, whereas strong negative decoupling represents the most unfavorable state.

$$DI = \frac{\Delta CO_2/CO_2}{\Delta GDP/GDP} \tag{2}$$

2.3. Index decomposition analysis (IDA-LMDI)

Decomposition analysis is one of the methods often used in energy policy decision-making. Since the 1970s, various decomposition methods have been applied to measure the influencing factors behind changes in CO_2 emissions. Among them, IDA provides detailed analyses and impact assessments at the sector level (Xu and Ang, 2013). Being one of the extended forms of the IDA method, the LMDI method is preferred when applied to CO_2 emission decomposition analysis using city-level data due to its reliable theoretical basis and wide applicability (Ang, 2004). In this paper, an LMDI decomposition model is constructed for six sectors, referring to the classic model of Ang (2005). Meanwhile, a modified LMDI decomposition model at industrial segment level is constructed according to Zhao et al. (2010) and Lin and Liu (2017); this model is also specifically constructed at the detailed industrial-segment level.

A classic LMDI decomposition model of six major economic sectors (refer to online Supporting Information) with 15 selected cities decomposes the changes in energy-related carbon dioxide emissions (C) into six factors, namely the carbon dioxide emission coefficient (CI), the structure of energy consumption (ES), the energy intensity (EI), the structure of industry (IS), GDP per capita (Y_per) and the scale of city's population (P), calculated based on city level total energy consumption (E) as well as GDP (Y). The six-sector decomposition formulas are expressed as follows, referring to Ang (2005), subscripts of which indicating fossil fuel type k used in sector i. We assume that $CI_{ik} = \frac{C_{ik}}{E_{ik}}$, $ES_{ik} = \frac{E_{ik}}{E_i}$, $EI_i = \frac{E_i}{Y_i}$, $IS_i = \frac{Y_i}{Y}$, $Y\_per = \frac{Y}{P}$. Then the CO_2 emissions (C) can be decomposed as Equation (3).

$$\begin{aligned} C &= \textstyle\sum_{ik} C_{ik} \\ &= \textstyle\sum_{ik} \frac{C_{ik}}{E_{ik}} \times \frac{E_{ik}}{E_i} \times \frac{E_i}{Y_i} \times \frac{Y_i}{Y} \times \frac{Y}{P} \times P \\ &= \textstyle\sum_{ik} CI_{ik} \times ES_{ik} \times EI_i \times IS_i \times Y\_per \times P \end{aligned} \tag{3}$$

Under the additive form of LMDI, the total CO_2-emission changing effect during period t compared to the basic period is shown in Equation (4). Therefore, we formulate the additive LMDI decomposition model based on two consecutive years as Equation (5). We assume that the CO_2 emission coefficients of the 17 sub-categories of fossil fuels are constant in a short time, so the change in the emission factor (ΔC_{CI}) is always zero.

$$\begin{aligned} \Delta C &= C^t - C^0 \\ &= \textstyle\sum (CI_{ik}^t \times ES_{ik}^t \times EI_i^t \times IS_i^t \times Y\_per^t \times P^t - CI_{ik}^0 \times ES_{ik}^0 \times EI_i^0 \times IS_i^0 \times Y\_per^0 \times P^0) \\ &= \Delta C_{CI} + \Delta C_{ES} + \Delta C_{EI} + \Delta C_{IS} + \Delta C_{Y\_per} + \Delta C_P \end{aligned} \tag{4}$$

$$\begin{aligned} \Delta C_{\text{emission coefficient}} &= \Delta C_{CI} = \textstyle\sum_{ik} w_{ik} \ln\left(\frac{CI_{ik}^t}{CI_{ik}^{t-1}}\right) \\ \Delta C_{\text{energy structure}} &= \Delta C_{ES} = \textstyle\sum_{ik} w_{ik} \ln\left(\frac{ES_{ik}^t}{ES_{ik}^{t-1}}\right) \\ \Delta C_{\text{energy intensity}} &= \Delta C_{EI} = \textstyle\sum_{ik} w_{ik} \ln\left(\frac{EI_i^t}{EI_i^{t-1}}\right) \\ \Delta C_{\text{industrial structure}} &= \Delta C_{IS} = \textstyle\sum_{ik} w_{ik} \ln\left(\frac{IS_i^t}{IS_i^{t-1}}\right) \\ \Delta C_{\text{econimic growth}} &= \Delta C_{Y\_per} = \textstyle\sum_{ik} w_{ik} \ln\left(\frac{Y\_per^t}{Y\_per^{t-1}}\right) \\ \Delta C_{\text{population}} &= \Delta C_P = \textstyle\sum_{ik} w_{ik} \ln\left(\frac{P^t}{P^{t-1}}\right) \end{aligned} \tag{5}$$

Where, $w_{ik} = \frac{C_{ik}^t - C_{ik}^{t-1}}{\ln C_{ik}^t - \ln C_{ik}^{t-1}}$

The use of fossil fuels in multiple industry segments among different cities varies by variety, quality, efficiency and is influenced by technological development and regional policies. Thus, the industry segment level LMDI decomposition model (refer to online Supporting Information) has been constructed to better observe how the score of industrial value added, energy efficiency and energy structure play different roles in this economic-environmental mechanism. The driving factors of CO_2 emissions at the detailed industrial segment level (C_I) are decomposed into four parts, which are the CO_2 emission coefficient for the industry segments (ICI, which equals to CI), the energy structure of the industry segments (IES), the energy intensity of the industry segments (IEI), and the value-add scale of each industry segment (IY), calculated with data for total energy consumption (IE) and value-add scale of output (IY), both at the detailed industrial segment level. Above formulas can be expressed as in Equation (6), with changing effect of each factor in consecutive years formulated as in Equation (7). We use the "analytical limit" (AL) strategy in Ang et al. (1998) to process the zero values in both the LMDI models with six sectors or that with 36 detailed industry segments (refer to online Supporting Information for details).

$$\begin{aligned} \Delta C &= C_I^t - C_I^0 \\ &= \textstyle\sum (ICI_{jk}^t \times IES_{jk}^t \times IEI_j^t \times IY_j^t - ICI_{jk}^0 \times IES_{jk}^0 \times IEI_j^0 \times IY_j^0) \\ &= \Delta C_{ICI} + \Delta C_{IES} + \Delta C_{EI} + \Delta C_{IY} \end{aligned} \tag{6}$$

$$\begin{aligned} \Delta C_{\text{emission coefficient of industry segments}} &= \Delta C_{ICI} = \Delta C_{CI} \\ \Delta C_{\text{energy structure of industry segments}} &= \Delta C_{IES} = \textstyle\sum_{jk} w_{jk} \ln\left(\frac{IES_{jk}^t}{IES_{jk}^{t-1}}\right) \\ \Delta C_{\text{energy intensity of industry segments}} &= \Delta C_{IEI} = \textstyle\sum_{jk} w_{jk} \ln\left(\frac{IEI_j^t}{IEI_j^{t-1}}\right) \\ \Delta C_{\text{GDP scale of industry segments}} &= \Delta C_{IY} = \textstyle\sum_{jk} w_{jk} \ln\left(\frac{IY_j^t}{IY_j^{t-1}}\right) \end{aligned} \tag{7}$$

2.4. Tapio Decoupling Effort Index

Based on decomposition results from the LMDI model, this paper also measures the decoupling efforts of the various cities in terms of their different driving factors. Each city's CO_2 emissions caused by the economic growth factor (ΔC_{Y_per}) are excluded from its total CO_2 emissions (ΔC), and the decoupling effort indicator DE is constructed based on this net effect, as in Equation (8) and Equation (9). When $\Delta C \geq 0$, or ΔC and ΔGDP are in the same direction, this will lead to $DE \leq 0$, indicating "no decoupling effort"; while $\Delta C < 0$ and $0 < DE < 1$ indicating "weak decoupling effort"; and with $DE \geq 1$ indicating "strong decoupling effort". The greater the change in urban CO_2 emissions relative to GDP growth, the greater the decoupling effort will be. To sum up, the larger the gap between a city's CO_2 emissions reduction and its GDP growth, the stronger are the decoupling efforts that have been made.

$$\Delta C - \Delta Y\_per = \Delta ES + \Delta EI + \Delta IS + \Delta P \tag{8}$$

$$\begin{aligned} DE &= -\frac{\Delta C - \Delta Y\_per}{\Delta GDP} \\ &= -\frac{\Delta ES}{\Delta GDP} - \frac{\Delta EI}{\Delta GDP} - \frac{\Delta IS}{\Delta GDP} - \frac{\Delta P}{\Delta GDP} \\ &= DE_{ES} + DE_{EI} + DE_{IS} + DE_P \end{aligned} \tag{9}$$

2.5. Data sources

In this study, the data required are the city-level CO_2 emissions accounts, the sectoral fossil fuels consumption, the GDP, the population, and the industrial value-added. The city level CO_2 emissions inventories and sectoral fossil fuels consumptions are calculated based on China Emission Accounts and Datasets (www.ceads.net) (Shan et al., 2018a, 2018b; Shan et al., 2019), which are sourced from city level

Table 2
Fifteen selected cities and their CO_2 emissions during 2005–2015.
Source: based on author's calculation

City type	City name	Total CO_2 emissions (Mt)		
		2005	2010	2015
Energy production cities	Taiyuan	158.72	182.89	174.14
	Yinchuan	10.29	34.32	67.38
	Daqing	30.47	34.70	44.51
Heavy-manufacturing cities	Tangshan	121.72	165.38	202.07
	Handan	103.46	114.70	142.98
	Chongqing	69.82	124.19	133.79
Light-manufacturing cities	Xuzhou	71.34	109.14	177.38
	Shijiazhuang	102.03	141.05	121.99
	Harbin	33.49	42.49	62.79
Leading cities in the high-tech industry	Ningbo	141.15	228.25	226.53
	Suzhou	97.50	174.63	225.44
	Tianjin	83.10	128.59	140.85
Leading cities in the service industry	Shanghai	147.90	181.89	178.27
	Nanjing	69.92	106.54	157.59
	Beijing	78.93	101.85	74.34

Statistical Yearbook 2006–2016. The GDP, population, and industrial value-added data are sourced from *Statistical Yearbook* 2006–2016 of sample cities. The outlined 36 industry segments for all 15 selected cities account almost to a proportion of 95% in the total industrial GDP, thus they can be seen as an appropriate substitute for the actual industrial segments of these 15 cities. The rest of the industry segments (such as the waste treatment industry) are not included due to inconsistent changes in the national economic classifications and these industries' relatively small proportions in GDP. In this study, we cover the years 2005–2015, and divide these years into two periods, from 2005 to 2010 and from 2010 to 2015, to reduce bias due to the churning behavior of industries within cities.

3. Results and main findings

3.1. Cities' emissions and their decoupling statuses

We get the city classification from Shan et al. (2018a, 2018b) in which cities are clustered into five groups, according to whether they are mainly service-based, high-tech, light manufacturing, heavy manufacturing, or energy producers. The top three cities with the largest CO_2 emissions (according to descending order of total CO_2 emissions in 2015) in each category are selected as the representative samples (see Table 2). The 15 cities, which cover almost all of the stages of China's industrialization phases, provide a good representation of how different types of cities perform in reducing their CO_2 emissions.

We first conduct a decoupling analysis of the sample cities to determine the relationship between economic growth and CO_2 emissions and to monitor the variations in decoupling statuses between the different time periods (refer to Section 2.2 for details). Most sample cities presented weak decoupling statuses during the period 2005 to 2010, while five cities showed strong decoupling during the period 2010 to 2015, with a decoupling index of less than zero. Besides high-tech and service-based cities, energy producing and light-manufacturing cities also achieved decoupling, such as Taiyuan and Shijiazhuang (see Fig. 1). The results of the decoupling show that the performance of low-carbon development varies not only among the cities' different industrialization phases but also within the same industrialization phase. Therefore, further studies are needed to find out how the different driving factors influence cities' CO_2 reductions outcomes.

3.2. Emission drivers

As is shown in the decomposition results of the LMDI six-sector model (see Table 3), all of the 15 sample cities mostly showed an increase in CO_2 emissions during the two research periods (2005 to 2010 and 2010 to 2015) but with Taiyuan, Shijiazhuang, Ningbo, Shanghai experiencing CO_2 reductions from 2010 to 2015. Meanwhile, the driving factors that influenced changes in CO_2 emissions among the representative cities with different industrialization phases show both commonness and individuality.

Economic growth *(Y_*per) was the largest contributor to increasing CO_2 emissions in cities of all types. For 12 of the 15 cities, the stimulating impact of economic growth on carbon dioxide emissions in the period 2010 to 2015 was relatively smaller than that in the period 2005 to 2010. Further, the contribution of the population effect (P) to CO_2 emission changes was also positive in most of the cases, indicating that an increasing population leads to increasing total CO_2 emissions. These findings are consistent with the view of Chen et al. (2018). The population effect on high-tech and service-based cities was positive and significant while it was negative on some energy producing or manufacturing cities due to a decline in population size (refer to online Supporting Information). Meanwhile, for all types of representative cities, the industry sector was the main source of carbon dioxide emissions. However, the driving factors of carbon dioxide emission reduction varied among cities undergoing different industrialization phases.

The *EI* and *IS* effects were the biggest driving factors behind

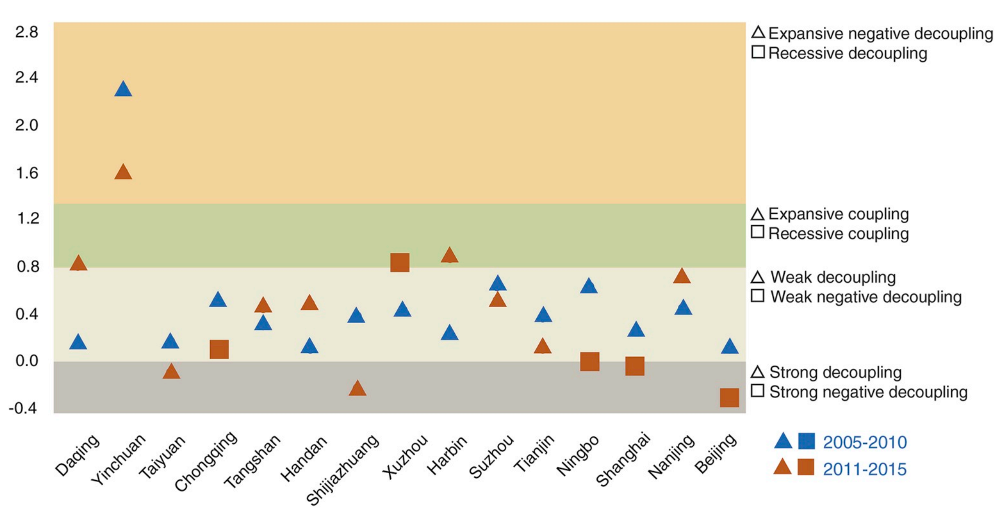

Fig. 1. Tapio Decoupling Classification Index of the sample cities.
Source: based on author's calculation

Table 3
Additive LMDI decomposition of six sectors (Mt CO_2).
Source: based on author's calculation

City type	City	Time period	ES effect	EI effect	IS effect	Y_per effect	P effect	Total effect
Energy production cities	Daqing	2005–2010	−0.004	−15.24	−1.20	18.84	1.83	4.24
		2010–2015	2.66	1.98	−6.14	11.91	−0.59	9.81
		2005–2015	3.37	−14.70	−7.37	31.32	1.44	14.05
	Yinchuan	2005–2010	1.30	9.24	0.53	8.16	4.80	24.03
		2010–2015	0.88	9.87	−0.28	23.33	−0.74	33.06
		2005–2015	2.83	20.55	0.64	23.57	9.49	57.09
	Taiyuan	2005–2010	0.92	−74.80	−13.61	99.62	12.04	24.17
		2010–2015	−22.41	−4.62	−48.59	65.97	0.90	−8.75
		2005–2015	−19.58	−75.18	−58.19	156.03	12.34	15.42
Heavy-manufacturing cities	Tangshan	2005–2010	14.98	−79.52	1.99	100.65	5.56	43.65
		2010–2015	−37.08	13.84	−9.03	71.68	−2.71	36.69
		2005–2015	−17.24	−77.02	−5.73	169.68	10.65	80.34
	Chongqing	2005–2010	2.92	−50.16	18.58	80.31	2.73	54.38
		2010–2015	−8.68	−29.25	−28.59	70.48	5.63	9.59
		2005–2015	−2.48	−71.84	−1.04	132.48	6.83	63.97
	Handan	2005–2010	−2.65	−70.12	11.48	66.15	6.38	11.24
		2010–2015	2.94	−5.58	−20.09	47.70	3.30	28.29
		2005–2015	0.17	−82.99	−6.41	118.55	10.20	39.52
Light-manufacturing cities	Shijiazhuang	2005–2010	0.71	−54.77	8.48	73.43	11.17	39.02
		2010–2015	−0.24	−59.24	−16.32	50.39	6.35	−19.06
		2005–2015	1.75	−99.74	−2.08	104.58	15.45	19.96
	Xuzhou	2005–2010	1.46	−31.84	−0.39	60.39	8.17	37.79
		2010–2015	1.50	10.95	−19.81	74.22	1.38	68.25
		2005–2015	15.26	−29.25	−14.81	124.32	10.52	106.04
	Harbin	2005–2010	−0.01	−19.58	−0.01	27.95	0.65	9.00
		2010–2015	7.63	1.10	−8.63	21.67	−1.47	20.30
		2005–2015	9.42	−20.18	−7.77	48.38	−0.56	29.30
Leading cities in the high-tech industry	Suzhou	2005–2010	−22.05	14.94	−18.60	97.20	5.65	77.14
		2010–2015	−4.51	1.41	−31.79	83.05	2.65	50.81
		2005–2015	−22.60	17.47	−44.19	169.07	8.19	127.94
	Tianjin	2005–2010	−7.05	−31.71	−5.46	67.65	22.05	45.49
		2010–2015	−7.70	−41.41	−16.78	54.98	23.17	12.27
		2005–2015	−12.26	−64.03	−18.88	112.25	40.67	57.76
	Ningbo	2005–2010	4.11	−43.66	5.14	101.58	19.93	87.10
		2010–2015	−1.04	−68.86	−21.51	83.28	6.40	−1.72
		2005–2015	3.23	−97.49	−11.89	166.65	24.89	85.38
Leading cities in the service industry	Shanghai	2005–2010	−1.15	−42.11	−26.93	72.11	32.07	33.98
		2010–2015	−17.68	−14.04	−36.51	56.11	8.49	−3.62
		2005–2015	−16.62	−50.88	−59.92	119.29	38.50	30.37
	Nanjing	2005–2010	6.36	−25.40	−6.48	50.15	11.99	36.62
		2010–2015	0.22	3.55	−18.94	62.58	3.62	51.04
		2005–2015	12.29	−28.03	−22.45	108.51	17.34	87.66
	Beijing	2005–2010	3.94	−34.18	−13.71	32.91	19.64	8.61
		2010–2015	−2.68	−26.52	−10.93	19.52	7.41	−13.21
		2005–2015	−2.66	−46.58	−28.50	52.06	21.10	−4.59

reductions in CO_2 emissions for all types of cities, indicating that improvements in efficiency in energy usage and differences in industrial structure between industry and services can significantly reduce the scale of CO_2 emissions in those cities. Further, the *EI* effect on CO_2 emissions reduction was particularly prominent during the period 2005 to 2010, especially for heavy-manufacturing cities. In comparison, CO_2 emissions reductions driven by the *IS* effect became more and more obvious over time, with a corresponding reduction in the volume of CO_2 emissions during the period 2010 to 2015 being greater than that from 2005 to 2010, except for Beijing. This may be due to government policies encouraging the city to adjust its industrial structure from secondary industries to tertiary industries since 2007. During this time, the state council of China issued a policy entitled "Several Opinions on Accelerating the Development of the Service Industry", where it required local governments to formulate policies aimed at increasing their service industries relative to their overall industrial structures and to make the services the leading industry. Therefore, we propose that the development path for urban CO_2 emission reductions could include two aspects: first, by improving the energy efficiency of existing energy-consuming industries; second, by transforming the industrial structure so that it encompasses a larger percentage of low-carbon emission service industries. These policy measures from the above two perspectives could be carried out simultaneously, but adjustments to the industrial structure show a time-lag effect.

It should also be noted that the *ES* effect makes a relatively small contribution to carbon dioxide emission reduction compared to the *EI* and *IS* effects. This may due to the fact that cities' resource endowments are relatively fixed and are considered rigid constraints, unless the adjustment of the energy structure is influenced externally, such as by government policies. In other words, the optimization of the energy consumption structure is time-consuming and is always driven by technological innovation, and this may not be the best option for all cities to use to fight climate change, especially energy-intensive cities that greatly depend on a local energy supply. In addition, increasing consumption percentage of clean energy and renewable energy in the energy structure may lead to an increase in energy intensity.

3.3. Decoupling efforts

The Tapio Decoupling Effort Index calculated according to the decomposition results of the LMDI model at the detailed 36 industry segment level is shown in Fig. 2 (refer to Section 2.4 for details). The darker red sections indicate more decoupling efforts; the darker blue sections indicate less decoupling efforts; and the blank sections indicate

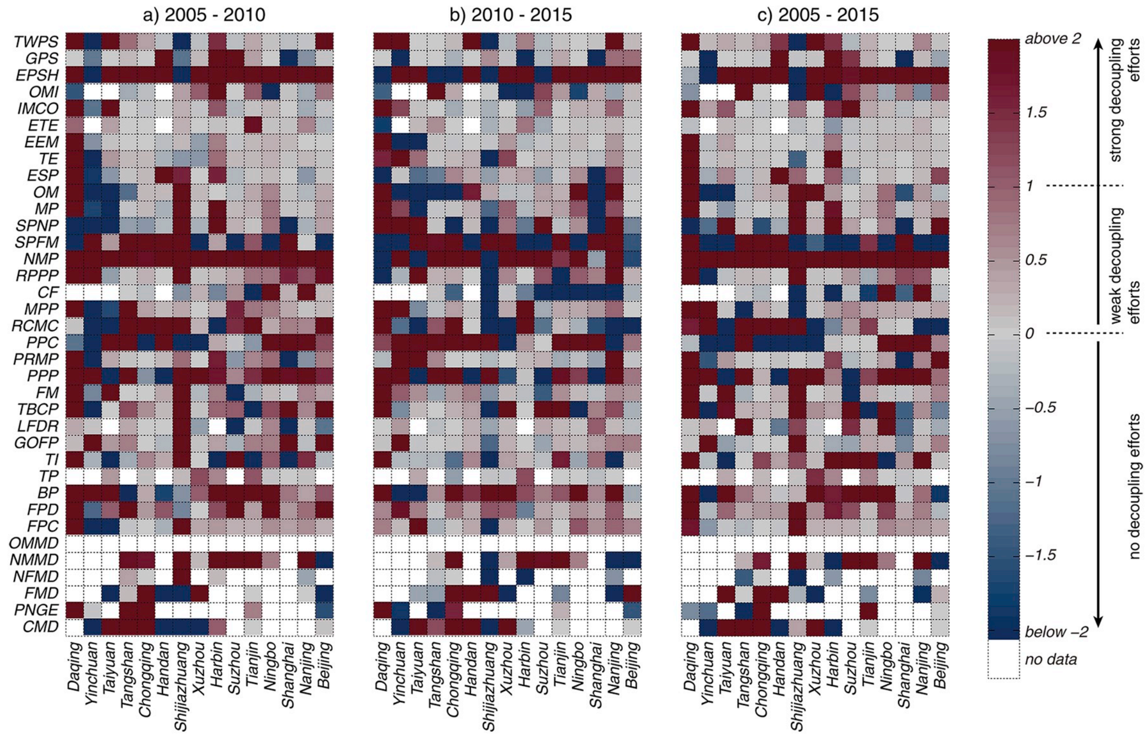

Fig. 2. Tapio Decoupling Effort Index of sample cities.
Source: based on author's calculation

that the industry is not above a designated size (it is missing value-added data). According to the performance of the 36 industrial segments in the 15 sample cities, the nonmetal mineral products segment (NMP) and the electric power, steam and hot water production and supply segment (EPSH) are the segments with the most decoupling efforts, while the smelting and pressing of ferrous metals segment (SPFM) and petroleum processing and coking segment (PPC) are the segments with the least decoupling efforts. Due to the small scale of CO_2 emissions in high-tech industries, such as electric equipment and machinery (EEM) and electronic and telecommunications equipment (ETE), the decoupling efforts of these industries were not making much difference. In terms of city performance, the decoupling efforts of 15 cities in the 36 segments varied from 2005 to 2015. From 2005 to 2010, Daqing and Shijiazhuang showed strong decoupling efforts in the NMP, metal products (MP) and rubber and plastic products (RPPP) segments. From 2010 to 2015, Nanjing exerted strong decoupling efforts in SPFM, NMP and the smelting and pressing of nonferrous metals (SPNP) segments. The decoupling efforts made by energy-producing cities were at the two ends of either strong decoupling efforts or no decoupling efforts. Light-manufacturing cities and leading cities in the service industry were often less involved in the energy or resource extraction industries during the periods under review.

4. Discussion and policy implication

The cities at different phases of industrialization show various decoupling statuses, driving factors and decoupling efforts; we also find that such heterogeneity exists in cities in the same industrialization phase. Cities represented by Taiyuan has implemented energy conservation and emissions-reduction plans for high CO_2 industrial emitters, striving to take into overall consideration production efficiency, and economic and environmental benefits. However, Yinchuan and Suzhou present the opposite phenomenon. Although they have also undergone industrial restructuring, their CO_2 emissions increased rather than decreased as a result of either a deterioration in their energy mix or inefficient energy consumption. To understand this, a further comprehensive analysis that combines economic performance, industrial segment decomposition and the decoupling effort index is discussed in this paper.

As typical energy-producing cities, both Taiyuan and Yinchuan rely on coal mining and oil refining as the pillar industries of their urban economic development, but their achievements in CO_2 emissions reduction are in stark contrast (see Fig. 3 and Fig. 4). Taiyuan authorities had been encouraging petrochemical enterprises to carry out energy-saving and to undertake GHG emissions-reduction technology-oriented equipment renovation since the 11th Five-Year Plan period (2006–2010). It further formulated and implemented the “Plan for Controlling GHG emissions in Taiyuan”, which called for reducing CO_2 emissions by 3.7% per unit of GDP annually during the 12th Five-Year Plan period (2011–2015) and achieving a 17% reduction by the end of 2015. These policies included setting strict controls on energy-intensive projects, accelerating the upgrading and transformation of resource-based industries, promoting the development of low-carbon industries, and vigorously developing the circular economy. The above policy measures have contributed to controlling Taiyuan's overall CO_2 emissions through exerting the *ES*, *EI* and *IS* effects. In contrast, Yinchuan also adjusted its energy structure but with an unsatisfactory outcome. During the period from 2005 to 2010, its petroleum processing and coking (PPC) segment reduced its energy production from oil and coal, but the rapid over-expansion of its output led to an increase in total CO_2 emissions. However, as other industries contributed little to CO_2 emissions reduction, Yinchuan's overall industry showed an expansive negative decoupling status between carbon dioxide emissions and economic growth during the period.

As a typical heavy-manufacturing city, Tangshan's economic development were highly dependent on the SPMF industry (such as steel manufacturing), which accounted for 45–60% of its GDP from 2005 to 2015 and contributed to 66.97% of its increased CO_2 emissions during this 10-year period. Although Tangshan had implemented certain energy-saving and emissions-reduction measures in its SPMF industries, the continuous expansion of its output still contributed to the increasing trend in its total CO_2 emissions. In addition, this paper also identifies

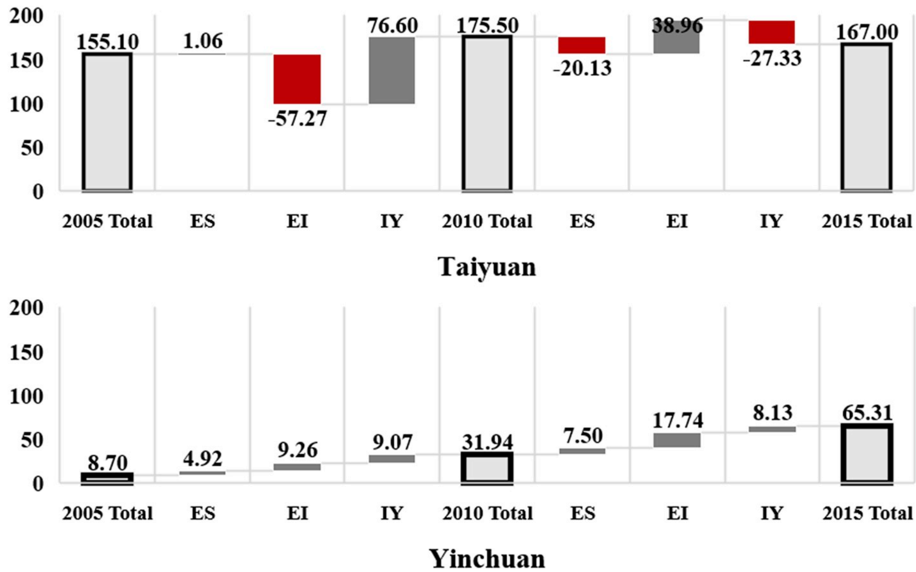

Fig. 3. Decomposition results comparison of Taiyuan and Yinchuan (Mt CO_2).

the six industrial segments that were driving CO_2 emissions, including CMD, PPC, SPFM, SPNP, NMP, and RCMC. Even for service cities like Nanjing, which are gradually shifting their industrial structure from manufacturing to tertiary industries, the above-mentioned driving industrial segments were still important factors in their increasing CO_2 emissions. For example, from 2005 to 2015, the RCMC and SPFM segments, respectively, accounted for 41.91% and 53.45% of the total CO_2 emission increasement in Nanjing. However, these segments do not bring relatively higher economic incomes to service cities. As a result, it is suggested that relevant industrial requirements are obtained through the production transfer from nearby manufacturing cities. Therefore, we suggest that energy-producing cities and heavy-manufacturing cities improve energy efficiency and moderately reduce the production scale of their CO_2-driving industrial segments. For light-manufacturing and high-tech cities, attention should be paid to both making adjustments to the industrial structure and to improving energy efficiency. For service cities, the above-mentioned CO_2-driving industrial segments should be gradually transferred to other nearby manufacturing cities, so as to focus on the development of service industries.

5. Conclusion

Cities are the center of human activity and constitute the key units of climate change mitigation. This study takes into consideration the diverse industrialization phases of Chinese cities when analyzing city-level emission patterns and drivers, as well as their decoupling statuses and efforts to reduce emissions and achieve economic growth. This study resulted in three important findings on CO_2 emissions reduction: **(i)** decoupling occurs not only in high-tech or service-based cities but also in energy-producing and manufacturing cities; **(ii)** both economic growth and population accretion are the main contributors to the increase of CO_2 emissions, while energy intensity and industrial structure are significant negative driving factors for CO_2 emissions for all of the sample cities. The energy structure makes a relatively smaller contribution to CO_2 emission reduction compared to the other factors. This indicates the importance of improving energy efficiency and of upgrading the industrial structure in mitigating CO_2 emissions for cities; and **(iii)** a point which demonstrates the novelty of this paper, is that cities at different industrialization phases show various decoupling

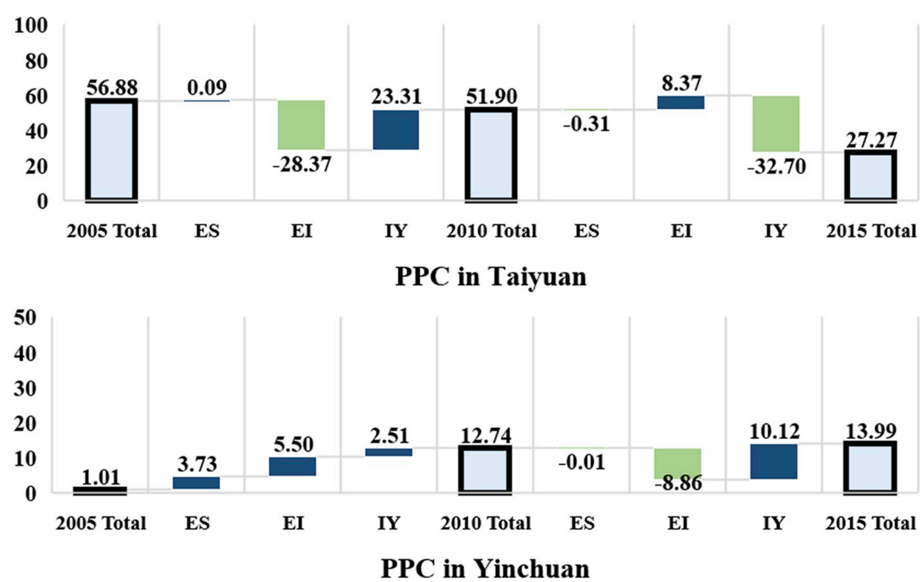

Fig. 4. Decomposition results comparison of key segments (PPC) (Mt CO_2).

statuses, driving factors and decoupling efforts, and such heterogeneity also exists in cities in the same industrialization phase. Achieving emissions reductions, however, will require that cities simultaneously make efforts to improve their energy mix, energy efficiency and industrial structure.

This paper provides examples on how to achieve emission reductions for other energy-producing or heavy-manufacturing cities in China; it also provides rich insight into emissions-reduction policies for other cities around the world. Firstly, in order to tackle climate change, rather than focusing on a single policy, policy portfolios should be put into practice. Furthermore, for different cities at different industrial development stages and with various economic foundations, there needs to be a requirement for diversified policy portfolios to reduce carbon emissions and fight climate change. For energy-producing and heavy-manufacturing cities, improving the energy efficiency of carbon-intensive industries and reducing the production scale of low-efficiency industries are found to be effective in tackling CO_2 emissions; while for light manufacturing and high-tech leading cities, optimizing the industrial structure is also useful in CO_2 emissions reduction. In addition, for leading cities in services, on the one hand, it is necessary to reduce or deflect the production capacity of CO_2-driving industrial segments, while on the other hand, it is important to focus on the development of service industries.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2019.109494.

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