China Economic Review 78 (2023) 101940

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

Carbon inequality in China: Evidence from city-level data

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ARTICLE INFO

JEL codes:
Q54 Q56 D39 D63

Keywords:
Carbon inequality
Gini
Concentration index
Decomposition

ABSTRACT

Carbon inequality has attracted increasing attention worldwide. Utilizing data from China's High Spatial Resolution Emission Gridded Database (CHRED), this paper presents the measured CO_2 emission inequality in China for the years 2005, 2012, 2015, and 2020. Results show that the Gini coefficients of carbon emission report a slight decrease from 0.411 to 0.385 and the distribution becomes more symmetric from 2005 to 2020. Linking carbon inequality to economic level, the positive concentration index (0.230 to 0.118) indicates asymmetricity between carbon emission and economic development. A further decomposition analysis reveals the industrial sector's uneven development, indicating that energy-intensive features can be blamed for a large proportion of carbon inequality. Our findings suggest that policymakers should not consider economic development level alone as the only indicator of the allocation of abatement, as economic structure, energy intensity, and climate conditions are all responsible for such inequality.

1. Introduction

Carbon inequality, on both international and household scales, has attracted increasing attention worldwide. Relatively equal distribution of emissions mitigation among countries is the first step in addressing global climate change, however, the allocation of carbon quota on the national level is far more critical, especially for the world's largest-emitting countries. Carbon inequality increases the difficulty of allocating a carbon budget. However, there has been limited inspection of carbon disparities among countries and individuals and thus there is little guidance regarding the assignment of mitigation tasks for specific countries. The assignment on the national level should also follow the global principle of "common but differentiated responsibilities and respective capabilities" proposed in the UN Framework Convention on Climate Change (UNFCCC). Hence, intra-national quota allocation requires a transparent domestic geographical distribution of carbon emission, which has great potential to shape future carbon policies.

In this paper, we examine carbon inequality on an intra-national scale in China. As China is the world's largest emitter, the Chinese government has enacted a raft of policies to support global cooperation on climate action. It has already shown impressive achievements in diversifying the energy mix, curbing CO_2 emissions, and lowering carbon intensity (Gallagher, Zhang, Orvis, Rissman, et al., 2019; Wang, Lu, Deng, Sun, et al., 2019). To confront severe climate change, the Chinese government proposed the "Double Carbon" goal (i.e., China will hit peak emissions before 2030 and realize carbon neutrality by 2060) to accelerate the process of carbon reduction. Achieving this goal faces unprecedented difficulty and thus an effective action plan for carbon reduction is urgently needed. As provinces and cities are the true implementors of emission mitigation, it is essential to ascertain a regional profile. The geographic

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https://doi.org/10.1016/j.chieco.2023.101940
Received 30 June 2022; Received in revised form 27 January 2023; Accepted 13 February 2023
Available online 16 February 2023
1043-951X/

distribution of carbon emissions reflects social and agroeconomic vulnerability levels and resembles an uneven distribution of wealth and well-being (Bierbaum, Holdren, MacCracken, Moss, et al., 2007; Dow & Downing, 2016). However, the regional allocation of abatement remains a daunting challenge.

Existing research has analyzed the schemes of allocation abatement quotas based on the objectives of minimizing marginal abatement costs (Wei, Ni, & Du, 2012; Zhang, Wang, & Da, 2014). Unique to preexisting research, this article aims to provide a profile of the spatial and temporal distribution of carbon emissions in place of designing an allocation scheme. Numerous studies have emphasized the trade-off between equity and efficiency when allocating emission quotas (Baer, Harte, Haya, Herzog, et al., 2000; Chakravarty, Chikkatur, de Coninck, Pacala, et al., 2009; Raupach, Marland, Ciais, Le Quéré, et al., 2007; Tavoni, Kriegler, Riahi, van Vuuren, et al., 2014; Wei et al., 2012; Wei & Rose, 2009; Zhang et al., 2014). As emissions are a byproduct of economic activity, emission inequality is closely associated with income inequality. The distribution and the disparity of CO_2 emissions are quite relevant to the welfare and the design of climate policies, as rich and poor areas have varying interests and capability for mitigation (Bolin & Kheshgi, 2001; Heil & Wodon, 1997; Meinshausen, Jeffery, Guetschow, Robiou du Pont, et al., 2015; Padilla & Serrano, 2006; Tavoni, Dannenberg, Kallis, & Löschel, 2011).

Unlike previous research that exploits provincial or household data, the current study conducted an inequality analysis by examining city-level CO_2 emissions. The cause of city-scale inequality being more suitable for allocation design can be explained twofold. At first, there is a growing impetus of cities' roles in mitigating climate change (Fong, Sotos, Michael Doust, Schultz, et al., 2015), and the potential for cities to reduce carbon emissions should be high (Allen, Dube, Solecki, Aragón-Durand, et al., 2018; IEA, 2016). Thus, the remarkable nationwide progress in climate mitigation for China can be credited to cities' efforts. Emission reduction targets are often made at the national level. The achievement of the target is inseparable to cities as they are closer to their industries and residents, allowing great flexibility and effectiveness in implementing policies, which leads to a more immediate impact on the reduction of emissions (C40, 2018; Cai, Cui, Zhang, Cao, et al., 2019).

Second, carbon inequality at the city level can be more comprehensive in measuring geographical disproportionality. For household emission inequality, input-output data and survey data are normally utilized (Wiedenhofer, Guan, Liu, Meng, et al., 2016; Xu, Han, & Lv, 2016). Household-level data from surveys is at a micro-level and cannot cover emissions from other sectors (e.g., industrial and transportation). Thus, it is not applicable for analyzing overall emissions in China, and it is more suitable for measuring individual well-being. Although the indirect household emissions estimated by input-output data can supplement the drawback, individuals are not the driving force in emission abatement. Furthermore, measurement bias by household data exists due to carbon leakage (Reinaud, 2008). Some households tend to purchase commercial services (e.g., dining out or buses and taxi services) instead of performing such services themselves (e.g., cooking or driving on their own), which distorts the actual measurement of emissions and results in an inaccurate estimation of inequality. However, city-level data helps to internalize indirect household emissions. Provincial-level data ignores intra-province disparities and limits variation to no more than 40 observations, leading to an underestimation of inequality. In contrast, the sample of data at the city level is larger than that at the provincial level, which helps improve the precision of measuring inequality. Issues are also present about ignoring intra-cities' inequality for city-level data; however, this is not as severe as provincial data, as it covers intra-provincial inequality.

This paper investigates two issues. The first is regarding the extent of the carbon inequality existing in China and how this inequality has changed in recent years as China has experienced dramatic changes. The second issue is to distinguish between the pure carbon inequality and carbon-economic inequality and to discern what causes inequality, owing to rich and poor areas having different varying interests and capabilities for mitigation. Revealing carbon inequality at the subnational level can provide increasingly specific information about the distribution of emissions, and the identification of the source of inequality offers policy implications on the assignment of the mitigation tasks.

The present study contributes to the existing literature in two ways. First, unique from previous studies that have used household-level or provincial-level data in China, this study utilizes data at the city level, providing a more comprehensive description of the CO_2 emissions in China. While other research has used data at the city level (Wang & Liu, 2017), their emission data is modeled using DMSP/OLS nighttime light imagery. This study uses data from CHRED 1.0 and 2.0, which is based on a bottom-up approach and is more reliable after cross-validation. In addition, the previous study only focused on the inequality index and lacked an in-depth analysis. Second, this study is not limited to the measurement of the inequality degree. We conduct further analysis into the causes of the changes in the inequality degree from multi-dimensions, including emissions sources, subgroups, and economic and social determinants. Previous studies have focused more on depicting the profile of the emission inequality or investigating the driving forces of CO_2 emissions instead of emission inequality (Auffhammer, Sun, Wu, & Zheng, 2016).

2. Methods and data

2.1. Measurement of inequality

A growing body of studies exists that uses basic inequality analysis tools to measure CO_2 emission inequality; these include the Lorenz curve, the coefficient of variation, Gini coefficient, and Theil or Atkinson indexes (Chen, Chen, & Chen, 2013; Duro & Padilla, 2006; Groot, 2010; Heil & Wodon, 1997, 2000; Mussini & Grossi, 2015; Padilla & Serrano, 2006). For most of these, however, data availability dictates that international inequality is estimated, consequently leaving countries' internal inequality unaccounted for. Sporadic research exists that calculates the CO_2 emission inequality at the region-level or household-level in China (Chen, Cheng, & Song, 2017; Chen, Cheng, Song, & Wu, 2016; Clarke-Sather, Qu, Qin, Zeng, et al., 2011; Wang & Liu, 2017). This article exploits the most common methods thereof—the Lorenz curve, Gini coefficient, Lorenz asymmetry coefficient, and concentration curve—to explore the carbon inequality. Based on the inequality index, inequality is decomposed using the Shapley method.

2.1.1. Carbon Lorenz curve

The Lorenz curve is the most common tool for analyzing income or wealth inequality. Following this concept, we use it to measure the inequality of CO_2 emissions. The Lorenz curve for CO_2 emission is a graph where the *x*-axis represents the cumulative share of the population of the sample ordered based on CO_2 emission per capita when *y*-axis is the cumulative share of CO_2 emission per capita. If all individuals emit the same amount of CO_2, the Lorenz curve will be the diagonal line—namely, the perfect equality line. If there is any inequality, the Lorenz curve line is considered to be below the perfect equality line; the further away the Lorenz curve is from the diagonal line, the more severe is the inequality in CO_2 emissions. The Gini coefficient and Lorenz asymmetric coefficient are two important indexes derived from the Lorenz curve, and they feature inequality. The Gini coefficient is used for measuring the extent of the inequality, while the Lorenz asymmetric coefficient supplements the Gini coefficient in assessing the Lorenz curve's degree of asymmetry and reveals the inequality's contributor.

2.1.2. Carbon Gini coefficient

The specific estimation of the Gini coefficient can be divided into two categories based on the data format: estimation based on household survey data and estimation based on grouped data.[1] Our data format can be regarded as combining the household survey data and grouped data. On the one hand, although our data is not based on a household survey, our data and the household survey data share a similar data format. We can regard the mean value of each city's carbon dioxide emission as the CO_2 emission of each household in order to estimate the Gini coefficient, and the city's population may be considered similar to the family size of the household. On the other hand, when the city is treated like a household, it implies that all individuals in the city have the same carbon emission, and this assumption does not fit the facts. Thus, it cannot be denied that our result could potentially underestimate the degree of carbon inequality to some extent. Due to certain data limitations, we focus on inter-city inequality and ignore the intra-city inequality of each city (Chotikapanich, Rao, & Tang, 2010). The Gini coefficient ranges from 0 (perfect equality) to 1 (perfect inequality). The Gini coefficient formula in the household survey data format is provided below.

$$G = \frac{2}{n^2 \overline{x}} \sum_{i=1}^{n} h(x_i - \overline{x}) \tag{1}$$

where G refers to the Gini coefficient of per-capita CO_2 emission. x is the observed CO_2 emission per capita, and x bar is the mean value of the x. n is the number of cities observed. h is the ranking of values of CO_2 emissions in ascending order. The value of this index can only describe the distribution of carbon emissions, but it is unable to identify the social and economic characteristics of the population.

2.1.3. Carbon Lorenz asymmetry coefficient

Even if the Gini coefficient is known, it is hard to shape the Lorenz curve, since various Lorenz curves are available for the same Gini coefficient. In short, the Gini coefficient cannot determine which classes (cities with low or high emissions) contribute more to inequality. To overcome this shortcoming, Damgaard and Weiner (2000) introduced the Lorenz asymmetry coefficient (LAC). A LAC value of less than one reveals that a relatively high number of cities with low emissions are contributing more to the inequality. Otherwise, the inequality would be mainly attributed to few cities with high emissions. A LAC value that is equal to 1 implies that all cities are making the same contributions to equality.

2.1.4. Carbon concentration curve and index

The Lorenz curve describes inequality based on one single dimension (indicator-population pair) instead of the relationship between two indicators (indicator-indicator pair). Therefore, a concentration curve has been proposed for illustrating how one indicator can be distributed across the population ranked by another indicator. In this study, the concentration curve plots the cumulative percentage of the CO_2 emission per capita against the cumulative percentage of the population ordered by the GDP per capita in ascending order. It indicates CO_2 emission concentration among the poor and rich cities and indicates whether rich cities' CO_2 emissions are evenly matched against their economic level. If the concentration index of the CO_2-economic pair is positive, the curve is considered to be below the equality line, thus indicating that rich cities have higher CO_2 emissions. The higher the concentration index, the severer the inequality. The formula is as follows.

$$G = \frac{\sum_{i=1}^{n} (2k - n - 1) x_i}{n \sum_{i=1}^{n} x_i} \tag{2}$$

where the x and n have the same meaning as indicated in eq. (1), and k denotes the ranking of the per capita GDP values in ascending order. Since the concentration index has been calculated, it is easy to obtain the Kakwani index, which equals the concentration index

[1] As for household survey data, the income of each household is known, and the order is ranked based on the income; thus, estimating inter and intra inequality is allowed, while for grouped data, only the average income and income shares of quintile or decile groups of the population are available, and the inequality is distorted, since inequality within the groups is ignored.

of CO_2 emission per capita (ranked by per capita GDP) minus the Gini coefficients of per capita GDP (Kakwani, 1977). The index represents the difference between the concentrations of per capita CO_2 emissions and per capita GDP.

2.2. Decomposition method of inequality

As part of attempts to further decompose CO_2 emission inequality, several attempts have been made to decompose inequality by subgroups and emission sources (Clarke-Sather et al., 2011; Heil & Wodon, 1997; Padilla & Serrano, 2006). Although a large amount of the literature has focused on decomposing CO_2 emission by driving forces, a limited but increasing number of researchers are applying various decomposition methods in order to identify inequality's determinants. Kaya factors, the logarithmic mean Divisia index (LMDI) method, and the Shapley decomposition method have been used for analyzing the factors influencing carbon inequality (Chen et al., 2017; Duro & Padilla, 2006; Padilla & Duro, 2013; Xu et al., 2016). Among these methods, the Kaya factors and LMDI methods can be subject to identity constraints, and they are not very flexible in equation format, while the Shapley decomposition method is based on a regression model and can therefore be used in a nonlinear model.

2.2.1. Decomposing inequality based on emission sources

Using the CO_2 emission inequality index, we can decompose inequality into a sum of the contributions generated by various emission sources. The Gini coefficient (G) for CO_2 emission can be expressed as follows (Lerman & Yitzhaki, 1985; Lopez-Feldman, 2006):

$$G = \sum_{k=1}^{K} S_k G_k R_k \tag{3}$$

where S_k is the share of source k in total CO_2 emissions; G_k denotes the Gini coefficient of source k; R_k is the Gini correlation of emission derived from source k with the distribution of total emissions. The partial derivative of the total CO_2 emissions' Gini coefficient with respect to a percent change ε in source k is as follows.

$$\frac{\partial G}{\partial \varepsilon} = S_k(G_k R_k - G) \tag{4}$$

In short, the impact of a small percent change in emissions from source k on total CO_2 emission equality can be expressed as follows:

$$\frac{\partial G/\partial \varepsilon}{G} = \frac{S_k G_k R_k}{G} - S_k \tag{5}$$

2.2.2. Decomposing inequality based on region

There is a great disparity in the degree of inequality among subgroups. The Gini coefficient can be decomposed based on groups, as shown in eq. (6) (Tomson, Isaksson, & Jansson, 2014).

$$G = p_j s_j G_{Wj} + p_j s_j G_{Bj} + 2 p_j s_j G_{Oj} \tag{6}$$

where p and s are the population and CO_2 emission share of group j, respectively. G_{Wj}, G_{Bj}, and G_{Oj} are the Gini coefficients of within-group, between-group, and overlapping parts, respectively. Thus, the three terms on the right-hand side denote the contribution of these three effects.

2.2.3. Decomposing inequality based on determinants

Shapley decomposition is increasingly being used for analyzing inequality indicators in order to identify the contributions of the inequality determinants (Shorrocks, 2013; Wu, Zheng, & Wei, 2017). The first step of Shapley decomposition involves constructing an emission decision function in order to estimate the explanatory variables' coefficients and then applying the inequality index into the equation and calculating these variables' contributions to inequality. Specifically, in order to measure the contribution of variable x to inequality, first, one must simultaneously place the sample mean value of x and the observed value of other variables into the equation and then infer the predicted emission value. Based on the predicted value, the inequality degree of the predicted emission (G_x) can be obtained when the impact of variable x is excluded. The difference between the predicted Gini coefficient (G_x) and the Gini coefficient based on the observed emission is the contribution of variable x. A complete decomposition procedure thus continues until all the explanatory variables are replaced by their sample means (Wan & Zhou, 2005).

First, we must construct a semi-log model for examining the impact factors of CO_2 emission. Following the traditional IPAT (Impact, Population, Affluence, and Technology) model, population, affluence, and technology are introduced into the emission decision function (Chen et al., 2017; Ren, Yuan, Ma, & Chen, 2014; Wang & Liu, 2017; York, Rosa, & Dietz, 2003). The population effect is expressed as the per capita value of the variables. The affluence effect, which uses the per capita GDP (*pergdp*) to denote economic development. The industrial structure, which refers to share of the industry (*share_ind*), and electricity intensity (*ele_intensity*), which refers to electricity consumption per unit GDP, indicate the technology effect. Along with economic variables, climatic conditions and political variables must also be considered; we therefore selected the heating day degree (*HDD18*) to embody the effect of geographical location on carbon emission and the share of fiscal expenditure compared to the GDP (*fiscal*) in order to reflect environmental regulations. The dependent variable is the carbon emission per capita (E) and the model is as follows:

$$In\ E_i = \alpha_0 + \alpha_1 pergdp_i + \alpha_2 share\_ind_i + \alpha_3 ele\_intensity_i + \alpha_4 HDD18_i + \alpha_3 fiscal_i + \mu_i \quad (7)$$

where u is the error term; α_0 denotes the constant term, and α_1-α_4 are the coefficients of the relevant variables. Based on the equation, it is feasible to decompose the CO_2 emission inequality based on these explanatory variables. Data regarding per capita GDP, share of industry, electricity consumption, and fiscal expenditure have been collected from the *China City Statistical Yearbook*, and data regarding *HDD18* were calculated based on data collected from the *China Meteorological Administration*; the reference degree was 18 °C.

2.3. Data

Data on CO_2 emissions at the city level have been collected from the China's High Spatial Resolution Emission Gridded Database (CHRED), with supplementation from city-level official statistics and numerous on-site investigations. In this study, CO_2 emission refers to total carbon emissions, including direct and indirect carbon emissions. Direct emission covers emissions from scope 1 (agricultural, industrial, energy, service, urban and rural residential, transportation, and industrial processes) and excludes carbon sinks from forestry or land use. Indirect emission consists of scope 2 and some parts of scope 3, i.e., emission from transportation and purchased power supply (or electricity generated outside the administrative boundary). This dataset is reliable because great efforts have been made in terms of cross-validation and data analysis for different city levels (Cai, Liang, Zhou, Wang, et al., 2018; Liu & Cai, 2018). The datasets include 287, 288, 293, and 335 cities for 2005, 2012, 2015 and 2020, respectively. The 2020 observation includes ethnic minority autonomous prefectures. To ensure that the results would be comparable, we only considered cities that had data for all four years; thus, 285 cities were deemed suitable for analysis.

Figure 1 displays the variation in total and direct carbon emissions in China from 2005 to 2020. Total emission increased from no more than 7000 mt in 2005 to nearly 12,000 mt in 2020, with a decreasing growth rate (as shown in Fig. 1a). The share of indirect emissions increased slightly, indicating greater use of outsourced electricity. Fig. 1b illustrates the components of direct emission. Industrial CO_2 emission was found to dominate direct CO_2 emissions, accounting for 87.9% and 85.6% in 2005 and 2020, respectively. There was no significant change in the relative components of direct emission during the period of 2005 to 2020; however, a tiny increase in emissions from the transportation and service industry was observed.

Figure 2 illustrates the geographical distribution of CO_2 emissions in 2005 and 2020. The East contributed 45.2% to total CO_2 emission in 2005, while the Middle and the West account for a similar proportion of 21.9% and 21.5%, respectively. The Northeast produced the remaining 11.4%. In 2020, emissions increased drastically, but the regional disparity did not show any significant change. The share of the East dropped by 1.3%, and that of the West increased by 2%.

3. Results and discussion

3.1. Inequality in CO_2 emission

3.1.1. Carbon inequality

Figure 3 illustrates the Lorenz curves for CO_2 emission in 2005, 2012, 2015, and 2020. The number in the first bracket refers to the carbon Gini coefficient, as it is sorted by carbon emission. The Gini coefficients during these four years were found to be around 0.4; this finding implied uneven regional distribution of carbon emissions. This distribution was a direct consequence of consecutive governments' long pursuit of unequal and carbon-intensive economic growth. The Gini coefficients decreased between 2005 and 2015 but increased slightly from 2015 to 2020. The textbox in the figure displays the difference and significance between Gini indices for two distributions in 2020 and 2005. The Gini coefficients were 0.411 and 0.385 in 2005 and 2020, respectively. The negative value of

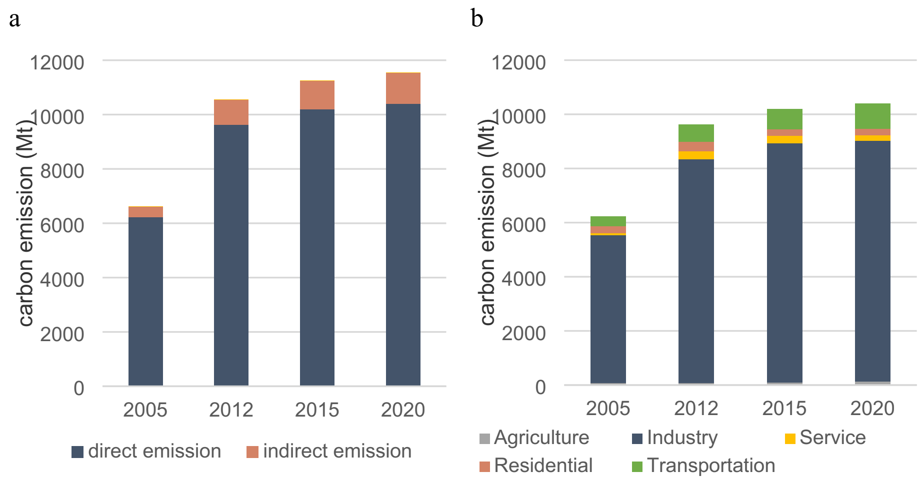

Fig. 1. Components of carbon emission in 2005, 2012, 2015, and 2020.

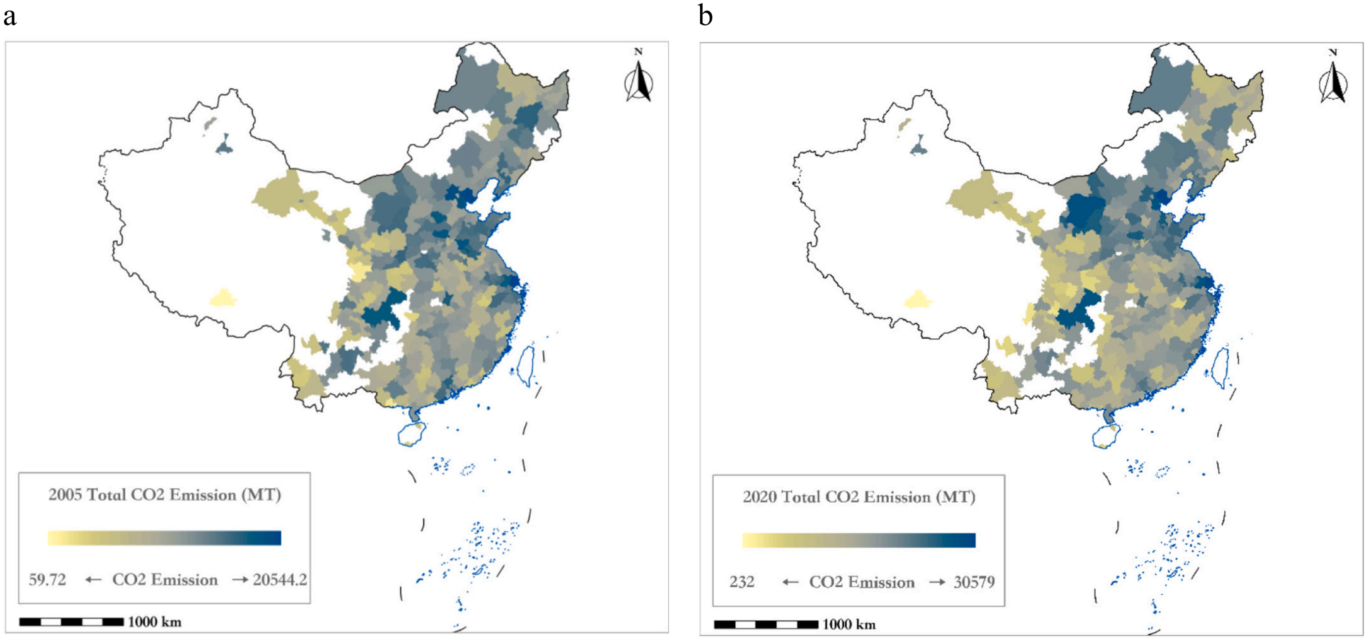

Fig. 2. Geographical distribution of carbon dioxide emission in 2005 and 2020.
Note: The blank area is not covered in our sample.

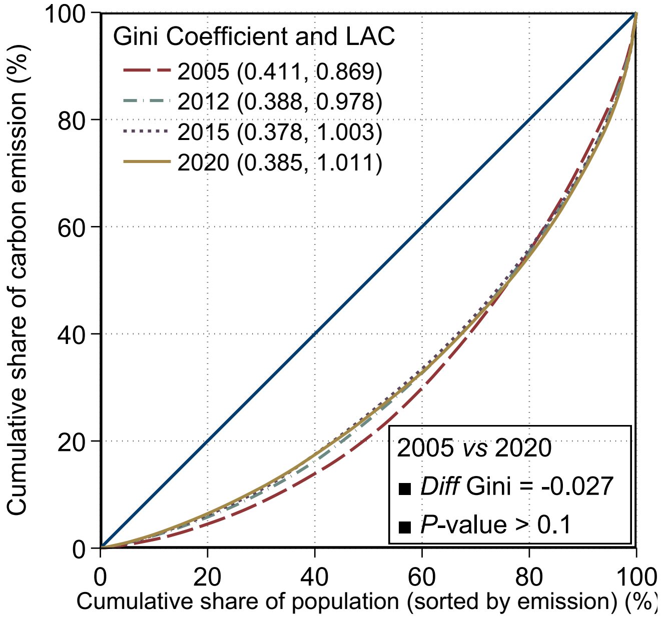

Fig. 3. Distribution of CO_2 emissions and Gini coefficients (ranked based on emissions).

the difference between these two years reflects a slight decline in the extent of inequality in the fifteen years of this period, but the reduction in the inequality was not significant. Even though the Gini coefficients were approximations, indicating a similar inequality degree, the inequality degree in 2020 was found to be subtly lenient compared to that in 2005. We can note that the curves of 2005 and 2020 intersect at a point where the cumulative share of the population is nearly 70%. The curve segment in 2020 is shown to be above the curve in 2005 at less than the cumulative share of the nearly 70% population; furthermore, it reverses when the population reaches over 70%. That is to say, cities of the 70% population with low emissions in 2005 were found to emit less CO_2 compared to that in 2020. It is worth noting that this population cannot represent rich and poor or top and bottom, as the curve is ranked based on emissions instead of income or GDP.

The Lorenz asymmetry coefficients (LAC) have also been estimated to quantify the visual finding comprehensively (The second bracketed number in Fig. 3 represents the Lorenz asymmetrical coefficient). It reveals an increasing trend. The coefficient for 2005 and 2012 was found to be less than one, whereas it was larger than but approximately equal to 1 for 2015 and 2020. This indicates that inequality has been mainly attributed to the large proportion of cities with low CO_2 emissions in 2005 and 2012. The cause of inequality has been transferred more to the few cities with high emissions in 2015 and 2020. Nevertheless, the Lorenz curve was found to be almost symmetrical in 2012, 2015, and 2020 as the LACs were approximately 1, while the LAC for 2005 was far from 1. In short, inequality in 2005 could be attributed to the low emission cities emitting too low carbon.

Table 1 depicts a research pool regarding analysis of CO_2 emission inequality based on data at different levels. Global Gini coefficients have been generally higher than China's, varying from 0.4 to 0.7. For research regarding China, the Gini coefficients based on regional or provincial data are between 0.2 and 0.3, while the research results at the household level are often higher, ranging from 0.4

Table 1
Gini coefficients of CO_2 emissions.

Region	Data	Gini coefficients (Year)	Reference
World	111 countries from 1960 to 1990	0.684 (1967) 0.584 (1990)	Heil and Wodon (1997)
	113 countries from 1971 to 1999	0.673 (1971) 0.585 (1999)	Padilla and Serrano (2006)
	137 countries in 1990 and 2002	0.630 (1990) 0.570 (2002)	Groot (2010)
	90 countries from 1971 to 2008	0.600 (1971) 0.400 (2008)	Grunewald, Jakob, and Mouratiadou (2014)
China	provincial-level data from 1997 to 2007	0.260 (2005) 0.250 (2007)	Clarke-Sather et al. (2011)
	5761 samples from 24 cities in 2010	0.580 (2010)[a]	Xu et al. (2016)
	13 income groups for five consumption categories in 2007 and 2012	0.430 (2007)[a] 0.390 (2010)[a]	Wiedenhofer et al. (2016)
	Provincial-level data from1997 to 2012	0.241 (1997) 0.302 (2000) 0.271 (2005) 0.236 (2010) 0.245 (2012)	Chen et al. (2016)
	Provincial-level data from1997 to 2014	0.320 (1997)[b] 0.343 (2000)[b] 0.257 (2005)[b] 0.249 (2010)[b] 0.226 (2014)[b]	Chen et al. (2017)

[a] Denotes Gini coefficients for household emission inequality.
[b] Indicates the residential sector.

to 0.6. Our results were lower than global emission inequality, which indicates China's emission distribution has been even higher than that of the world. Compared with available research for China, this paper had moderate Gini coefficients, since the provincial-level data tend to underestimate inequality by ignoring disparities inside provinces, and household data only capture overall household inequality. The comparison reflects whether the data's level and reliability are highly relevant to the inequality degree (Steininger, Lininger, Meyer, Muñoz, et al., 2015). A large sample is essential for measuring inequality. City-level data may be affected by issues such as ignoring of intra-city inequalities. However, the drawback is not as severe as the provincial data, as it, at least, considers intra-provincial inequality at the city level.

As the Gini coefficient is not sensitive to the top of the distribution (Trapeznikova, 2019), other inequality measures, e.g., Coefficient of variation (CV) and Theil index, are also calculated to be complementary. Table 2 compares the values of these three measures. The CV measure has evolved differently compared to the Gini coefficient and the Theil index over 15 years. An increasing CV value indicates that the emission variability is relative to the mean or that the dispersion will keep growing by year; the disparity of emission declined from 2005 to 2015 and increased in 2020. Thus, the inequality changes in emission may not coincide with emission variability for China.

As shown in Fig. 4, we have presented distributions for the per capita CO_2 emission and CO_2 intensity for both 2005 and 2020. The average per capita CO_2 emission climbed from 6.8 tons in 2005 to 11.5 tons in 2020, while carbon intensity dropped from 0.5 in 2005 to 0.2 in 2020. Fig. 4a demonstrates the change in the distribution of per capita emissions over time. Corresponding to the LAC results depicted in Fig. 3, per capita CO_2 emissions in many cities were under 10 tons in 2005, while the density of emissions under 10 tons dropped considerably in 2020. This density drop in 2020 is attributed to the increasing number of cities with emissions between 10 and 30 tons. Furthermore, the shape of the distribution in 2015 reflects a longer tail, beyond 150 tons. Fig. 4b reveals an opposite distribution to that in Fig. 4a. More cities were centered around the interval of the carbon intensity (nearly 0.3 [kg/constant 2005 Yuan]) in 2005 to 0.2 [kg/constant 2005 Yuan] in 2020), thus indicating that more cities showed lower carbon intensity in the last fifteen years. This finding could be a reflection of the abatement progress.

3.1.2. Carbon-economic inequality

Research has shown that top income inequality and carbon emissions are intensely and tightly linked (Hailemariam, Dzhumashev, & Shahbaz, 2020). Thus, it is essential to explore the economical characteristics of emitters.

The analysis above only illustrates emission distribution ranked by emission, and the Gini coefficient is a single-dimensional measure, which cannot distinguish characteristics of the population (for example, who emits more or who emits less). In order to further investigate the distribution of CO_2 emissions across the population based on level of economic development, the concentration index or carbon-economic inequality index must be calculated. The concentration index is a bivariate measure of inequality that measures emission inequality in relation to the ranking of economic status (Koolman & Van Doorslaer, 2004). As shown in Fig. 5, the bracketed number is the concentration coefficient. The concentration curves in the period are shown to be below the diagonal with a positive concentration index. This reveals that rich cities (economically rich) emit more CO_2 than poor cities. Nevertheless, the concentration curve for 2020 is located no further than that for 2005—that is, below the diagonal. The concentration index in 2020 (0.118) is significantly lower than that in 2005 (0.230), implying that a there was a lower emission concentration from the rich cities in 2020 compared to the concentration in 2005, and more poor cities have been increased their emissions gradually. In short, the poor 50% of the population moved from emitting around 30% in 2005 to 40% in 2020.

As some emission amount changes could be attributed to income distribution at the city level, we also estimated the income inequality in order to compare it with the emission equality (ranked in terms of emission). Table 3 summarizes the inequality values of emission and economy. It seems that there was a slight decoupling of economic inequality and carbon inequality in 2020 while there were no significant differences between them before 2015. To further investigate the relationship between emission inequality and income inequality, we estimated the Kakwani index in order to explore the progressivity of per capita emission over per capita GDP. The Kakwani index computes the inequality difference in emission distribution between rich and poor cities and inequality in GDP distribution. The Kakwani index values were found to be below zero for these four years, thus indicating a regressive emission distribution relative to income. It indicates that the share of emissions produced by rich cities is lower than their share of GDP and that poorer cities tend to have higher carbon intensities. Thus, CO_2 emission is more equally distributed compared to GDP distribution; this also verifies the theory of the Kuznets curve for CO_2 emission (Clarke-Sather et al., 2011); emissions in rich cities witness a fall after they reach a turning point with the economic development.

Figure 6 displays the distribution of per capita CO_2 emission and carbon intensity based on per capita GDP groups (similar to income groups). Fig. 6a illustrates that total emission for the richest 4th and 5th quantiles first increased and then decreased, while the 1st, 2nd, and 3rd quantiles remained on an upward trend. This finding leads to the obvious conclusion that the higher the per capita GDP, the higher the per capita CO_2 emission (except for the 5th quantile in 2020). One explanation for the relatively low emission of the 5th quantile cities lies in the relatively low direct emission, which could be attributed to the energy transition of these rich cities.

Table 2
Inequality measures for CO_2 emission.

Measure	2005	2012	2015	2020
Gini coefficient	0.411	0.388	0.378	0.385
Coefficient of variation	0.87	0.881	0.907	0.923
Theil index	0.289	0.269	0.265	0.274

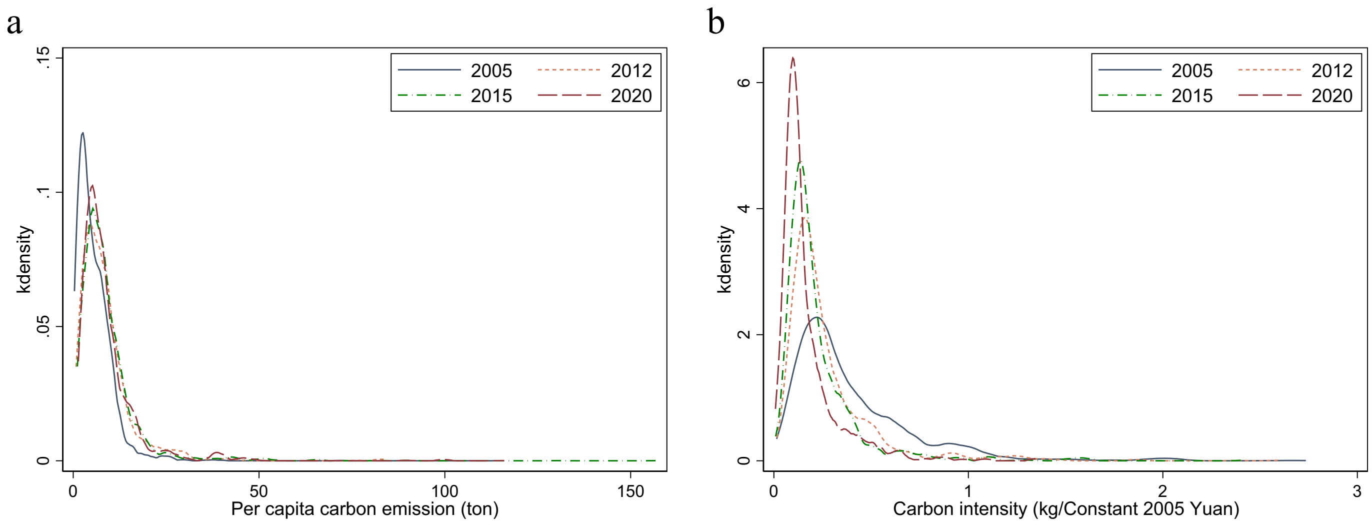

Fig. 4. Kernel density for CO_2 emission per capita and CO_2 intensity in 2005, 2012, 2015, and 2020.

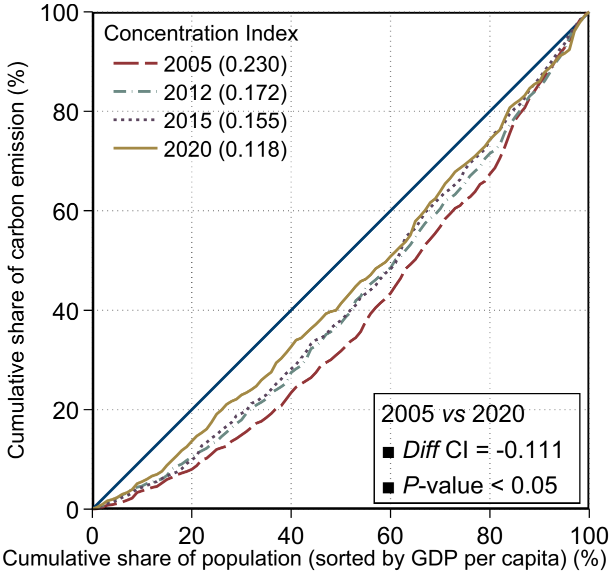

Fig. 5. Distribution of CO_2 emission and concentration coefficients (ranked by per capita GDP).

Table 3
Comparison of carbon emission inequality and economic inequality.

Year	Gini coefficient			Concentration index	Kakwani index
	CO_2 emission	GDP per capita	*Difference*		
2005	0.411	0.401	−0.01	0.230	−0.171
2012	0.388	0.368	−0.021	0.172	−0.196
2015	0.378	0.357	−0.021	0.155	−0.202
2020	0.385	0.324	−0.061*	0.118	−0.206

The Environmental Kuznets curve (EKC) theory proposes an inverted U-shape for pollution as the economy grows. More developed cities' residents tend to have stronger preferences for a more convenient, clean, and sustainable living environment. Therefore, under the energy ladder theory, it is natural for rich cities to consume more modern fuels (e.g., electricity) in order to replace traditional solid fuels. In contrast, poor cities often find it hard to extensively use modern fuels because of their affordability, availability, and accessibility issues.[2] Overall, the CO_2 emission growth rate is slower than the GDP growth rate, thus indicating that economic development does not necessarily prompt carbon emissions. Furthermore, the CO_2 emission gap between the high-income and low-income groups is much lower than that with regard to GDP.

Meanwhile, the more affluent the city, the higher its indirect emission. To meet new electricity demands, rich cities often choose to purchase it from other cities, since it is not environment-friendly and not worthwhile to produce by themselves, considering its relevant opportunity costs (e.g., take the case of Beijing) (Liu, Guan, Crawford-Brown, Zhang, et al., 2013). Thus, rich cities' purchase of fuels from other cities lowers their emission on the supply side. Their energy transition from traditional fuels to commercial fuels reduces direct emissions on the demand side, and their emissions are thus classified as indirect emissions. All these factors have led to the decrease in direct emission but increase in indirect emission among certain income groups. From this perspective, future research should focus more on accounting for consumption-based emissions; this could help to present a more comprehensive result (Davis & Caldeira, 2010). As shown in Fig. 6b, carbon intensity in China experienced a remarkable fall from 2005 to 2020. Contrary to per capita emission distribution trends among the classes, richer cities showed lower carbon intensities. In the beginning, the richest cities experienced a relatively faster fall rate for carbon intensity, and later, their marginal reduction in carbon intensity diminished.

3.2. What drives the inequality change?

3.2.1. Decomposition of CO_2 inequality by emission source

Figure 7a-d shows the decomposition results by emission source for the period. The CO_2 emission from the industry sector clearly plays a dominant role in inequality, which exceeds 85%. Other emission sources have limited influence on inequality. The contribution of residential emissions shows a minute decrease from 2% in 2005 to 0.9% in 2020. There is an increasing role of indirect emission on

[2] The emission factors of modern fuels are lower than those of solid fuels.

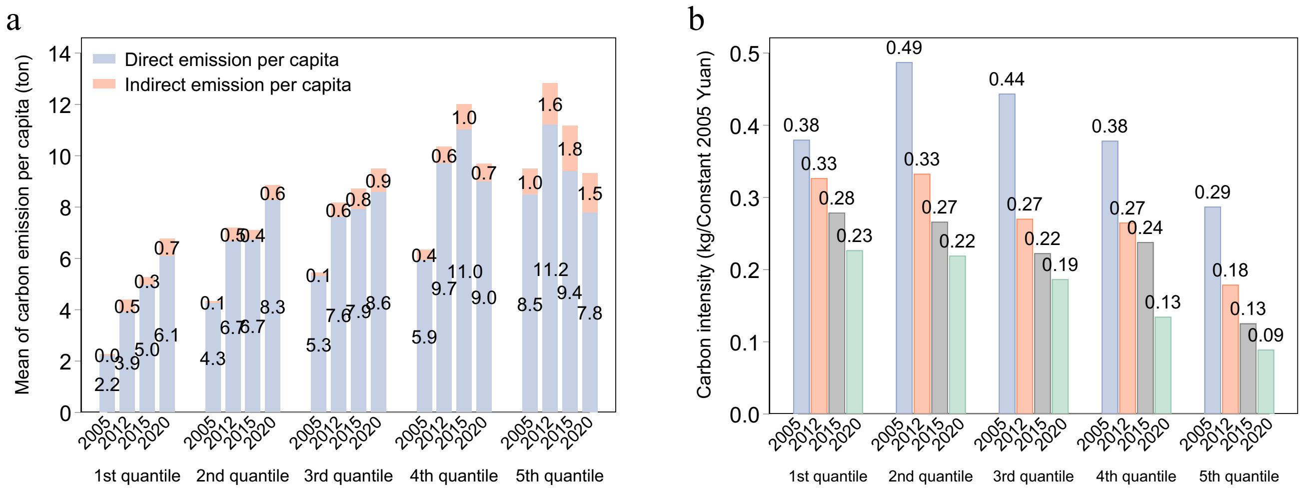

Fig. 6. Distribution of CO_2 emission and emission intensity by GDP groups.

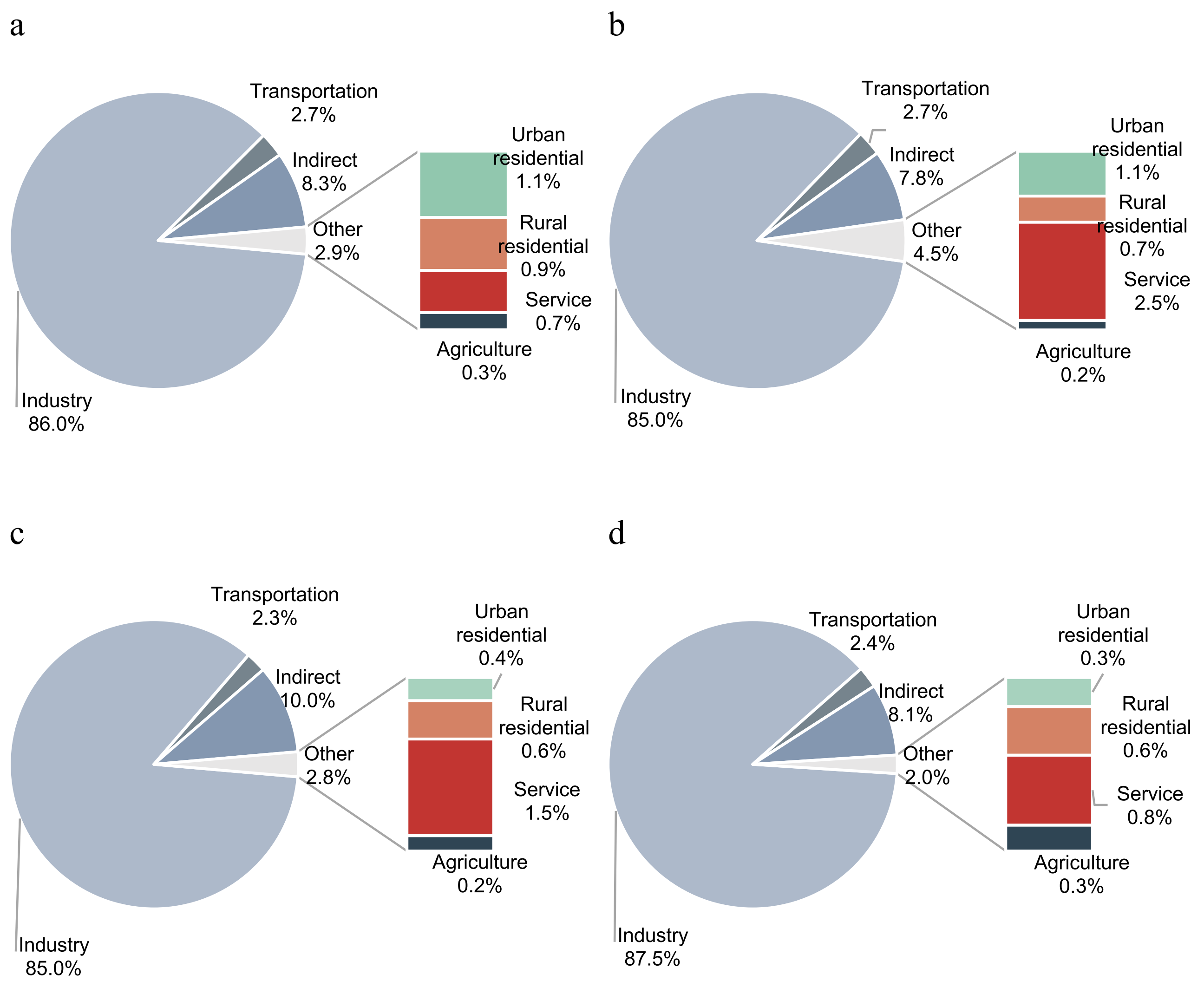

Fig. 7. Decomposition of CO_2 emission inequality by emission source for 2005, 2012, 2015, and 2020.

inequality from 2005 to 2015 and decreased slightly from 2015 to 2020. Nevertheless, it can be suggested that the almost steady composition of emission sources has a finite effect on the inequality change.

Based on the decomposition by emission source, we estimated the marginal effect of each source. Table 4 displays the impact that a 1% change in the respective emission source would have on total CO_2 emission inequality. The marginal effect of CO_2 emission from the industry sector is increasingly positive, signifying that a 1% increase in industrial emissions would result in a 0.159% increase in inequality in 2020. In other words, the increase in industrial emissions worsens inequality. The change in transportation emissions will cause the largest decrease in inequality. In addition, the role of indirect emission on inequality is uncertain. The increase in indirect emissions boosted the extent of inequality in 2005; however, it helped to relieve the inequality in 2020. There was no significant divergence in the magnitude of these marginal effects between 2005 and 2020.

3.2.2. Decomposition of CO_2 inequality by region

Here, we divided China into four regions: West, Middle, East, and Northeast, and decomposed the inequality among these four regions. Table 5 illustrates the regional heterogeneity of inequality for these years. Inequality in the East and Middle regions emerged as a declining trend, whereas the inequality degree in the West and Northeast regions worsened. At the start of 2005, the Northeast region had the lowest inequality, while in 2020, the East region had the lowest inequality. The West region witnessed the highest inequality during the period. China's intensifying efforts to reduce CO_2 emissions may explain the drop in inequality in the East and Middle regions. China's emissions are concentrated in the East and Middle regions; thus, they bear the brunt. Meanwhile, these two regions choose to transfer their energy-intensive industries to the West and Northeast regions, where outsourcing emission increases inequality. We consider that the result may be somewhat limited by the large missing values in the Western cities.

Figure 8a-d shows that within-group inequality is responsible for approximately 30% of the total inequality for 2005 and 2020. The contribution of between-group inequality experienced a sharp decrease from 25% in 2005 to 12% in 2015. We can infer that reducing the between-group inequality helps relieve the overall inequality. Among the within-group inequality, the three regions' contributions were relatively stable, while that of the East region declined slightly during this period. The East region contributes the most to inequality. It is consistent with the results in Table 5 as the contribution is not only calculated by the inequality degree, but also is related to the emission share of the total emission. No more than 20% of the overall inequality ascribes to the rest regions. Therefore, reducing the emission inequality of city groups in the remaining regions would only have a limited effect in reducing the overall inequality. The overlap-group effect gives rise to 47%–58% overall inequality, representing a large proportion of overlapping per capita emissions among the three regions.

3.2.3. Decomposition of CO_2 inequality by determinants

Model specification is vital in regression-based inequality decomposition. The first step is to decompose the determinants by constructing an emission-generating function. The semi-log form is common for inequality decomposition in economics (Wan, 2002, 2004), and we estimate the emission equation in semi-log form. Thus, inequality can be measured over actual emission while the advantages of the functions are preserved. Fig. 9 displays the change in these determinants contributing to emission inequality from 2005 to 2020.

The changes regarding emissions might be attributed to how income is distributed within and between cities. However, in this study, we are unable to analyze the impact of income distribution within the city due to data unavailability. Fig. 9a and b show the relative contribution of the determinants to the emission inequality. Among the five determinants, the contributions of per capita GDP (*pergdp*), industrial structure (*share_ind*), and electricity intensity (*ele_intensity*) to emission inequality dropped from 2005 to 2020. Meanwhile, the contribution of HDD18 and the share of fiscal expenditure to the GDP (*fiscal*) increased. Clearly, the electricity intensity underwent a drastic decline in the contribution to the inequality, from 18.1% in 2005 to 0.6% in 2020. Basically, energy efficiency is one of the most necessary factors in driving emissions. However, due to the data limitation at the city level in China, we settled for using the electricity intensity (electricity consumption per unit GDP) to substitute the efficiency factor. As we only investigated five determinants of carbon emission, a large proportion of the inequality can be ascribed to the residues. However, the incomplete statistical accounting system hinders further research in analyzing emission inequality determinants (e.g., the availability of data on energy structure or coal-electricity generation at the city level). Overall, the contribution variation of all these factors caused a slight reduction in inequality over the ten years.

The EKC theory can explain the falling contribution of the per capita GDP and industry share to inequality. With economic development and the adjustment of economic structure, emissions increase in poor cities, while they decrease or stagnate in affluent cities. This results in a more even distribution; namely, a lower contribution of the factors to inequality. The decline of heating degree

Table 4
Marginal effects of emission source on CO_2 emission inequality (%).

Sector	2005	2012	2015	2020
Agriculture	−0.01	−0.007	−0.008	−0.01
Industry	0.065	0.119	0.114	0.159
Service	−0.004	−0.007	−0.016	−0.012
Rural residential	−0.017	−0.013	−0.009	−0.005
Urban residential	−0.01	−0.008	−0.007	−0.01
Transportation	−0.033	−0.039	−0.05	−0.064
Indirect	0.008	−0.045	−0.024	−0.059

Table 5
Gini coefficient of CO_2 emission by region in China.

Region	2005	2012	2015	2020
East	0.352	0.277	0.265	0.278
Middle	0.437	0.452	0.412	0.373
West	0.491	0.473	0.499	0.534
Northeast	0.227	0.307	0.309	0.298

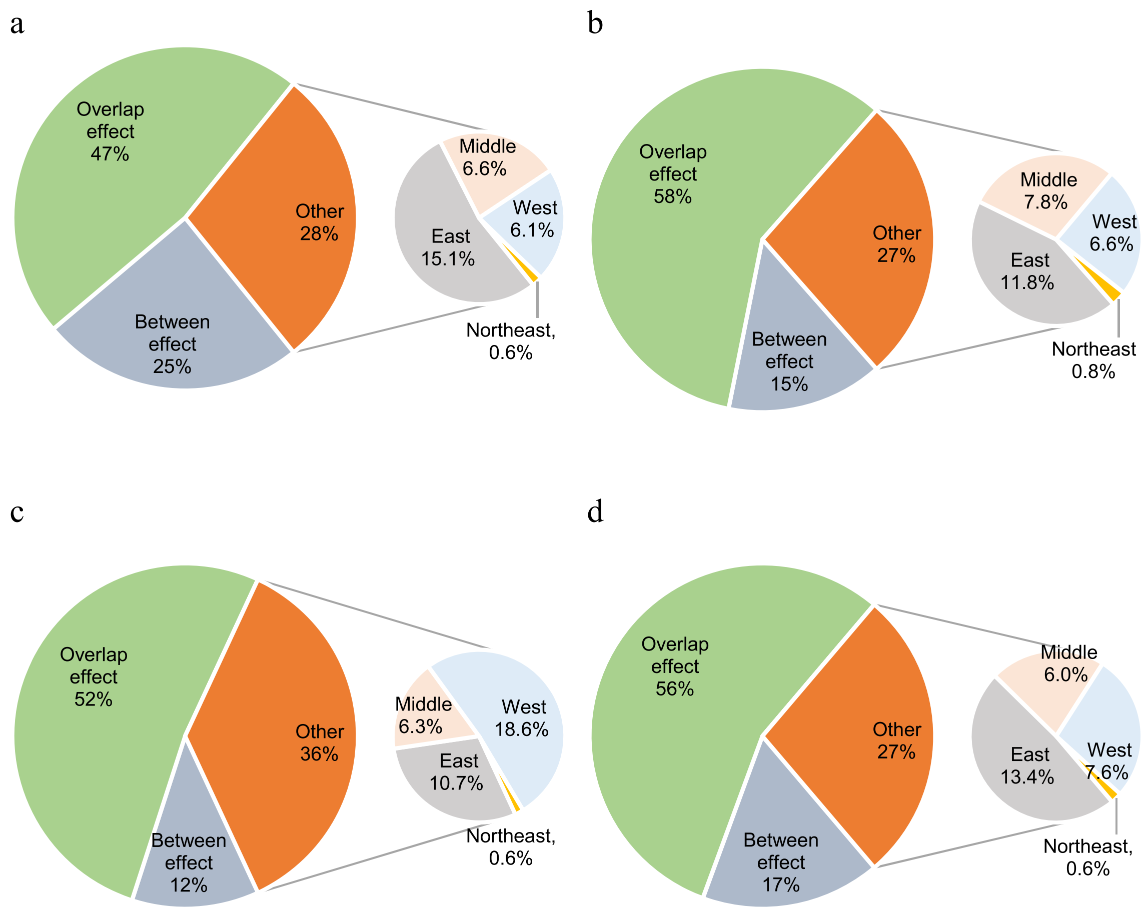

Fig. 8. Decomposition of CO_2 emission inequality by region for 2005, 2012, 2015, and 2020.

days from 2005 to 2020 led to lower emissions from heating demand, meaning more cooling demand and more emissions in summer. However, due to the economic constraints of poor households, it is difficult for them to increase the purchase of air-conditioners and the usage of electricity on air-conditioners (Auffhammer & Wolfram, 2014; Davis & Gertler, 2015). In contrast, wealthy households have more adaptive capacity to raise their demand. Hence, the contribution change of climate change to inequality is positive. Besides, environmental regulation plays an increasing role in emission inequality.

Figure 9c indicates the decomposition results and the marginal effect. Except for the *fiscal*, the other four determinants all had negative marginal effects on inequality, particularly the change of the share of industry, which had over 1% effect on alleviating the inequality. The intuition behind the results is that the industry expansion has occurred in poor cities in recent years as the rich cities have transformed the economy. Thus, the increase in emissions caused by industry occurs mainly in poor cities. With the environmental regulation enhancement, the marginal effect of the fiscal expenditure on the inequality degree changes from positive to negative. This implies that the regulation becomes more effective because it is common for local governments to pursue near-term development gains at the expense of the environment in the early years.

4. Conclusion

This study investigated the CO_2 emission inequality and analyzed the determinants of inequality from various dimensions, which

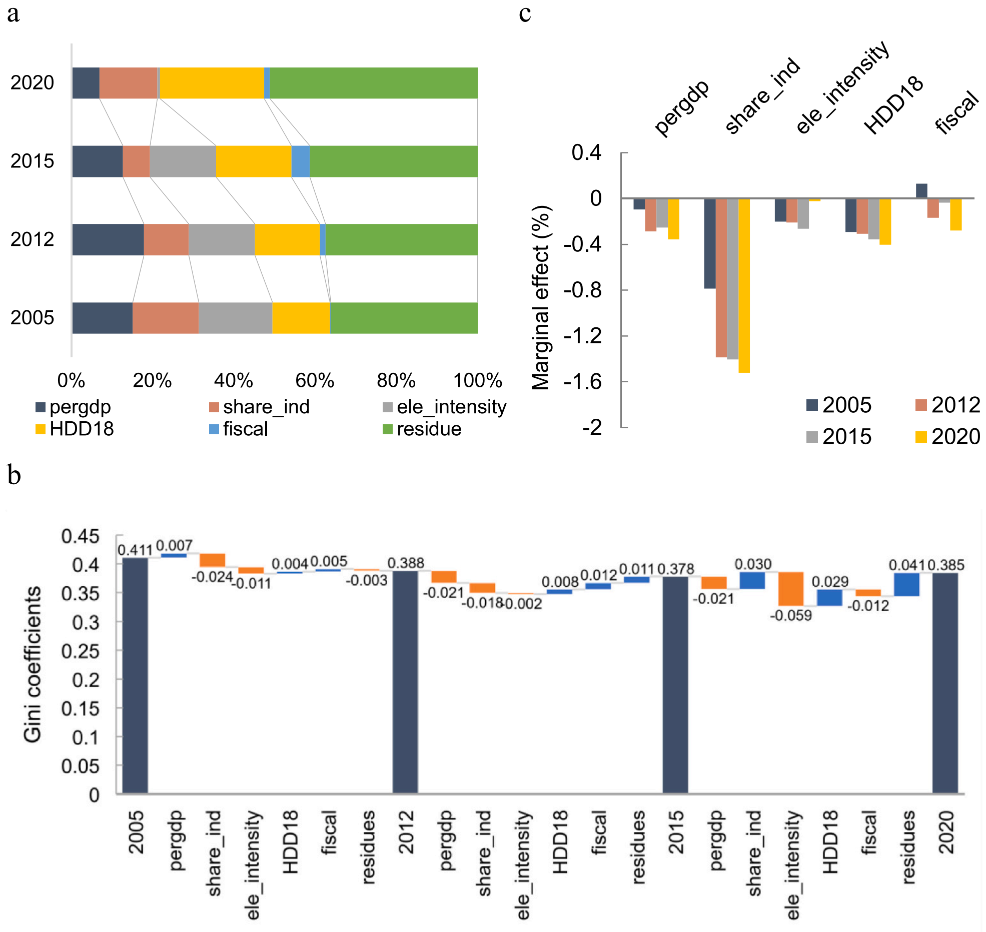

Fig. 9. Decomposition of CO_2 emission by determinants. **a,** Decomposition of CO_2 emission inequality by determinants in semi-log form. **b,** Absolute contribution change of the determinants. **c,** Marginal effect of the determinants.

lays the groundwork for further research regarding the allocation scheme of CO_2 emission. Using data at the city level relieved the carbon leakage at the household level and provided a more modest inequality value by analyzing the total emission. Further decomposition of the emission inequality helps policy-makers identify the determinants in reducing the emission inequality and boosting mitigation and adaptation of climate change.

Results show that the inequality degree experiences a tiny decrease from 0.411 to 0.385 between 2005 and 2020. More cities with low emissions were responsible for the inequality in 2005, while the inequality was relatively symmetric in 2012, 2015, and 2020. By calculating the carbon-economic concentration index and Kakwani index, we found that although wealthier cities are prone to emitting more CO_2 emissions, the CO_2 emission is regressive relative to the GDP. More affluent cities always have high emissions; however, their share of emissions does not exceed their share of GDP. This means that several poor cities have high emissions, and there is an obvious trend of increasing emissions from poor cities. Overall, great spatial disparity of carbon intensity exists in China, and there has been a slight decoupling of income and carbon inequality in recent years.

To explain the subtle decline of inequality degree for the decade, we decomposed the inequality by emission source, region, and determinants. Three findings emerged from the analysis. (1) Industrial emission dominated the carbon inequality in these fifteen years, and the overall contributions to the inequality of the seven sectors did not show remarkable changes. (2) The improvement of inter-regional equality helped narrow the emission inequality gap over the fifteen years despite the distribution of overlap-regional emission being more uneven. (3) The decreased contributions of the per capita GDP, the share of industry, and the energy intensity to the overall inequality endeavored to lessen inequality from 2005 to 2020. Due to the industrial transfer, developing cities emit more than before, while developed cities witness lower manufacturing sector emissions. Climate condition becomes a great contributor to inequality. However, all these determinants have a negative effect on inequality, implying that the change of these variables helps reduce inequality.

The results suggest that economic development level should not be the only factor when creating policy regarding the emissions quotas allocation. Greater efforts are needed to improve quota allocation by accounting for the regional heterogeneity in industrial structure, technology level, and climatic conditions. For example, constructing a comprehensive index that cooperates with multidimensional variables and assigns different weights according to their contribution to the emission distribution. Inspired by the results of decomposition, there are various approaches to mitigate inequality. First, due to cities' unequal economic development levels, mitigation policy concentrated on alleviating the income inequality is critical for extenuating CO_2 emissions. Second, as the share of industry plays a pivotal part in lessening the inequality during 2005 and 2020, we expect that the adjustment of the share of industry has a decreasing influence in alleviating emission inequality in the future. Given the proportion of electricity intensity, technology improvement is essential for relieving inequality, including improving energy efficiency in the manufacturing and residential sectors. Moreover, reducing emissions in developed cities is inevitable for space heating, especially for northern cities. In a sense, amelioration of heating conditions helps narrow the emission gap. Due to data availability, it is difficult for us to investigate the effect of variables like energy structure and the development of energy-intensive industries on emission inequality. Therefore, it is essential to compile reliable and comprehensive data at the city level to fill the statistical data gap.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

Acknowledgements

The research was financially supported by National Natural Science Foundation of China (72103061 and 72274206) and Hunan Provincial Natural Science Foundation of China (2021JJ40139).

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