City-level emission peak and drivers in China

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Abstract

China is playing an increasing role in global climate change mitigation, and local authorities need more city-specific information on the emissions trends and patterns when designing low-carbon policies. This study provides the most comprehensive CO_2 emission inventories of 287 Chinese cities from 2001 to 2019. The emission inventories are compiled for 47 economic sectors and include energy-related emissions for 17 types of fossil fuels and process-related emissions from cement production. We further investigate the state of the emission peak in each city and reveal hidden driving forces. The results show that 38 cities have proactively peaked their emissions for at least five years and another 21 cities also have emission decline, but passively. The 38 proactively peaked cities achieved emission decline mainly by efficiency improvements and structural changes in energy use, while the 21 passively emission declined cities reduced emissions at the cost of economic recession or population loss. We propose that those passively emission declined cities need to face up to the reasons that caused the emission to decline, and fully exploit the opportunities provided by industrial innovation and green investment brought by the low-carbon targets to achieve economic recovery and carbon mitigation goals. The proactively peaked cities need to seek strategies to maintain the downward trend in emissions and avoid an emission rebound and thus provide successful models for other non-declined cities to achieve an emission peak.

Keywords: CO_2 Emissions; Emission Peak; Drivers; City; Climate Change

1 Introduction

With the accelerating climate emergency, decision-makers need specific sub-national information on sources of carbon emissions, reduction potentials, and mitigation measures. Cities are at the heart of climate change mitigation and the sustainability of human development [1]. On the one hand, cities are emission and development hotspots, with urban economic activity accounting for 80% of global GDP, 60-80% of energy consumption, and 75% of carbon emissions [2-4]. On the other hand, cities are basic administrative units capable of carrying out targeted emission reduction measures. Although more than 500 cities have committed to low-carbon and carbon neutrality goals worldwide, there is still lacking agreement on how to best account for emissions and achieve decarbonization at the city level [5].

This is particularly the case in China - the world's largest developing country with the highest national energy consumption [6] and CO_2 emissions [7, 8]. China has been working hard to target its climate change mitigation goals at the national level (e.g., achieving the peak of national emissions before 2030, reducing its emission intensity by 60-65% by 2030 compared to the level of 2005, and achieving carbon neutrality by 2060) [9-11]. Fortunately, China has made great strides in the progress of emission reduction. The latest accounts of China's national emissions have found that the 2020 carbon intensity mitigation target was achieved ahead of schedule in 2018 [12]. The next step strategies of emission reduction in China should be focused on the cities with specific attention to their development levels and emission patterns.

Cities in China show huge differences in terms of emission patterns and interactions between emissions and economic development. Although some cities have achieved emission decline in recent years, the reasons could be quite diverse. Human efforts towards decarbonization (e.g., decarbonizing industry and improving the efficiency of production) could have led to emission decline in some cities, whereas other drivers such as economic recession or population loss could have contributed to a decrease in emissions in other cities [13]. Therefore, the reasons for cities' emission decline and peak need to be carefully examined.

Following the concept of the Environment Kuznets Curve [14-17], carbon peaks are hypothesized to follow the development of the economy and a process of industrialization followed by deindustrialization [18, 19]. Highly industrialised cities with well-established infrastructure and post-industrialised cities with service-oriented economic structures (e.g., Beijing and Shanghai) have already peaked their CO_2 emissions and achieved decoupled economic growth from emissions [20, 21]. Emerging cities with lower per capita GDP but fast growth (e.g., Langfang in Hebei and Luoyang in Henan) are vital to the national emissions peak, given their large numbers and their large absolute emissions. Their emission peaks will appear after those economically advanced cities (post- and highly industrialised cities) [22, 23]. Heavy-industrial cities with reliance on energy-intensive manufacturing and coal consumption (e.g., Tangshan in Hebei and Dezhou in Shandong) might start to level off CO_2 emissions after years (e.g., 2025 in the case of Dezhou [24]). Energy cities that are mainly based on extractive industries (e.g., Yulin in Shaanxi, Ordos in Inner Mongolia, and Lvliang in Shanxi) are usually underdeveloped, and their potential emission peak is further in the future and depends on technical upgrading and a more balanced and diversified industrial portfolio [25].

Exploring the status of emission peaks in cities and the hidden drivers needs a detailed, transparent, and accurate accounting of historical emissions of cities over longer time periods. Although numerous studies presented city-level emissions, long time-series emission inventories for cities are still rare [26]. First, most studies focused only on individual well-developed metropolises (e.g., Shanghai [20, 27, 28] and Chongqing [29]), or selected cities with high population density [21]. Second, research mostly accounted for emissions for a single year, missing dynamic changes in city emissions [30, 31]. Third, previous accounts only considered one or several specific economic sectors based on activity data from point sources or mobility records [32-35], lacking a comprehensive overview of city emissions covering all economic sectors. Fourth, some studies downscaled national or regional emissions to cities based on simple indicators (e.g., population density, value-added, and output), ignoring the specific characteristics of cities in contrast to the larger administrative unit [36]. Fifth, these emission inventories are inconsistent and incomparable across cities, due to differences in sources of activity data, emission factors, and the selected accounting scope. As a result, huge uncertainties in the emissions of cities have been witnessed by previous studies. For example, self-reported emissions of American cities are on average 18.3% less than the estimates based on atmospheric measurements [37].

Here, we present the most comprehensive and long-reaching time series (2001 to 2019) of CO_2 emission inventories of 287 Chinese cities, which cover 98%+ of China's population, 99%+ of GDP, and 97%+ of CO_2 emissions (compared to the national emissions from EDGAR [38]) in 2014. Our city-level emission inventories include energy-related emissions from 17 types of fossil fuels and process-related emissions from cement production. The inventories are compiled for 47 economic sectors consistent with the System of National Accounts in China. The city-level emission inventories are consistent with our previous national emission accounts [7, 8] in terms of methods, scope, and data sources, allowing for comparison across scales. The emission inventories of cities can be found in the supplementary document and can be freely downloaded from Carbon Emission Accounts and Datasets for Emerging Economies (CEADs).

Using emission data, we identify the status of emission peaks of cities with the Mann-Kendall (MK) trend test and their degree of decoupling of emissions and social development indexes (i.e., level of economic development and size of the population). We further quantify the contributions of key drivers to the emission decline in cities. We conclude this study by providing policy recommendations for achieving emission peaks and carbon neutrality in different cities.

2 Materials and methods

2.1 Emission accounts

There are several approaches to account for the emissions of a city [39]. Production-based emissions (PBE) account for emissions that result from the production of goods and services within a city [31]. Whereas, consumption-based emissions (CBE or carbon footprints) link local consumption of goods and services to emissions along the entire supply chain using input-output or lifecycle analysis and thus include the emissions along the entire supply chain [26, 40]. Extraction-based emissions (EBE) make it possible to trace back all local emissions to the point where fossil fuels are extracted [41], even if these fuels are processed in and re-exported from an intermediate city. In comparison, the Intergovernmental Panel on Climate Change (IPCC) administrative-territorial approach captures all direct emissions from human economic activities within the territory of a city. Unlike PBA, it does not include emissions from international aviation or shipping [42, 43]. Territorial emissions are widely used for designing low-carbon policies and allocating responsibility for global climate change targets. Therefore, we adopt the territorial approach when compiling the emission inventories for cities in this study.

We consider both fossil fuel-related emissions from 47 socioeconomic sectors and 17 types of fossil fuels, as well as process-related emissions from cement production. The inventories are constructed as 47 by 17 matrixes. Each column presents emissions from one type of fossil fuels or industrial process. 47 rows present the socio-economic sectors, which are consistent with the System of National Accounts (SNA) in China. To follow the accounting scope of territorial emissions and avoid double accounting, emissions associated with electricity/heat use are allocated to the power sector, based on the fossil fuel inputs for electricity/heat generation.

Eq. (*1*) and Eq. (*2*) are used to calculate the fossil fuel-related and process-related emissions, respectively. CE_{ij} represent emissions from the combustion of fuel i in sector j; AD_{ij} refers to activity data (i.e., consumption of corresponding fossil fuel types and sectors); NCV_i (net caloric value), CC_i (carbon content), and O_{ij} (oxygenation efficiency) are emission factors for fuel i. CE_{cement} are process-related emissions from cement production, which are calculated as the product of activity data (AD_{cement}, i.e., production of cement) and emission factor (EF_{cement}, i.e., emissions per unit cement production).

$$CE_{ij} = AD_{ij} \times NCV_i \times CC_i \times O_{ij} \tag{1}$$

$$CE_{cement} = AD_{cement} \times EF_{cement} \tag{2}$$

City-level activity data (AD_{ij} and AD_{cement}) are collected from cities' statistical yearbooks or downscaled from the corresponding provincial data based on socioeconomic indexes [31, 44, 45]. We exclude the amount of non-energy use in the chemical sectors (i.e., fossil fuels used as chemical raw inputs) as well as the energy loss during transportation and transformation. The emission factors of fossil fuels (NCV_i, CC_i, and O_{ij}) are collected based on a wide survey of over 4,243 state-owned Chinese coal mines in China [8, 46]. The emission factors of process-related emissions (EF_{cement}) are collected from Liu, et al. [46].

2.2 Emission decline and peak

To assess the status of emissions peak in each city (including both fossil fuel and cement-related emissions), we introduce an integrated approach based on several conditional functions, the Mann-Kendall (MK) trend test [47], and decoupling analysis. Emission peaked cities are defined as those that have reduced emissions significantly for more than five years while their economy and population grow stably over the period.

First, we limit the analysis to cities with a time series of emissions inventories longer than 12 years and identify the year each city has its maximum emission. If the maximum emission is observed within the most recent five years, we think the decline of the emissions is not long enough to be considered a trend that can continue into the future. We classify these cities to be at a non-declined stage [48].

Second, for cities with declining emissions for more than five years, we apply the MK test to check if the cities' emissions fall significantly (i.e., passed the MK test with a p-value less than 0.05) within the descending period. If yes, the city will be considered to have continuously declined its CO_2 emissions (i.e., emission declined cities); otherwise, it will be seen as still being at a plateau phase [47]. The MK trend test is a nonparametric statistical method recommended by the World Meteorological Organization (WMO) and has been widely used to detect time-series trends of climate sequences (e.g., temperature [49, 50] and carbon emissions [51]), hydrological characterization (e.g., precipitation [52] and streamflow [53, 54]), and other factors.

Third, for those emission declined cities, we test the degree of decoupling of their emissions and social development indexes, see section 2.3 below. If the cities have a strong decoupling of emissions and social development indexes (i.e., emission decline with stable development in economy and population), we consider the city as an emission peaked one; otherwise, the city will be seen as a passively emission declined one.

2.3 Decoupling

The concept of decoupling is widely used to describe the relationship between environmental pressure (e.g., greenhouse gas emissions) or resource use and economic development, which is seen as a key indicator for regional sustainable development. "*Decoupling occurs when the growth rate of an environmental pressure is less than that of its economic driving force (e.g. GDP) over a given period* (page 1)" [55]. Although it is controversial whether absolute decoupling can be achieved at a global scale [56-58], some studies have found evidence of achieving decoupling at regional levels [59-65].

Several indexes have been developed to quantify the degree of decoupling based on the elasticity changes in GDP and the environmental pressure [66-71]. Following previous studies [68, 71], we calculate the decoupling index (DI_{GDP}) in Eq. *(3)*, in which GDP_1 and CE_1 refer to the GDP and CO_2 emissions of reporting year while GDP_0 and CE_0 refer to the base year. Three categories of decoupling are defined based on the decoupling index: absolute decoupling ($DI_{GDP} > 1$) refers to a decline of emissions; relative decoupling ($0 < DI_{GDP} \leq 1$) refers to the growth of emissions being no faster than the growth of GDP; and no decoupling ($DI_{GDP} \leq 0$) refers to a situation where emissions grow to the same extent or faster than GDP. To involve cities that are experiencing economic recession, we include the degree of decoupling in the second and third quadrants of the cartesian coordinates (x-axis: changes in GDP; y-axis: changes in CO_2 emissions) [69], as shown in Table 1.

$$DI_{GDP} = (\Delta GDP\% - \Delta CE\%)/\Delta GDP\% = \left(\frac{GDP_1 - GDP_0}{GDP_0} - \frac{CE_1 - CE_0}{CE_0}\right)\Big/\frac{GDP_1 - GDP_0}{GDP_0} \tag{3}$$

Many previous studies only investigated the decoupling between economic growth and CO_2 emissions. However, decoupling could occur between emissions and any socioeconomic indicator. For example, some recent studies explored the degree of decoupling of emission growth from population growth, the changing structure of energy consumption, and government expenditure [72, 73]. Population growth is a key driving factor of CO_2 emissions, reducing emissions should be achieved independent of changes in population or urban decline. That means we need to achieve decoupling of emissions and population as well. Therefore, we further quantify the degree of decoupling of emissions and population (DI_{pop}) in cities (shown in Eq. (*4*) and Table 1).

$$DI_{pop} = (\Delta POP\% - \Delta CE\%)/\Delta POP\% = \left(\frac{POP_1 - POP_0}{POP_0} - \frac{CE_1 - CE_0}{CE_0}\right)\Big/\frac{POP_1 - POP_0}{POP_0} \tag{4}$$

Table 1 Decoupling index and quadrant of the cartesian coordinates (x-axis: changes in GDP or population; y-axis: changes in CO_2 emissions)

	1st quadrant	2nd quadrant	3rd quadrant	4th quadrant
GDP or population	+	-	-	+
CO_2 emissions	+	+	-	-

$DI \leq 0$	No decoupling	n/a	Recessive no decoupling	n/a
$0 < DI \leq 1$	Weak decoupling	n/a	Recessive weak decoupling	n/a
$DI > 1$	n/a	Recessive strong decoupling	n/a	Strong decoupling

Note: we calculate the decoupling index of CO_2 emissions versus GDP and population growth separately. Each city has two decoupling indexes, one is for emissions and economic growth, and the other one is for emissions and population growth.

2.4 Index decomposition analysis

This study employs Index Decomposition Analysis (IDA) [74] to quantify the driving forces of emission changes in cities. Compared to other decomposition models, such as the Structural Decomposition Analysis (SDA) [75], IDA has fewer data requirements and can capture the effects of structural changes in emissions and economy [63, 76, 77]. We decompose the changes in cities' emissions into six drivers based on the Kaya identity [78-80], as shown in Eq. (*5*).

$$
\begin{aligned}
CO_2 &= int_C \times Stru_{en} \times int_{en} \times Stru_{econ} \times Eco \times Pop \\
&= \sum_{ij}\left(\frac{C_{ij}}{En_{ij}} \times \frac{En_{ij}}{En_j} \times \frac{En_j}{GDP_j} \times \frac{GDP_j}{GDP} \times \frac{GDP}{Pop} \times Pop\right)
\end{aligned} \tag{5}
$$

in which,

$int_C = C_{ij}/En_{ij}$ is carbon intensity in sector j and is calculated as emissions per energy use;

$Stru_{en} = En_{ij}/En_j$ is the proportion of energy i (i.e., coal, oil, and gas) in total energy use in each sector and reflects the sectoral energy consumption;

$int_{en} = En_j/GDP_j$ is energy intensity, which is quantified as energy use per GDP;

$Stru_{econ} = GDP_j/GDP$ is sector j's share (i.e., primary, secondary, and tertiary industry) in GDP, which reflects the economic structure;

$Eco = GDP/POP$ is GDP per capita and reflects the economic level;

Pop is the population of the city.

To quantify the contribution of each driver to cities' emissions, we employ the log mean Divisia index method (LMDI) [74], as shown in Eq. (*6*). LMDI has inherent advantages regarding path independence, its ability to handle zero values with no unexplained residual terms, and its consistency in aggregation [81, 82].

$$
\begin{aligned}
&\Delta CO_2 = CO_2^t - CO_2^0 = \Delta C_{int-carbon} + \Delta C_{Stru-energy} + \Delta C_{int-energy} + \\
&\Delta C_{stru-economy} + \Delta C_{economy} + \Delta C_{population}
\end{aligned} \tag{6}
$$

GDP and population of cities are collected from the "China city statistical yearbook" [83]. GDP is adjusted to 2010 constant price based on the deflator of each province [84]. The consumption of different energy types is converted to tons of standard coal equivalent. To match the scope of GDP, we only include the fossil fuel-related emissions from economic sectors (excluding the emissions from household energy use) in the decomposition analysis.

2.5 Limitations and uncertainties

There are some limitations in the method, in particular laying in the accounting of city-level emissions and the index decomposition analysis, and thus lead to uncertainties.

First, there are uncertainties in the city-level emission accounting, mainly caused by the data availability of cities. For example, only 39% of cities published comprehensive data on energy use in their statistical yearbooks in 2014 (i.e., energy balance table, sectoral energy consumption, and data on energy transformation). The remaining 61% of cities only have data on sectoral energy consumption of industry (covering more than 70% of the total energy consumption of a city). For the remainder beyond the industrial energy consumption in the 61% of cities, we use socioeconomic indexes (e.g., population, GDP, and industrial output) to downscale from provincial data based on the assumption that the city has the same per capita household emissions and same emission intensity as the respective province. Despite these uncertainties, this method is still the most accurate approach for cities. Reliable and transparent city-level energy statistics are needed for more accurate emission accounts in the future.

We compared our emissions with a bottom-up study aggregated from enterprise-level point sources [63, 85]. The results show that our total estimates of all the cities are 11% higher than the bottom-up emissions, due to the choice of different sources of activity data and emission factors. However, about one-third of the cities in the two databases have emissions differences of more than 25%. The differences are likely caused by different definitions of city boundaries in the two databases.

Second, our analysis of the emission drivers using the concept of Kaya identity has limitations. Although the concept of Kaya identity is one of the most popular tools used by scholars and the IPCC to examine the drivers of greenhouse gas emissions [86-88] and even to predict future emissions under different scenarios [89, 90], there are shortcomings of potential interaction effects between the driving factors like multicollinearity and endogeneity in regression analysis [91, 92]. Thus, they can only serve as heuristics.

3 Results

3.1 Differences in city emissions

Chinese cities have a huge range of emissions (ranging from 2.12 to 258.71 million tons in the year 2014), per capita emissions (0.58 to 149.41 tons), and emission intensity (0.02 to 1.59

tons per thousand constant 2010 CNY), indicating a huge disparity of cities' emissions as well as their size and level of development (shown in Figure 1).

Figure 1 CO2 emission patterns of cities in 2014. a) total CO2 emissions of cities in million tons; b) per capita emissions in tons; c) emission intensity in tons per thousand constant 2010 CNY. Darker shaded cities have higher values. Considering the data availability, we use the emissions in 2014 to show the patterns of cities. The year 2014 has the largest data points of 252 cities. We assume that the differences in emission patterns of the cities keep unchanged for the short time period.

The top ten cities in total emissions (as shown in Figure 2) are either megacities due to the large size of the economy and high consumption (e.g., Shanghai and Nanjing in Jiangsu) [93, 94] or energy-intensive manufacturing cities (e.g., Tangshan in Hebei and Yulin in Shaanxi). In contrast, the bottom-ranked cities (namely, Huangshan in Anhui, Ganzi in Sichuan, Greater Khingan in Heilongjiang, Wuzhou in Guangxi, and Hechi in Guangxi) have relatively small economies with a low level of industrialization. The top ten cities contribute 18.2% of the 252 cities' total emissions in 2014, with 8.5% of the total population and 15.3% of GDP, while the bottom half or 126 cities emitted 19.0% of total emissions with 41.5% of the population and 24.7% of GDP. Such inequality in cities' emissions provides us with substantial room for emission reduction when focusing on those super-emitting cities and sectors [31].

The heterogeneity of cities' carbon emissions is a reflection of differences in the structure of energy and economy. Although coal is dominating cities' emissions (on average rising from 70.3% in 2000 to 75.4% in 2007, then declining to 67.0% in 2019), the share of coal-related emissions ranges from 0.51% in Haikou (a tourism city in Hainan) to 97.3% in Shizuishan (a coal mining city in Ningxia). Natural gas's proportion in cities' total emissions ranges from 0.0% (Hechi in Guangxi) to 39.8% (Zhongshan in Guangdong), with an average proportion rising from 1.3% (2000) to 5.8% (2019). Energy-production and heavy manufacturing sectors are the major sources of emissions, accounting for respectively 40.9% (ranging from 0% to 92.6%) and 36.8% (0.3% to 92.4%) on average in 2014. Service sectors emit another 10.2% of emissions, followed by household energy use (4.8%), light manufacturing (4.1%), agriculture and construction (2.5%), and high-tech manufacturing (0.7%).

Figure 2 Structure of emissions in the top ten cities, 2014. a) CO2 emissions by energy type in million tons; b) CO2 emissions by economic sectors in million tons. Similar to Figure 1, we use the emissions in 2014 to show the structure of the top ten cities.

3.2 Emission peak in cities

With the slowdown of emission growth at the national level [80], some cities also declined their emissions or entered a plateau phase. Figure 3 shows that of the 218 cities with more than 12 years of observations of emission inventories, 59 (27.1%) cities have declined their emissions (i.e., emissions declined for more than five years). 20 (9.2%) cities are at a plateau phase in terms of emissions (i.e., emissions declined for more than five years but might rebound to a higher level afterward). The remaining 139 (63.8%) cities are still increasing their emissions or reduced emissions temporarily for less than five years.

Figure 3 Emission peak of cities.

The emission decline has been observed not only in developed and highly industrialized regions (e.g., Beijing and Shanghai), but also in rural and laggard regions (e.g., Zhangye in Gansu), energy-producing cities (e.g., Fuxin in Liaoning and Shuangyashan in Heilongjiang), and manufacturing cities (e.g., Changchun in Jilin and Shenyang in Liaoning). That is to say, cities could peak their emissions with any level of development and with any structure of economy or energy.

Although 59 cities have declined their emissions, the reasons could differ. Some cities peaked emissions on their own initiative by actively reducing their emission intensities (e.g., improving the structure of energy and sectors, improving production and energy efficiency). Those proactively peaked cities have decoupled economic and population growth from emissions. In other words, their emissions decreased while the economy and the population kept growing. In contrast, some cities reduced emissions due to factors such as economic recession or population loss [95]. In this case, these passively emission declined cities show a coupling between their emissions and economic level, and population.

We calculate the degree of decoupling of CO_2 emissions versus GDP and population in cities (shown in Figure 4). If both the GDP and population of a city are strongly decoupled from its emissions after the peak, the city is defined as a proactively peaked city (located in the fourth quadrant of the cartesian coordinates). Otherwise, if either GDP or the population of a city is not strongly decoupled from emissions, it is defined as a passively emission declined city, rather than an emission peaked city.

The results show that among the 59 cities that have achieved emission decline, 38 cities (defined as proactively peaked cities) have strongly decoupled both GDP and population from emissions after the emission peak (shown as cities in the 4th quadrant). Four cities (Shenyang, Hohhot, Fuxin, and Mudanjiang) that had declining GDP after the emission maximum year, are in the recessive 3rd quadrant of Figure 4-a. They are, therefore, defined as passively emission declined cities in terms of the economic dimension. Meanwhile, 19 cities are passively emission declined ones in terms of the dimension of population. Fuxin (a coal mining city in Liaoning) is an example of a passively emission declined city in terms of both economic and population dimensions. The emissions in Fuxin peaked in 2011 at 35.49 million tons and then kept decreasing to 19.90 million tons in 2016 (-10.9% per year on average). Meanwhile, GDP and population in Fuxin also decreased by 12.0% (from 45.0 to 39.6 billion CNY) and 1.6% (from 1.92 to 1.89 million people), respectively.

Figure 4 Decoupling of CO2 emissions and economic growth (a) and population growth (b) for cities. For cities that have declined their emissions, the decoupling indexes are calculated from the peak year to *the most recent inventory year. For cities at the plateau stage and non-declined cities, the decoupling indexes are calculated based on the most recent five years period.*

3.3 Emission drivers for proactively peaked and passively emission declined cities

Figure 5 shows the contribution of key emission drivers in 59 cities that have declined emissions, including both proactively peaked and passively emission declined cities. Generally speaking, the economic level is the major driver to increase emissions with a median contribution of 167% of all emission declined cities. Population is the second major driver with a median contribution of 7%. A decrease in energy intensity is the major driver for emission reduction in cities (a median of -197%). The decline in the share of the secondary industry (a median of -77%) and coal consumption (a median of -10%) are the other two factors that reduce cities' emissions. Other drivers play minor roles to increase emissions.

We find that the effects of drivers vary widely across cities, especially between the proactively peaked and passively emission declined cities (as shown in Figure 5-b to k). For example, the median decreasing effect of energy intensity on emissions in proactively peaked cities is 217%, which is much stronger than that (97%) in passively emission declined cities. Similarly, proactively peaked cities show a larger decline in the share of coal in the energy mix (a median of 22%) than passively emission declined cities (a median of 4%). What's more, the economy and population in all proactively peaked cities are increasing. But in some passively emission declined cities, the economy and population contributed to a decline in emissions due to a recessive economy and shrinking population. Therefore, proactively peaked cities reduced their emissions via efforts such as reducing coal consumption and energy intensity whereas the emission decline in passively emission declined cities was to a large extent the result of an economic recession and population decline.

Figure 5 Boxplots of emission drivers of cities that have declined emissions. Subfigure a) shows the contributions of drivers in all emission declined cities; subfigures b-k) show the differences of drivers between proactively peaked cities and passively emission declined cities.

We use Beijing, Taizhou (Zhejiang), Fuxin (Liaoning), and Shenyang (Liaoning) as representative cities to show the detailed role of emission drivers in different types of cities (shown in Figure 6). Beijing and Taizhou peaked emissions proactively, while Fuxin and Shenyang are cases of passively emission declined cities.

The decline in carbon and energy intensity in Beijing led to a decline of 0.8 and 35.7 million tons of emissions (2010-2019), respectively, while economic and population growth increased emissions by 46.1 million tons in total. Such a decline in carbon and energy intensity reflects the improvement of production and energy efficiency. The structural change in energy use and composition of sectors also contribute another 13.7 and 11.4 million tons of emission decline from 2010 to 2019. Those decreasing effects more than offset increased emissions from economic and population growth during these periods. Similarly, Taizhou's energy intensity decreased its emissions by 37.3 million tons after the emission peak, which offset the total emission increase from economic (21.8 million tons) and population growth (1.5 million tons). These cities have thus achieved a strong decoupling of emissions and economic growth and embarked on the path toward low-carbon development.

As for passively emission declined examples, Fuxin's population shrank from 192.1 in 2011 to 189.0 thousand in 2016 and thus contributes to a decline of 0.4 million tons in the city (or 3%). We also notice that the shrinkage in Fuxin's secondary industry decreased the city's emissions by another 12.1 million tons. The reason is that Fuxin is gradually losing its pillar industry (i.e., coal mining and production), due to the exhaustion of coal resources. Fuxin had to shut down a large number of coal mining enterprises and started an economic transformation since 2001. The share of the coal industry in Fuxin's industrial output has dropped from 32.4% in 2001 to 2.3% in 2021. Meanwhile, the effect of energy intensity only decreased the city's emissions by 0.7 million tons (or 4%). This declining model, based on exhausted coal resources, can serve as an example of the difficulties in cities and sectors that transition away from fossil fuels. Shenyang is another representative case of passively emission declined cities. It suffered a serious economic recession from 2014 to 2019 (per capita GDP decreased from 92.9 to 79.1 thousand CNY), which reduced the emissions by 10.1 million tons. Similar to Fuxin, the economic recession in Shenyang is also caused by a sharp loss in pillar industries. Shenyang is a typical old industrial base in Northeast China from the last century. However, the share of its secondary industry decreased by 12.1% from 2014 to 2019, thus contributing to 19.6 million tons of emission reduction.

Figure 6 Emission drivers of representative cities that have achieved emission decline. The representative time points for each city are chosen as the year emission peaked and the latest year with available data. Coal%, Oil%, and Gas% reflect the effect of changes in the energy mix; primary%, secondary%, and tertiary% reflect the effects of structural change in industries; c-int is the carbon intensity (CO_2 emissions per unit of energy use); e-int is the energy intensity (energy use per GDP); eco stands for economic level, which is quantified by GDP per capita; pop is population, which reflects the size of the city.

4 Discussion and conclusion

This study provides the most comprehensive emission inventories of 287 Chinese cities from 2001 to 2019. Cities show huge inequality in emissions, GDP, and population. We then investigate the state of emission peak in each city and reveal the hidden driving forces. 59 cities have declined their emissions for at least five years, 38 of them peaked the emissions proactively and 21 cities reduced emissions passively with a recessionary economy or population loss.

Our study shows that, first, 287 Chinese cities have huge heterogeneity in the structure of energy and economy, emission patterns, and the phase of emission peak. Therefore, instead of using a one-size-fits-all approach, the emission targets of cities need to be set individually considering cities' resource endowment, industrialization level, socio-economic characteristics, and development goals. Super-emitting cities with laggard technologies and production efficiency should develop stringent policies and targets for emission reduction [31], while less developed regions could have more emission space for economic development.

Second, the experiences and lessons learned from the 59 emission declined cities can be used as benchmarks for other cities. In general, economic level and population growth are two key drivers of increasing CO_2 emissions, while declining shares of secondary sectors and coal consumption considerably contribute to emission reductions. However, the impact of emission drivers varies considerably among these cities, especially for the proactively peaked and passively emission declined cities. The decreasing effects of energy intensity and the coal share in the energy mix contribute largely to the emission reduction of proactively peaked cities. In this way, these cities successfully reduced their emissions without harm to their economy. We suggest that these proactively peaked cities should take the leading role in achieving the emission reduction faster and set precedents for China to fully realize the Dual-Carbon goals (i.e., achieving carbon emission peak by 2030 and carbon neutrality by 2060). By doing so, these proactively peaked cities could create more space for less-developed regions. In contrast, passively emission declined cities need to face up to the fact that the emission decline is mainly caused by a recessive economy, exhausted natural resources, insufficient competitiveness of industry, or even shrinking population, rather than by vigorously promoting low-carbon actions. These passively emission declined cities need to fully exploit the opportunities and financial budget/investment brought by the Dual-Carbon goals (e.g., reducing carbon and energy intensity or achieving economic structural transition through industrial innovation and green investment).

In this context, local authorities can borrow the concept of the common but differentiated principle of global climate change mitigation, also applied in the Intended Nationally Determined Contributions (INDCs), and formulate a bottom-up mitigation framework in combination with an eco-compensation mechanism that allows for payments from highly resource-consuming regions to less-consuming regions reflecting their diverse development and emission conditions. All participants who submit Intended Regionally Determined Contributions to emission reduction should establish clear verification mechanisms, detailed timelines, and implementation routes, which should be supervised by multi-level governments and third-party organizations.

Conflict of interest statement

The authors declare that they have no conflict of interest.

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Author contributions

Yuli Shan led the study and drafted the manuscript with inputs from Dabo Guan and Klaus Hubacek. Yuru Guan and Yuli Shan prepared the data (emission inventories of cities) with inputs from Jiashuo Li, Ya Zhou, and Li Li. Ye Hang, Heran Zheng, and Yanxian Li revised the draft.

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Electronic appendix & Data availability

Supplementary data (the emissions of all cities) are available at Science Bulletin online. The data has also been uploaded to CEADs - Carbon Emission Accounts and Datasets for emerging economies (www.ceads.net) for free download.

Figures

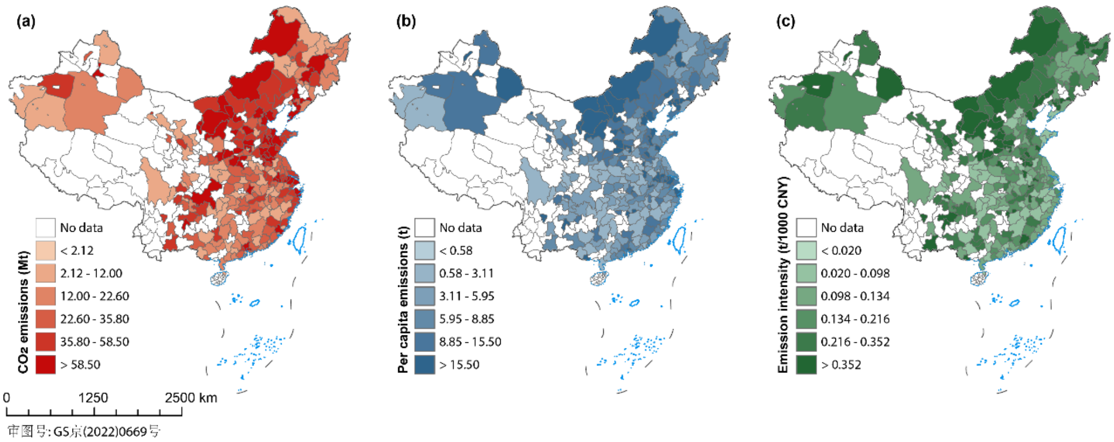

Figure 1 CO_2 emission patterns of cities in 2014. a) total CO_2 emissions of cities in million tons; b) per capita emissions in tons; c) emission intensity in tons per thousand constant 2010 CNY. Darker shaded cities have higher values. Considering the data availability, we use the emissions in 2014 to show the patterns of cities. The year 2014 has the largest data points of 252 cities. We assume that the differences in emission patterns of the cities keep unchanged for the short time period.

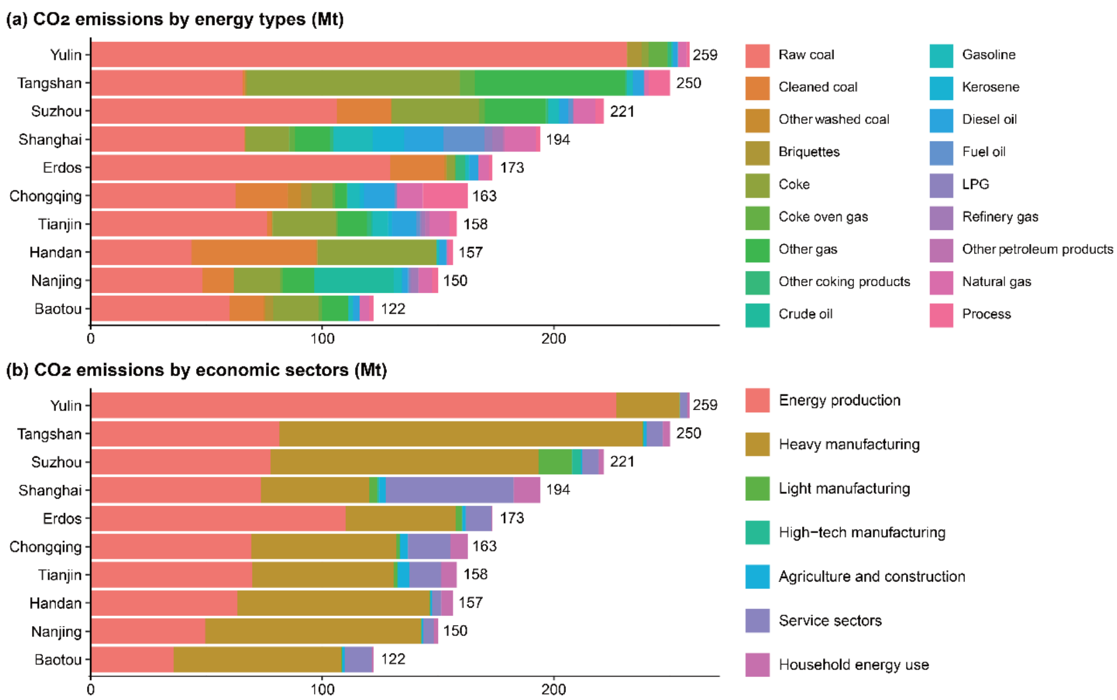

Figure 2 Structure of emissions in the top ten cities, 2014. a) CO_2 emissions by energy type in million tons; b) CO_2 emissions by economic sectors in million tons. Similar to Figure 1, we use the emissions in 2014 to show the structure of the top ten cities.

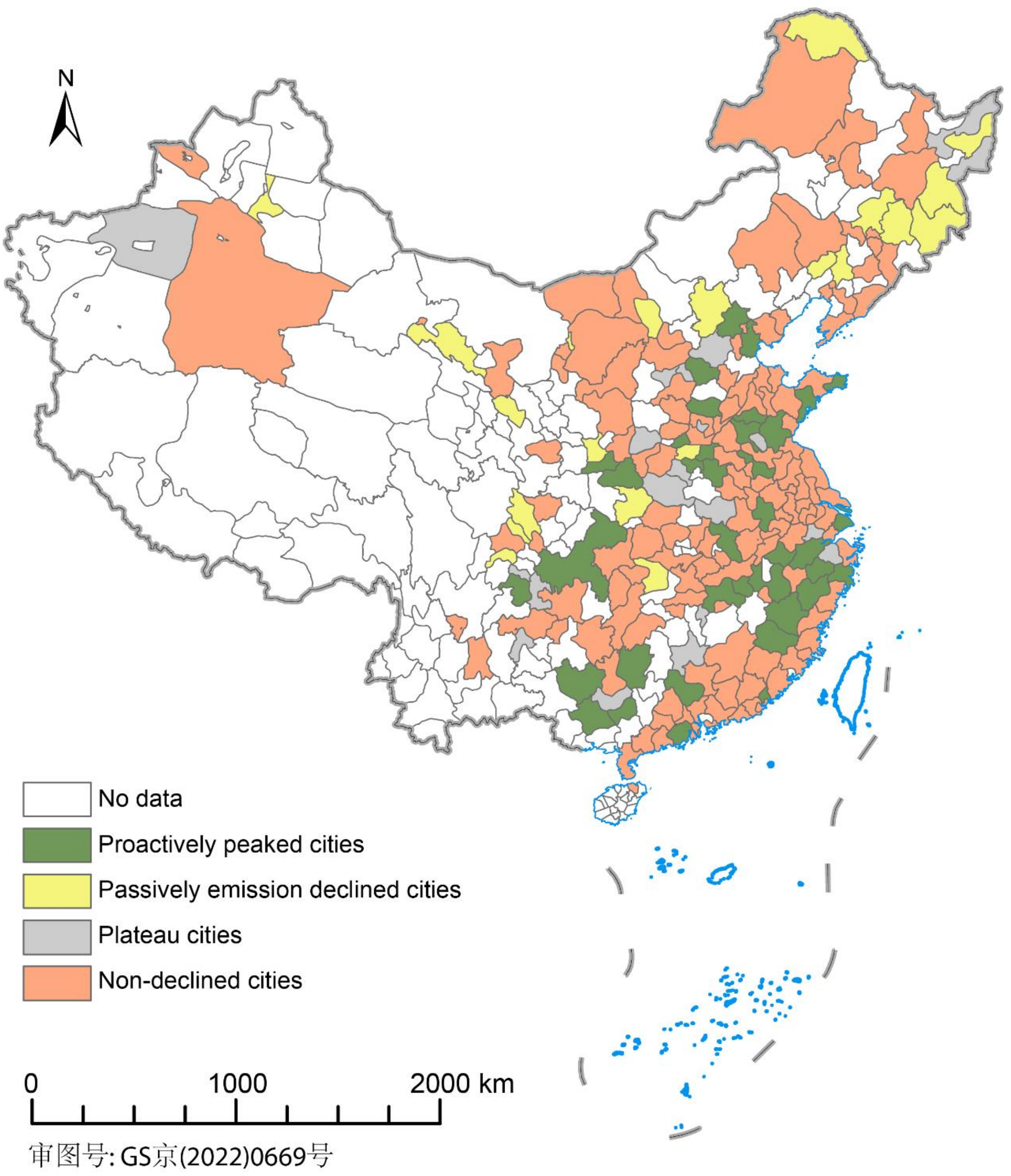

Figure 3 Emission peak of cities.

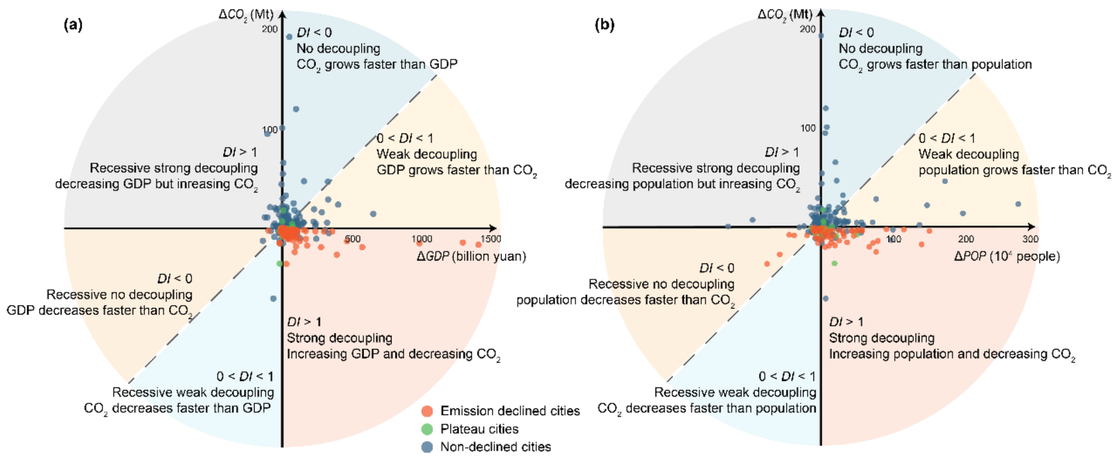

Figure 4 Decoupling of CO_2 emissions and economic growth (a) and population growth (b) for cities. For cities that have declined their emissions, the decoupling indexes are calculated from the peak year to the most recent inventory year. For cities at the plateau stage and non-declined cities, the decoupling indexes are calculated based on the most recent five years period.

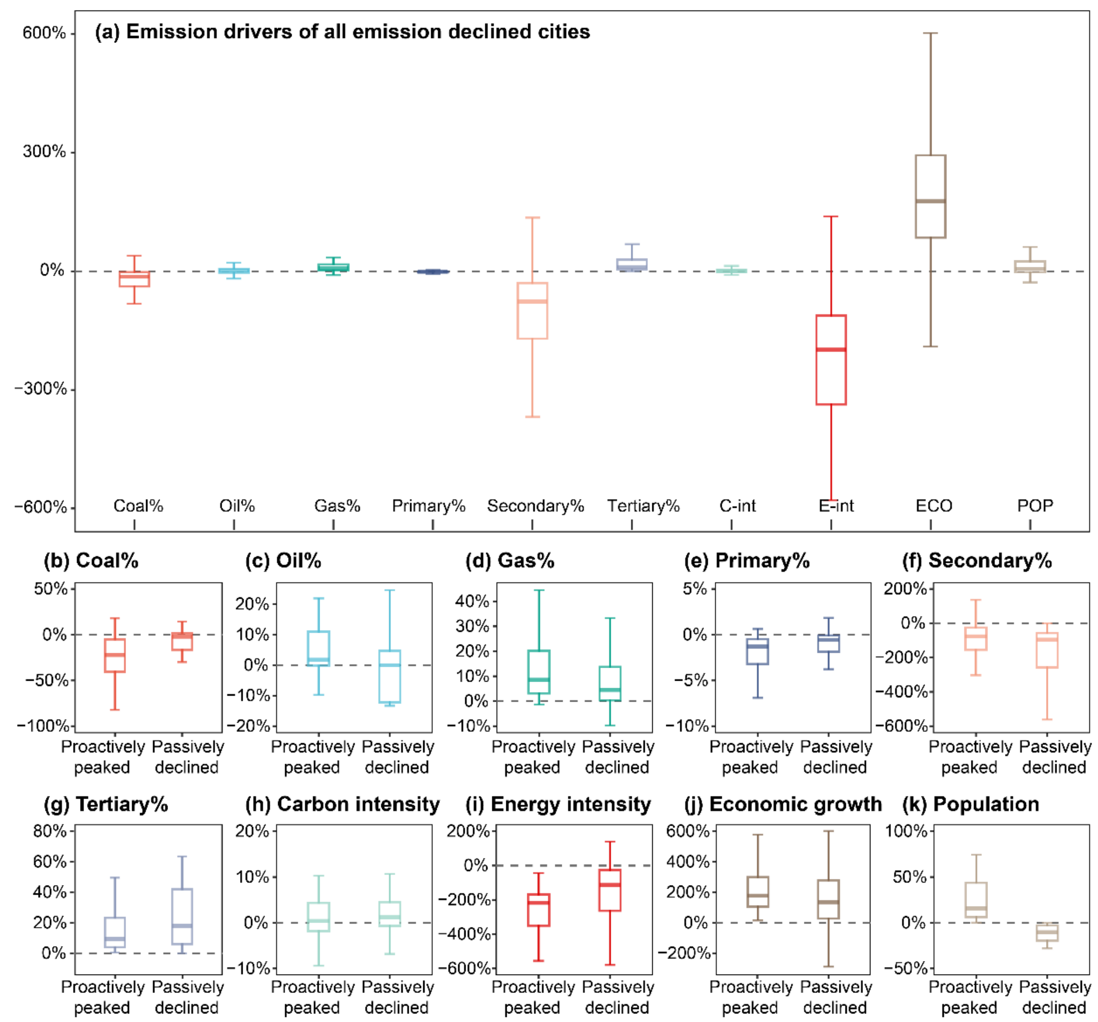

Figure 5 Boxplots of emission drivers of cities that have declined emissions. Subfigure a) shows the

contributions of drivers in all emission declined cities; subfigures b-k) show the differences of drivers between proactively peaked cities and passively emission declined cities.

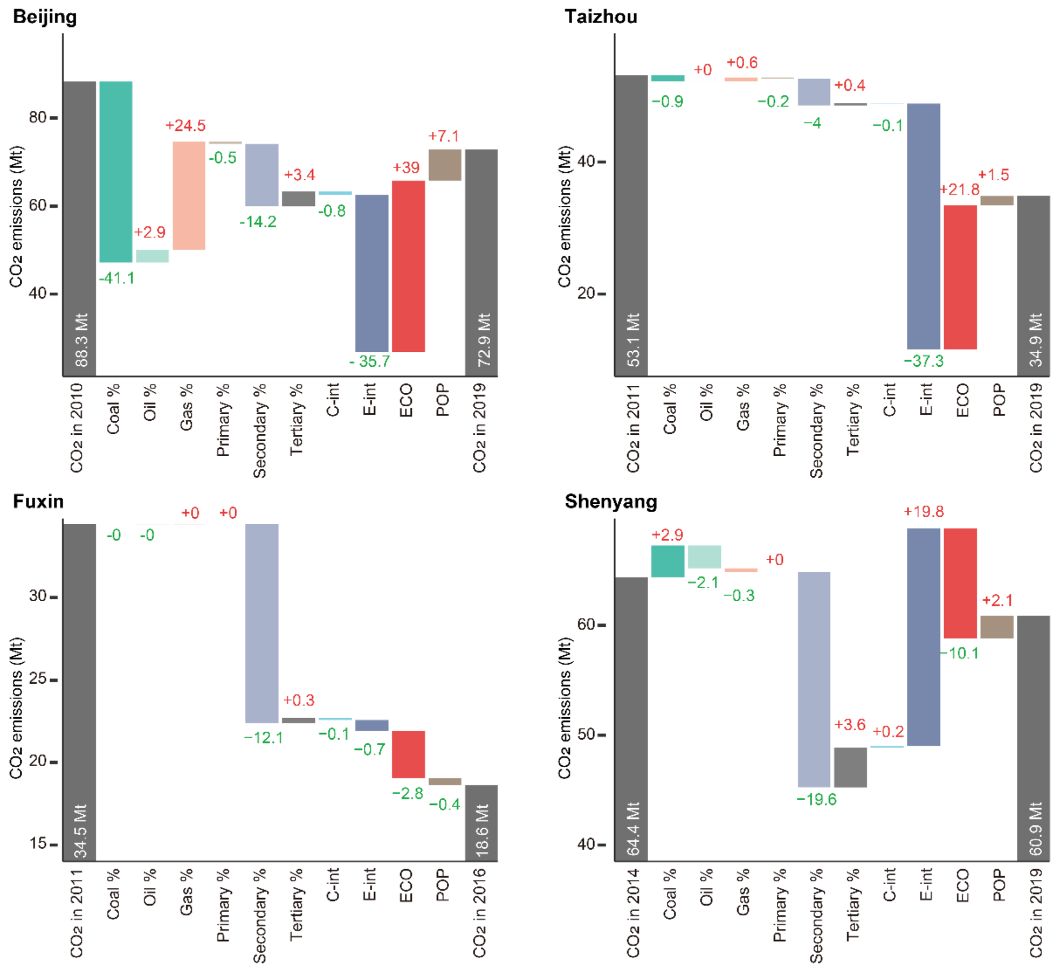

Figure 6 Emission drivers of representative cities that have achieved emission decline. The representative time points for each city are chosen as the year emission peaked and the latest year with available data. Coal%, Oil%, and Gas% reflect the effect of changes in the energy mix; primary%, secondary%, and tertiary% reflect the effects of structural change in industries; c-int is the carbon intensity (CO_2 emissions per unit of energy use); e-int is the energy intensity (energy use per GDP); eco stands for economic level, which is quantified by GDP per capita; pop is population, which reflects the size of the city.