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DOI:
10.1016/j.oneear.2020.12.004

One Earth

Article

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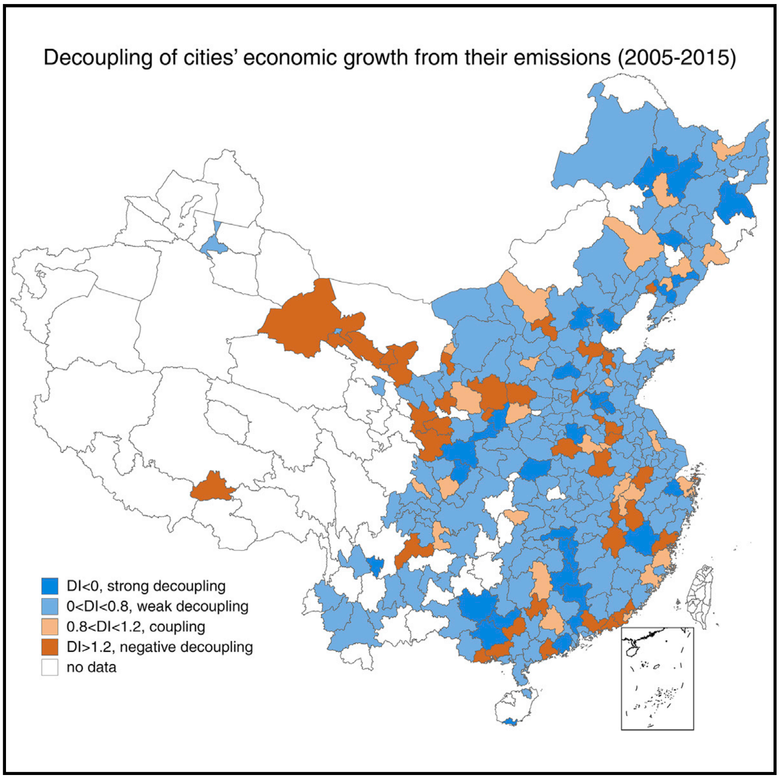
Graphical abstract



Highlights

- 11% of Chinese cities achieved strong decoupling of GDP from CO_2 from 2005 to 2015
- 65.6% of the cities achieved weak decoupling
- A city-level inverted-U relationship (or EKC) between CO_2 and GDP is weakly confirmed
- Decline in emission intensity via efficiency gains is vital to achieving decoupling

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In brief

This study presents emission inventories of 294 Chinese cities and examines the extent to which economic growth has decoupled from emissions from 2005 to 2015. We further explored the driving forces of cities' emission-GDP decoupling and conclude that improvement in production and carbon efficiency is the most important driver. The emission-GDP decoupling lessons in China may have significant implications for other developing and fast-growing economies in pursuit of low-carbon development.

Shan et al., 2021, One Earth *4*, 124–134
January 22, 2021
https://doi.org/10.1016/j.oneear.2020.12.004

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Chinese cities exhibit varying degrees of decoupling of economic growth and CO_2 emissions between 2005 and 2015

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https://doi.org/10.1016/j.oneear.2020.12.004

SCIENCE FOR SOCIETY Cities contribute to over 80% of global gross domestic product (GDP) and account for at least 75% of global CO_2 emissions. As such, they are well placed to lead climate change mitigation efforts. Decoupling economic growth from emissions is key to low-carbon development, particularly in fast-growing countries, such as China. In this work, we estimated CO_2 emissions for 294 Chinese cities and examined the extent to which economic development is decoupled from emissions. Results show that 11% of the cities have negative emission growth between 2005 and 2015, whereas their economy continued to grow (i.e., strong decoupling). A total of 65.6% of cities exhibit slower growth of emissions than economic growth (i.e., weak decoupling). We find that decline in emission intensity via improvement in production and energy use efficiency is the most important driver that leads to a decoupled economy. Other developing economies could learn from China's experience in emission-GDP decoupling to design their own low-carbon development pathways.

SUMMARY

Cities, contributing more than 75% of global carbon emissions, are at the heart of climate change mitigation. Given cities' heterogeneity, they need specific low-carbon roadmaps instead of one-size-fits-all approaches. Here, we present the most detailed and up-to-date accounts of CO_2 emissions for 294 cities in China and examine the extent to which their economic growth was decoupled from emissions. Results show that from 2005 to 2015, only 11% of cities exhibited strong decoupling, whereas 65.6% showed weak decoupling, and 23.4% showed no decoupling. We attribute the economic-emission decoupling in cities to several socio-economic factors (i.e., structure and size of the economy, emission intensity, and population size) and find that the decline in emission intensity via improvement in production and carbon efficiency (e.g., decarbonizing the energy mix via building a renewable energy system) is the most important one. The experience and status quo of carbon emissions and emission-GDP (gross domestic product) decoupling in Chinese cities may have implications for other developing economies to design low-carbon development pathways.

INTRODUCTION

With the accelerating climate emergency, decision makers need specific sub-national information on sources of carbon emissions, reduction potentials, and effectiveness of mitigation measures. Cities are emissions and development hotspots given that urban economic activity accounts for 80% of global gross domestic product (GDP), 60%–80% of energy consumption, and 75% of carbon emissions.[1–3] Most global population growth in the next couple of decades is estimated to take place in urban areas in developing countries.[4] Given higher per capita emissions of urban populations due to higher income and urban lifestyles,[5,6] achieving low-carbon development in cities is of great significance to global climate change mitigation.

A city's emission growth is usually closely coupled with its GDP;[7] however, some cities have shown a decoupling of GDP from emission growth (i.e., GDP growing faster than emissions).[8] At this moment, such decoupling is only examined in high-income cities in China, such as Beijing, Shanghai, Chongqing, and Guangzhou, as a result of data limitations.[9,10] Given that China is the largest emitter and one of the fastest growing countries in the world with numerous cities and huge regional heterogeneity in terms of economic development, size, and structure, the patterns of decoupling should be studied with as many cities as possible.

Previous studies on the decoupling of emissions and economic growth in Chinese cities encountered several challenges and mainly focused on the accounting of emissions. First, most studies adopted a top-down approach that downscales national or provincial emissions to the city level by using socioeconomic indexes.[11,12] The top-down approach assumes that cities have characteristics similar to those of their larger administrative unit at which data are available, assuming similar economic structure, energy mix, lifestyles, or climatic conditions.[13] These are strong assumptions potentially leading to inaccurate estimates of emissions. Second, most studies only calculated urban emissions for a particular time point rather than for a longer time span,[14] which makes it difficult to observe changes and understand underlying mechanisms. Third, existing accounts of emissions of cities use different methods, system boundaries, and data sources, making them incomparable with each other.[15]

This study overcomes these challenges by compiling an extensive emission dataset for 294 Chinese prefecture-level cities for the years 2005, 2010, and 2015. These cities covered 54.9% of China's territory and 94.4% of the population, and their GDP and emissions accounted for 99.4%[16] and 95.4%[17] of the national values in 2015, respectively. We estimated the emissions by using a bottom-up approach that aggregates the emissions of all enterprises and industrial factories to the corresponding city. We calculated both scope 1 emissions from fossil fuel combustion and industrial processes and scope 2 emissions from net imports of electricity (see experimental procedures).

We then examined the extent of decoupling of economic growth and CO_2 emissions in each city with the Tapio decoupling index (DI)[18] and compared the decoupling degree of cities with their economic development stage and structure. We then investigated and compared the drivers of emission change and the degree of decoupling for cities. Finally, we simulated four scenarios of different declines in emission intensity to show the potential decoupling of economic development and CO_2 emissions in Chinese cities.

Our study provides baselines and quantitative evidence for the reduction of emissions in Chinese cities with the degree of decoupling over time. Given that Chinese cities are at different phases of industrialization and urbanization from the east to the west of China, what Chinese cities are experiencing is informative for efforts to reduce emissions in other developing and transition economies and is thus of significance to global emission reduction.

RESULTS

Emissions patterns in cities

Scope 1 emissions of cities, shown in Figure 1, increased by 41.7% from 6,248 million metric tons (mt) in 2005 to 8,855 mt in 2010 and then by another 16.5% to 10,315 mt in 2015. Per capita emissions show similar trends. Average per capita emissions of 294 cities increased by 35.2% from 5.3 metric tons (t) in 2005 to 7.1 t in 2010 and by another 11.9% to 8.0 t in 2015.

Despite the rapid growth of scope 1 emissions, emission intensities (emissions per unit of GDP) of cities show a downward trend over the same time period from 3.2 t per 1,000 yuan on average in 2005 to 2.5 in 2010 and then a further decline to 1.8 in 2015. The average emission intensity in 2015 was 44.2% lower than the 2005 level, indicating that China has fulfilled its commitments to the Paris Agreement of reducing its emission intensity by 40%–45% of the 2005 level by 2020 cahead of schedule, and before even signing the agreement. The decline in emission intensity implies that cities' GDP was growing faster than their emissions. The total GDP of cities was 19,410 billion yuan in 2005, 36,114 in 2010 (+86% from 2005, at a 2005 constant price level), and 57,390 in 2015 (+59% from 2010, in 2005 at a constant price level). City GDP grew twice as fast as emissions between 2005 and 2010 and 3.5 times as fast from 2010 to 2015.

In terms of emission structure, secondary sectors (such as manufacturing, energy production and supply, and construction) were the most important source of scope 1 emissions by contributing from 78.3% (in 2015) to 83.3% (in 2010) of total emissions. There was an increasing trend of emissions in the tertiary sector (1.0% in 2005, 0.9% in 2010, and 2.8% in 2015) and transport (5.7% in 2005, 6.0% in 2010, and 7.3% in 2015), indicating an expansion of the service sectors and inter-city travel in China.

Scope 2 emissions from imported electricity for cities are shown in Figure 2. A total of 188 cities were net importers of electricity in 2015 (shown in red), and the remaining 152 cities were net exporters (shown in blue). Total scope 2 emissions in net-importing cities almost doubled from 397 mt in 2005 to 779 mt in 2010 and further increased to 1,085 mt in 2015, which accounted for 13.5% in 2005, 13.2% in 2010, and 15.2% in 2015 of the cities' combined scope 1 and scope 2 emissions.

Cities and their emissions show considerable regional heterogeneity, including differences in the degree of urbanization and size and structure of the economy.[19,20] Generally, richer cities have higher per capita emissions. The Spearman correlation coefficient between per capita GDP and per capita emissions was 0.584 at a significance level of 99%. The top 10% cities in terms of per capita GDP contributed 32.9% of the national GDP and emitted 18.8% of China's territorial emissions in 2015, while the bottom 10% cities contributed only 4.1% of the GDP and 4.3% of emissions.

Average per capita emissions and emission intensity of the capital region (Beijing, Tianjin, Hebei, and Shandong) were 10.1 and 0.2 t per 1,000 yuan in 2015, and those of the Yangtze river delta (Shanghai, Jiangsu, and Zhejiang) were 9.6 and 1.2 t, respectively. Regions with an energy-intensive economic structure also had high emissions, such as Shanxi-Shaanxi-Inner Mongolia (16.6 t per capita and 0.42 t per 1,000 yuan in 2015).

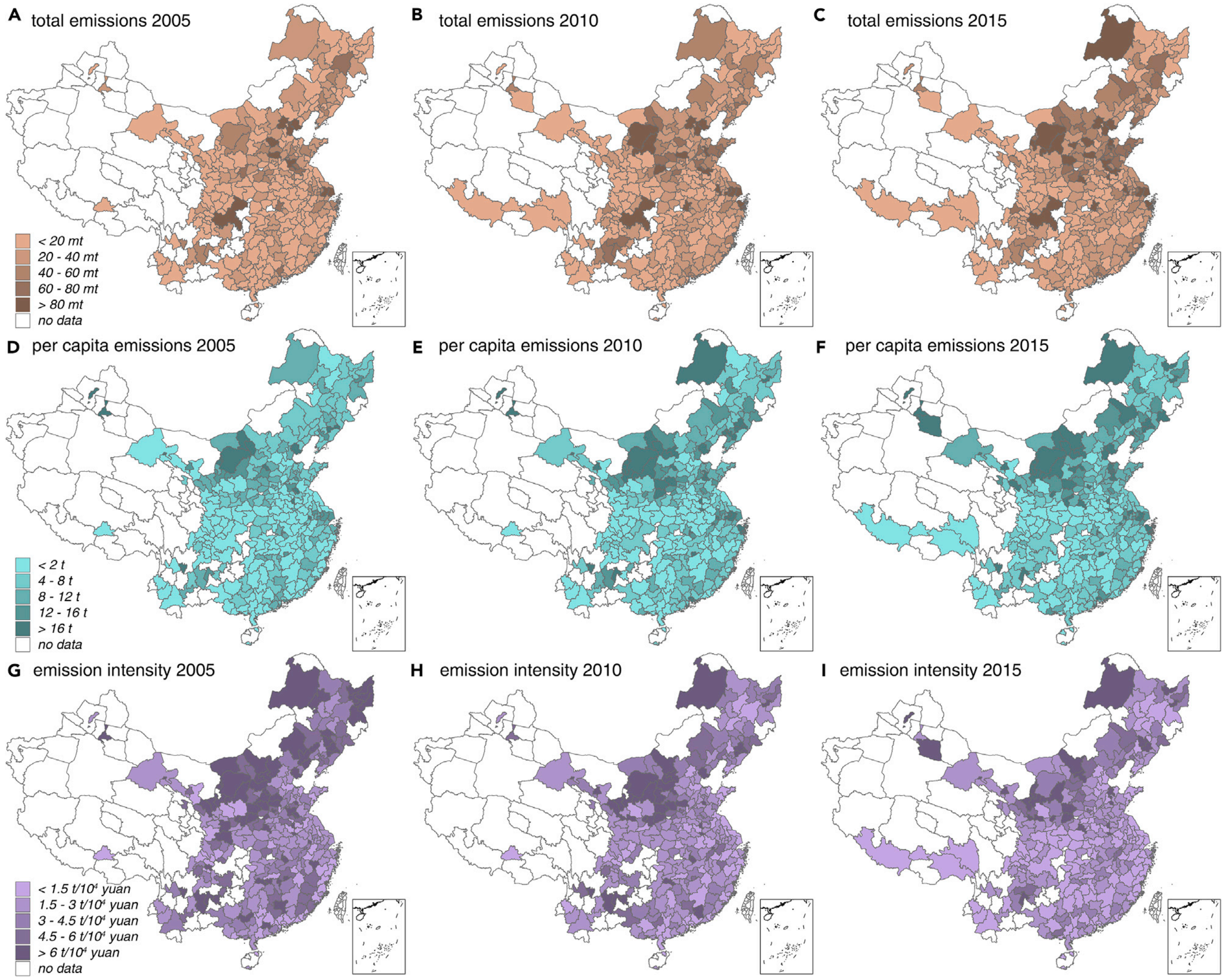

Figure 1. Scope 1 emissions of cities
(A–C) Scope 1 emissions of cities.
(D–F) Per capita emissions.
(G–I) Emission intensity.
The dataset covers 286 cities in 2005, 293 cities in 2010, and 294 cities in 2015 as a result of changes in administrative divisions.[16]

Shanxi-Shaanxi-Inner Mongolia contributed 68.9% (or 2.4 billion t) of China's total coal production in 2018,[21] and coal mining was the largest part of its cities' industrial output (e.g., 80.8% of Yangquan city's GDP in 2015).

Decoupling of economic growth and emissions

Despite the fact that China has weakly decoupled its economic growth from carbon emissions at the national level (China's DI was 0.55, indicating weak decoupling between 2005 and 2015), decoupling analysis at the city level is still lacking and may provide more important information on how the development of cities contributed to national decoupling trends. We calculated the DIs for each city over the period of 2005–2015.[18] Cities are grouped into four categories with different degrees of decoupling: strong decoupling (DI < 0), weak decoupling (0 < DI < 0.8), coupling (0.8 < DI < 1.2), and negative decoupling (DI > 1.2) (see also Table S1 and the experimental procedures). We included 282 cities in the decoupling analysis dependent on the availability of consistent emissions and economic data for the period from 2005 to 2015.

Figure 3A shows that a number of cities have strongly or weakly decoupled their economic growth from emissions from 2005 to 2015, accounting for 11.0% or 65.6% of all cities in China, respectively. If we separate the period of 2005–2015 into two (as shown in Figures 3B and 3C), we find that more cities achieved decoupling of economic growth and carbon emissions during 2010–2015 than during 2005–2010. Between 2005 and 2010, 46 (or 16.3%) cities had strongly decoupled, and the number increased to 79 (or 28.0%) between 2010 and 2015. The number of cities that showed a tight link between economic and emission growth decreased from 33 (or 11.7%) between 2005 and 2010 to 31 (or 11.0%) between 2010 and 2015, and the number of negatively decoupled cities declined from 68 (or 24.1%) to 51 (or 18.1%).

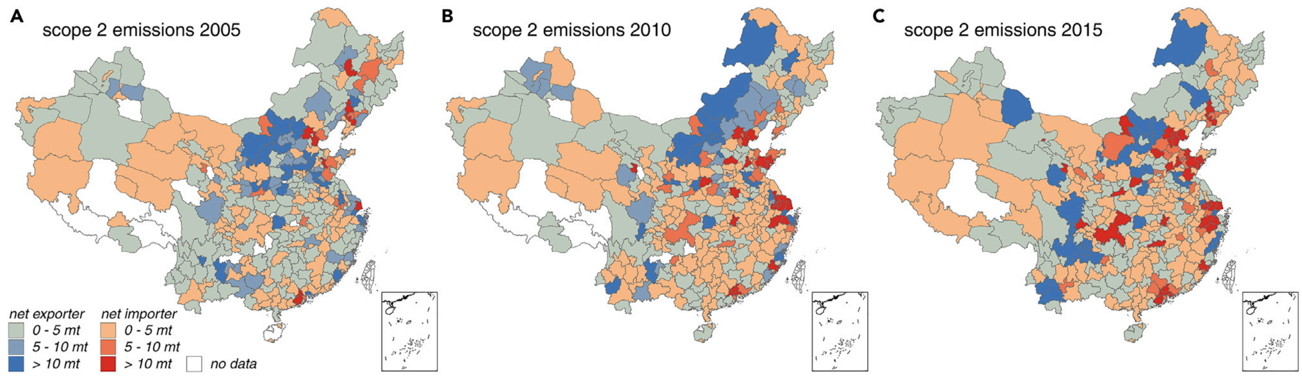

Figure 2. Scope 2 emissions of cities

Scope 2 emissions of cities in 2005, 2010, and 2015. More cities are covered than the estimates of scope 1 emissions because data on net-imported consumption of electricity cover more areas geographically than scope 1 data.

Cities' DI values had a weak negative correlation with their per capita GDP in 2015 (with a correlation coefficient of −0.109 at a significance level of 10%) but a positive correlation with their per capita emissions (with a correlation coefficient of 0.117 at a significance level of 5%) and emission intensity (with a correlation coefficient of 0.214 at a significance level of 1%), indicating that cities with a higher degree of decoupling tend to have higher per capita GDP but lower per capita emissions and emission intensity. For example, the average per capita GDP of strongly decoupled cities in 2015 was 52,200 yuan, whereas the average per capita GDP of weakly decoupled, coupled, and negatively decoupled cities was 47,2000, 40,200, and 24,300 yuan, respectively. Meanwhile, the average per capita CO_2 of strongly decoupled, weakly decoupled, coupled, and negatively decoupled cities was 6.0, 7.7, 10.1, and 8.4 t, respectively. Thus, rich cities tend to be more likely to achieve decoupling of economic growth and emissions. This finding is in line with the environmental Kuznets curve (EKC) hypothesis that assumes that per capita emissions of an economy will first increase and then decrease with increasing growth of per capita GDP.[22–24] Our empirical result weakly confirms such an ''inverted-U curve'' relationship for Chinese cities, as shown in Figure 4 (see the experimental procedures for more details).

There is little correlation between cities' degree of decoupling and their economic structure. We grouped the cities into five categories characterized by their dominating economic sector (i.e., industry with the largest share of GDP): energy production, heavy manufacturing, light manufacturing, high-tech manufacturing, and service sectors.[19] A statistical test of group means (t test results displayed in Table S2) indicates that, apart from cities dominated by the service economy (which have a relatively higher extent of decoupling), there is no significant difference in the average degree of decoupling of cities dominated by energy production, heavy manufacturing, light manufacturing, and high-tech industry, respectively. The message is that cities could achieve decoupled economic growth from emissions with any economic structure, even for cities dominated by the extraction of highly polluting natural resources. Thus, it is not necessary for every city to pursue service-oriented structural transformation. Moreover, there is the real danger that mitigation based on outsourcing of polluting industries (potentially to places with less-efficient technologies and less-stringent environmental policies) can lead to a backfire effect with overall increasing emissions at the national level.[25]

Drivers of cities' emissions and extent of decoupling

We decompose each city's CO_2 emissions into four factors (economic structure, emission intensity, per capita GDP, and population) to quantify the effects of economic restructuring, improvement of carbon efficiency (i.e., productivity and energy mix), economic growth, and population growth on a city's emissions as well as its extent of decoupling. Figure 5 shows the average contributing effects of the drivers in four city categories. Detailed results of each city are presented in Tables S3–S8.

While decline in emission intensity (improvement in production and energy use efficiency) was shown to be the most important driver for carbon emission reduction, it should be pointed out that economic growth could lead to increased emissions and counteract decoupling efforts. That is, between 2005 and 2015, for cities that experienced strong decoupling, the reduction in emissions led by efficiency improvement could still surpass the emission surge due to economic growth. However, for weakly decoupling cities, the increase in carbon efficiency only offset 76.2% of emission growth in the presence of economic growth.

Economic restructuring toward less energy-intensive manufacturing could reduce emissions and DI, but its reduction effect was far smaller than improvement in efficiency. For example, the share of manufacturing in strongly decoupled cities declined from 2010 to 2015 and thus decreased emissions by 26.2% and DI by 0.20. Furthermore, the effects of economic restructuring relied heavily on the development stage of cities. For example, the share of manufacturing in negatively decoupled cities kept increasing from 2005 to 2015, leading to increases in cities' emissions and DI. One of the possible reasons could be that strongly decoupled and high-income cities substantially developed their service sectors and outsourced their manufacturing sectors to less-developed regions. As a result, less-developed cities were still developing their manufacturing sectors and their emissions and economic growth were still coupled, or even negatively decoupled. Therefore, the effectiveness of emission

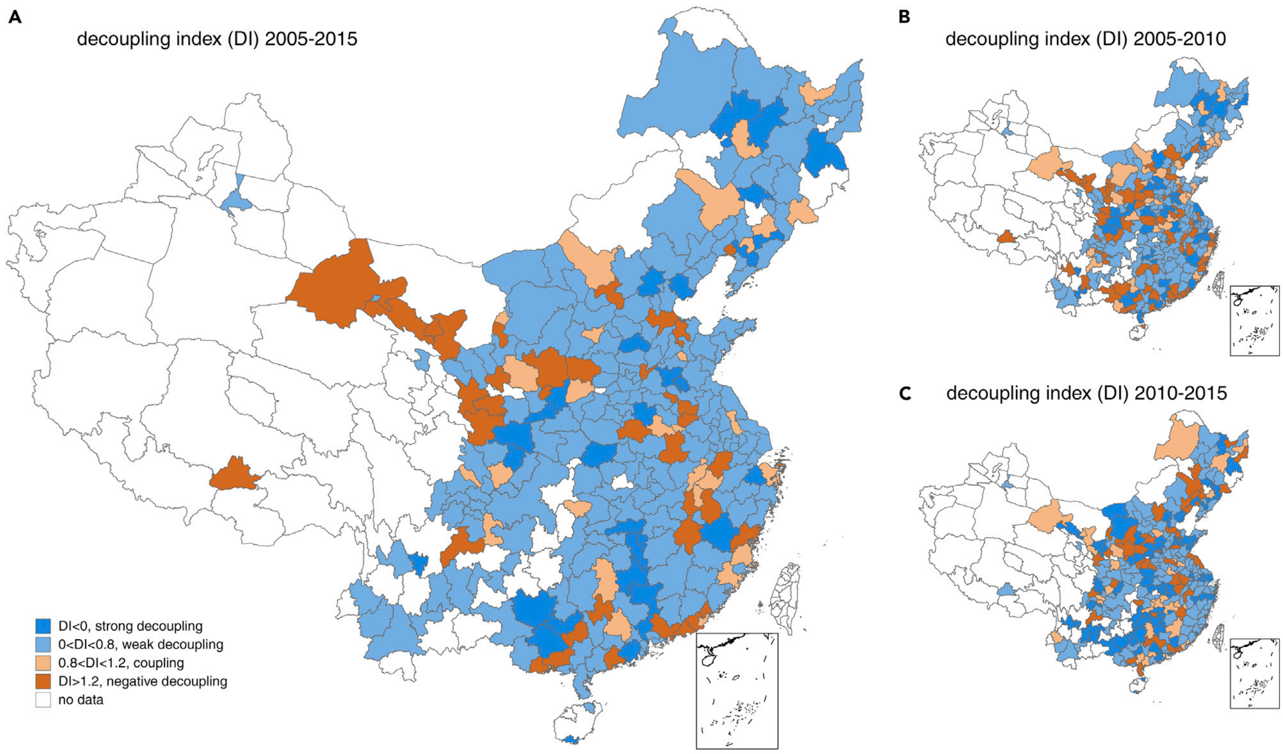

Figure 3. Decoupling of cities' economic growth from their emissions

(A) The 10-year extent of decoupling of cities from 2005 to 2015.

(B and C) The 5-year extent from 2005 to 2010 and 2010 to 2015.

The decoupling index is calculated for 282 cities over the period of 2005–2015. A strongly decoupled city has increasing GDP but decreasing emissions, a weakly decoupled city has increasing emissions but at a slower rate than GDP growth or has decreasing emissions but at a faster rate than GDP decline, a coupled city's GDP and emissions are increasing or decreasing at the same rate, and a negatively decoupled city has decreasing GDP but increasing emissions, or its emissions grow faster than GDP or GDP decreases faster than emissions.

reduction via economic restructuring and relocation is limited from a national perspective.

Different contributions of drivers have been found in cities with similar economic structure. We take Jincheng in Shanxi and Shuangyashan in Heilongjiang as examples because both of them have coal mining as their dominating industry. The emission intensity of Jincheng decreased from 5.6 t per 1,000 yuan in 2010 to 2.6 t in 2015, having a negative effect (−1.29) on the city's DI, offsetting the increase from economic growth (0.65). As a result, Jincheng's total emissions decreased from 32 mt in 2010 to 22 mt in 2015, while its GDP kept growing from 56.7 to 85.3 billion yuan over the same period. Jincheng's DI value from 2010 to 2015 was −0.62 (strongly decoupled). Meanwhile, the effect of a decline in emission intensity on DI (−0.18) in Shuangyashan was not sufficient to offset the increase from economic growth (1.23) over the period of 2010–2015. As a result, Shuangyashan's DI from 2010 to 2015 was 0.81 (coupling), and its emissions increased by 9.8% while its GDP increased by 11.9%.

Therefore, we suggest that reducing cities' emission intensity to achieve decoupling of economic growth and emissions is an effective and feasible way to realize a low-carbon development. Our scenarios show that an additional 3.2%, 6.7%, 9.6%, and 11.3% of cities could have achieved strong decoupling over the period of 2005–2015, if their emission intensities in 2015 decreased by 5%, 10%, 15%, and 20%, respectively. Meanwhile, the number of coupled cities and negatively decoupled cities will decrease from 29 (or 10.3%) to 16 (or 5.7%) and from 37 (13.1%) to 23 (8.2%) under the strongest scenario, respectively (as shown in Figure 6 and Table S9).

DISCUSSION

This study presents internally consistent CO_2 emission inventories for 294 Chinese cities for the years 2005, 2010, and 2015. We include scope 1 emissions from fossil fuel consumption and industrial processes and scope 2 emissions from imported electricity consumption. Our accounts show that, while total emissions and per capita emissions increased in most of the cities, their growth significantly slowed down after 2010. We weakly confirm an inverted-U curve relationship (or EKC) between emissions and GDP (i.e., per capita emissions first increase then decrease with the growth of per capita GDP). A total of 84% of the cities experienced a decrease in emission intensity, which fulfilled the country's conservative commitment to the Paris Agreement by reducing emission intensity ahead of schedule.

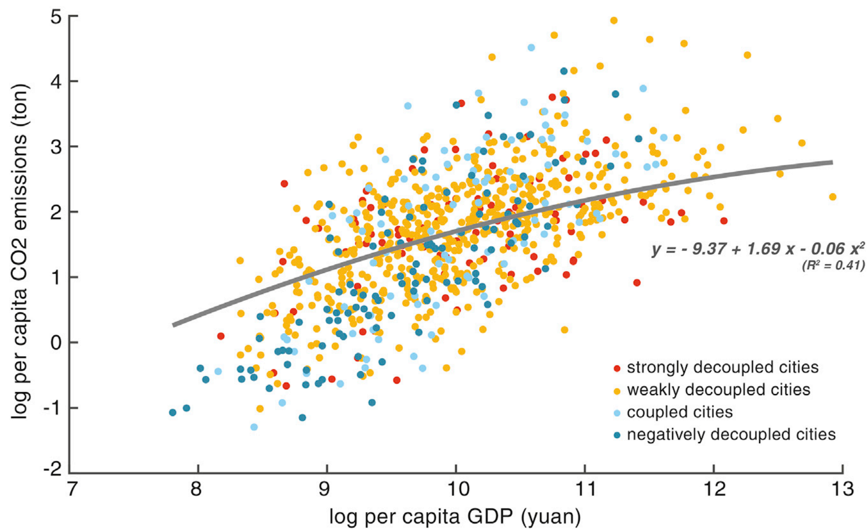

Figure 4. Environmental Kuznets curve

The gray curve stands for the fitted curve for full-sample regression, and its second-order coefficient is significant and negative (at a significance level of 5%), which confirms the hypothesis of the environmental Kuznets curve. Dots show cities in clusters of four extents of decoupling.

Analysis of the decoupling of emissions and GDP shows that 11.0% (or 31) of the cities have achieved strongly decoupled economic growth from emissions from 2005 to 2015, exhibiting an absolute decline in emissions along with an increase in GDP. Almost two-thirds (or 65.6% and 185) of cities have achieved weak decoupling with emission growth being smaller than their GDP growth. Although there was slow emission growth or even an emission decline in decoupled cities, they kept adding CO_2 to the atmospheric and increasing CO_2 concentration. Ultimately, we need to keep reducing emissions and reach net zero CO_2 emissions globally around 2050 to meet the goal of 1.5°C warming.[26]

Our analysis finds that economic transformation toward service sectors and less energy-intensive manufacturing has limited effects on emission reduction. Cities could achieve decoupled economic growth from emissions with any economic structure, even in highly polluting resource-dominated cities or low-income cities. Thus, it is not necessary for every city to pursue service-oriented structural transformation. Meanwhile, emission intensity reduction via improvement in production and energy use efficiency has been identified as the most important driver and is even able to offset the increase in emissions from economic growth in strongly decoupled cities. Our scenarios show that up to 243 (or 86.2%) of cities could have achieved strong or weak decoupling from 2005 to 2015, if their emission intensity by 2015 had declined by 20%, *ceteris paribus*.

One effective approach to reduce emission intensity is to build a renewable energy-based system. In the past decade, the supply of renewable energy has quickly increased in China. Total consumption of hydropower and wind power and the non-renewable but low-carbon intensive nuclear power quickly increased from 107 mt of standard coal equivalent (or 7.3% of total energy consumption) in 2000 to 744 mt (or 15.3% of total energy consumption) in 2019. Meanwhile, the consumption of coal peaked in 2013 at 2,810 mt, and the proportion of coal consumption to total consumption of energy decreased substantially from 70.2% in 2011 to 27.7% in 2019, although coal still dominates electricity supply. Such a quick replacement of coal with other forms of energy, including renewables, has led to a peak of China's overall emissions in 2013.[7] For an example at the local level, Shenzhen has taken great efforts to develop its renewable energy system. Shenzhen is one of the first low-carbon pilot cities for low-carbon development in China and has successfully replaced most of its coal power infrastructure with cleaner energy systems (such as natural gas, solar power, wind power, nuclear power, and biomass energy).[27] Benefiting from a series of initiatives, Shenzhen has achieved a strong decoupling of economic growth and emissions between 2010 and 2015, and its overall emission intensity in 2015 was 0.2 t per 1,000 yuan, which is ranked as the fourth lowest in China.

Given the abundance and the low price of coal, many developing countries, including China, still use coal as their primary energy resource. In this regard, so-called "clean" coal technologies are seen as a potential solution to reducing carbon emissions,[28] and the government needs to invest more in such technologies and promote their applications to high-coal-consuming industries.[29] Carbon capture and storage (CCS) could be an effective approach to mitigate carbon emissions, but it is not yet universally applied mainly due to economic and social barriers. On the one hand, the current costs for emitting CO_2 are much lower than applying CCS technology. On the other hand, there is no wide public acceptance for CCS technology, which increases the difficulty of applying CCS technology at a large scale.[30] There were only 17 large-scale CCS facilities globally in 2018 and they can capture up to 30 mt of CO_2 emissions per year (about 0.08% of global annual emissions). These CCS facilities have already accrued costs of $28 billion during the time period from 2007 to 2017.[31] After the coronavirus disease 2019 (COVID-19) pandemic, it would be quite challenging to collect the investments required to scale-up CCS infrastructures; while such is likely to incur further competition between investments made in CCS and renewable energy, which calls for well-designed investment strategies that can contribute to the mitigation of carbon emissions.

Further reduction in emission intensity in cities might need support from other cities or the central government as not all cities have the infrastructure, knowledge, and capital to improve their carbon performance. An inter-city network similar to the C40 Cities Climate Leadership Group and Local Governments for Sustainability (ICLEI) could be designed for Chinese cities to provide a platform for cities to exchange best practices of low-carbon development and learn from each other.

The findings of this study are of significance for countries in the Global South, especially for fast-growing countries (such as India and Brazil) and countries with high coal consumption (such as Indonesia and Vietnam, whose coal consumption increased

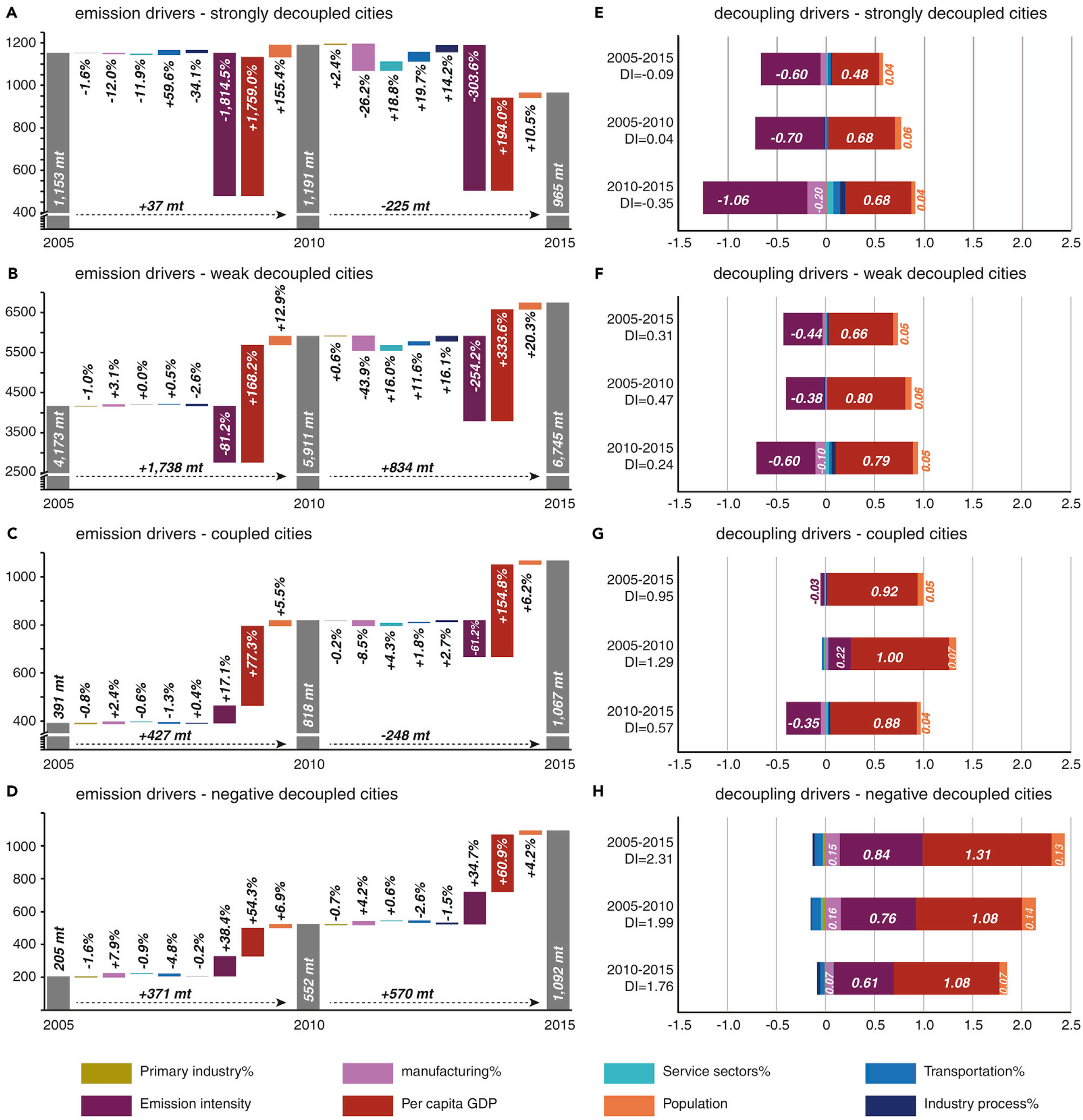

Figure 5. Emission drivers in four city groups in terms of decoupling index

(A–D) The contribution of each factor to the changes in emissions.

(E–H) The contribution of each factor to the changes in decoupling index.

The five factors in the second line of the legend make up the economic restructuring factor.

by more than 20% in 2019). China plays an important role in the South-South co-operation via South-South trade and the Belt and Road Initiative, especially in the transmission and application of solar and wind power technologies.[32] The experience and status quo of carbon emissions and emission-GDP decoupling in China may have implications for other developing economies to achieve decoupled economic development and a path toward low-carbon future.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Yuli Shan (y.shan@rug.nl).

Materials availability

This study did not generate new unique materials.

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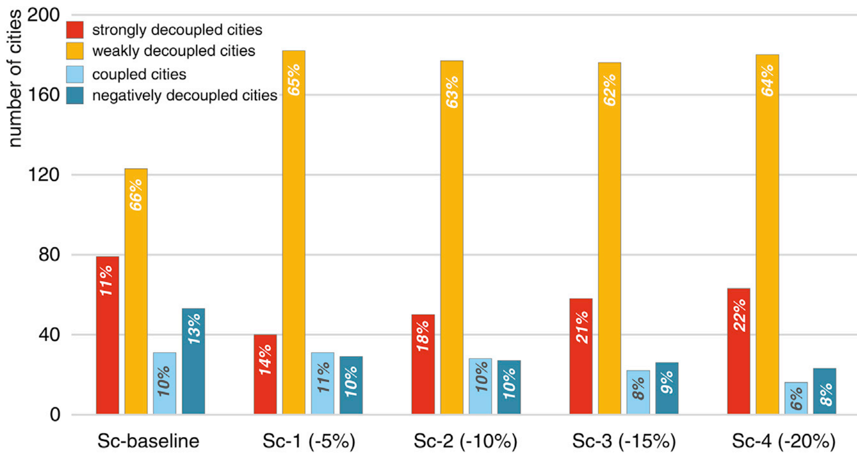

Figure 6. Cities' degree of decoupling over the period of 2005–2015 under different scenarios

The baseline scenario (Sc-baseline) refers to the current situation without additional decrease in emission intensity. Sc-1, Sc-2, Sc-3, and Sc-4 assume that the emission intensities of cities in 2015 decrease by 5%, 10%, 15%, and 20%, respectively. Numbers over the bars refer to the percentage of represented city types in all cities.

Data and code availability

The city-level emissions generated during this study are available at Mendeley Data[33] and the China High Resolution Emission Database.[34–36]

Cities' emission accounts

We account for emissions for cities in a hybrid model that combines both bottom-up and top-down approaches. The top-down approach is mainly based on statistical data from governments, such as energy consumption and industrial production, whereas the bottom-up approach first calculates emissions of individual units, such as enterprises, and then aggregates them to city boundaries. The hybrid model can improve the accuracy of cities' emission inventories and can track emission sources at fine spatial granularity. Detailed methods can be found in our previous studies.[37–39]

Our emission inventories cover both scope 1 and scope 2. Scope 1 emissions refer to direct emissions from fossil fuel combustion and industrial processes within a city's administrative boundary, while scope 2 emissions refer to emissions induced by net-imported electricity.[40] Emissions are calculated as the product of activity data (energy consumption or industrial production) and emission factors.[41,42]

Scope 1 emissions (E_{direct}) are calculated in seven parts (see Equation 1): emissions from agriculture (E_{agr}), fossil fuel use in industries ($E_{ind\text{-}en}$), industrial processes ($E_{ind\text{-}pro}$, including cement and lime production), service sectors (E_{ser}), transportation (E_{tran}), fossil fuel use in urban households (E_{urban}), and fossil fuel use in rural households (E_{rural}):

$$E_{direct} = E_{agr} + E_{ind\text{-}en} + E_{ind\text{-}pro} + E_{ser} + E_{tran} + E_{urban} + E_{rural}. \quad \text{(Equation 1)}$$

$E_{ind\text{-}en}$ and $E_{ind\text{-}pro}$ are calculated with fossil fuel consumption and industrial production of each industrial enterprise. E_{agr}, E_{ser} , E_{urban} , and E_{rural} are downscaled from provincial emissions according to the area of farmland, the population in built-up areas, the urban population, and the rural population of each city, respectively. E_{tran} is accounted for in four parts: emissions from road (estimated based on driving records of vehicles), rail (downscaled from the provincial emission base on the length of railways in each city), shipping (estimated based on routes of ships by the Automatic Identification System), and air traffic (downscaled from the provincial emission base on airport throughput of cities).

The emission factors of fossil fuel combustion and industrial processes were collected from China's national greenhouse gas inventories.[43,44] Carbon content and oxidation rate coefficients are differentiated by sector, fossil fuel type, and combustion device.

Scope 2 emissions ($E_{indirect}$) are calculated based on net-imported electricity (see Equation 2):

$$E_{indirect} = EF^{*} \left(E_{ele\text{-}consumption} - E_{ele\text{-}production}\right), \quad \text{(Equation 2)}$$

where EF refers to the emission factor of electricity, and $E_{ele\text{-}consumption}$ and $E_{ele\text{-}production}$ refer to electricity consumed and generated, respectively, within a city boundary. We use the average emission factors of regional grids for cities.[45] Electricity consumption was collected from the City Statistical Yearbooks,[46–48] and electricity production was collected from power plants (including both thermal and renewable plants).

Decoupling index

The concept of decoupling was popularized by the Organisation for Economic Co-operation and Development[49] to describe the relationship between environmental pressure and economic growth. "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."[49] Numerous studies, such as Juknys,[50] Marques et al.,[51] and Akizu-Gardoki et al,[52] have proposed different indices to quantify the extent of decoupling. Tapio[18] was the first to separate the decoupling indexes into eight categories with range of elasticity.[53] On the basis of the categories, we could focus on cities with the same degree of decoupling and explore the factors that affect their emissions and degree of decoupling.

According to Tapio,[18] the decoupling index of cities could be calculated according to Equation 3. Cities can be grouped into eight categories based on their decoupling index and changes in GDP. As our sample cities achieved economic growth from 2005 to 2015, they all fall into the following four categories.

(1) $DI_{Tapio} < 0$: strongly decoupled cities have increasing GDP but decreasing additional annual emissions.
(2) $0 < DI_{Tapio} < 0.8$: weakly decoupled cities have increasing emissions but at a slower rate than growing GDP or decreasing emissions but at a faster rate than the declining GDP.
(3) $0.8 > DI_{Tapio} < 1.2$: coupled cities' emissions and GDP are increasing or decreasing at the same speed.
(4) $DI_{Tapio} > 1.2$: negatively decoupled cities have decreasing GDP but increasing emissions, or their emissions grow faster than GDP or GDP decreases faster than emissions.

$$DI_{Tapio} = \Delta CO_2\% \Big/ \Delta GDP\% = \frac{\left(CO_2^t - CO_2^0\right)\Big/CO_2^0}{\left(GDP^t - GDP^0\right)\Big/GDP^0}. \quad \text{(Equation 3)}$$

Environmental Kuznets curve

The EKC hypothesizes that emissions or other forms of environmental degradation of an economy first increase and then decrease with economic growth.[23,24,54] Empirical evidence has been limited and contradictory and is dependent on spatial and time scales and types of pollution and environmental degradation. Rather than being universally applicable it only holds in specific contexts. For example, Haseeb et al.[55] confirmed the EKC hypothesis between GDP and CO_2 emissions in BRICS economies; Liu et al.[56] found that there was an inverted U-shaped relationship between per capita GDP and CO_2 emissions during the period of 2000–2015 according to a panel of 125 countries. However, low-income countries showed a U-shaped relationship. Wang et al.[24] applied the EKC concept to 50 Chinese cities and confirmed an EKC relationship between cities' per capita GDP and per capita CO_2 emissions over the period of 2000–2016. They also estimated a turning point of cities' per capita emissions (out of sample) at a per capita GDP of around US$21,000 (in 2011 purchasing power parity).

Table 1. U test results

	All cities		Top 15% cities in per capita GDP (>48,050 Yuan)	
	Lower bound	Upper bound	Lower bound	Upper bound
Interval	7.802	12.924	10.780	12.924
Slope	0.784	0.191	0.763***	−0.964**
Overall t value	–		1.79**	
Modified interval	7.802	20	–	–
Slope	0.784***	−0.627*	–	–
Overall t value	1.52*		–	–
Modified interval	7.802	25	–	–
Slope	0.784***	−1.205**	–	–
Overall t value	1.95**		–	–

***p < 0.01, **p < 0.05, *p < 0.1.

We applied panel data regressions to estimate the relationship between per capita GDP and per capita emissions for 282 Chinese cities in the years of 2005, 2010, and 2015. The specification is shown in Equation 4. Results are shown in Figure 4 and Table S10.

$$\text{logemission}_{ij} = \alpha + \beta_1 \text{loggdp}_{ij}^2 + \beta_2 \text{loggdp}_{ij} + \kappa_i + \epsilon_{ij}, \quad \text{(Equation 4)}$$

where logemission stands for the natural logarithm of per capita scope 1 emissions (excluding emissions from household energy consumption), and loggdp represents the natural logarithm of per capita GDP. The subscripts i and j stand for the city and the year, respectively. We control for the city fixed effects by including a vector κ_i. The constant α and coefficients β_1 and β_2 are what we obtain from the estimation.

We apply statistical tests and robust standard errors to pre-empt potential issues in our panel data model, including heteroskedasticity, serial correlation, and cross-sectional dependence.[57] We first tested for groupwise homoskedasticity using the modified Wald test. The result rejects the null hypothesis of homoskedasticity at the significance level of 1%. Next, we tested for serial correlation within the panel using the the Wooldridge test for autocorrelation in the panel data.[58,59] The results reject the null hypothesis of no first-order autocorrelation at the significance level of 1%. We then applied Friedman's test of cross-sectional independence,[60] and the results cannot reject the null hypothesis of no cross-sectional dependence. Hence, we used robust standard error clustered at the city level to deal with heteroskedasticity and serial correlation issues.[61] The results are shown as model 2 in Table S10.

The gray curve in Figure 4 stands for the fitted curve for full-sample regression, and its second-order coefficient is significant and negative (at a significance level of 5%). We further applied the U test algorithm developed by Lind and Mehlum[62] to test for the existence of an inverted-U curve relationship between per capita emissions and per capita GDP.[63] The test results are shown in Table 1.

The logarithm of per capita GDP of Chinese cities in the period of 2005–2015 are in the interval [7.802, 12.924]. Within this interval, the U test shows no inverted-U-shaped relationship. However, if we increase the upper bound of the interval to, for example, 20 or 25, we find that an inverted-U shape exists at the significance level of 10% and 5%, respectively. These findings indicate that per capita emissions and per capita GDP in Chinese cities follow an inverted-U-shaped relationship, but the relationship is not explicitly realized in the period 2005–2015. This is because the status quo of the overall city development in China does not reach the turning point of the inverted-U curve.

We take a further step to illustrate this phenomenon. We estimate the panel data fixed effect model using the top 15% cities in per capita GDP (greater than 48,050 yuan). The U test shows that the inverted-U curve exists within this subsample at the significance level of 5%. This shows that the lower-income cities are still far from the turning point and flatten the estimated curve.

Decomposition analysis

Decomposition analysis methods have been used extensively to quantify the contribution of socioeconomic drivers to changes in environmental pressures.[7,64] Beyond the decomposition of emissions, some studies attempted to identify the drivers of the extent of decoupling.[53,65,66] This study takes a two-step approach to decompose the extent of decoupling of cities.[67]

We first investigated the emission drivers of cities. Index decomposition analysis (IDA),[68] structural decomposition analysis (SDA),[69] and production-theoretical decomposition analysis (PDA)[70] are the three most widely used decomposition methods. Each method has its own advantages and disadvantages. The SDA is based on input-output analysis, which can distinguish between contributions from technical change, structural change, composition, and level of consumption.[71] It can also capture the indirect effects of demand and has high data requirements; the input-output tables are not available for most cities. Meanwhile, the IDA has fewer data requirements and can capture structural change, i.e., change in relative contributions of sectors on emissions.[71] The PDA decomposes emissions based on production theory.[72–75] Compared with the IDA, the PDA is less intuitive and straightforward and may lead to ambiguous conclusions when quantifying the effects of structural changes.[76] Given that the economic structure is a key factor that affects cities' emissions and that city-level input-output tables are not available for most cities, the IDA was used in this study.

Different approaches are used for the IDA, such as the Laspeyres index and the Divisia index. The log mean Divisia index method is recommended when analyzing energy and environmental indicators because of its "theoretical foundation, adaptability, ease of use and result interpretation, and some other desirable properties in the context of decomposition analysis."[77] We followed the method developed by Ang[68] to decompose cities' emissions.

We defined four driving factors to explain the changes of cities' emissions: changes in economic structure (S), efficiency (T), economic level (E), and population (P), shown in Equations 5 and 6.

$$CE = S \times T \times E \times P = \frac{\Sigma CE_i}{CE} \times \frac{CE}{GDP} \times \frac{GDP}{Pop} \times Pop, \quad \text{(Equation 5)}$$

$$\Delta CE = CO_2^t - CO_2^0 = \Delta CE_S + \Delta CE_T + \Delta CE_E + \Delta CE_P. \quad \text{(Equation 6)}$$

In Equation 5, CE refers to scope 1 emissions of a city (excluding household emissions), further separated into five sub sectors (CE_i) to show the effect of economic restructuring. We considered five sub-sectors based on our emission inventory: primary industry, manufacturing, service sectors, transportation, and industry processes. GDP and Pop refer to value added and population of cities, respectively. In this way, changes in CO_2 emissions (ΔCE) can be decomposed into four parts: changes related to industrial structure change (ΔCE_S), efficiency change (ΔCE_T), economic development (ΔCE_E), and population growth (ΔCE_P).

Then, we link Equations 3 and 6 to decompose the decoupling index into four parts that are caused by changes in industrial structure (DI_S), efficiency (DI_T), economic level (DI_E), and population (DI_P).

$$DI_{Tapio} = DI_S + DI_T + DI_E + DI_P = \frac{\Delta CE_s / CO_2^0}{(GDP^t - GDP^0)/GDP^0} + \frac{\Delta CE_T / CO_2^0}{(GDP^t - GDP^0)/GDP^0} + \frac{\Delta CE_E / CO_2^0}{(GDP^t - GDP^0)/GDP^0} + \frac{\Delta CE_P / CO_2^0}{(GDP^t - GDP^0)/GDP^0}. \quad \text{(Equation 7)}$$

The socioeconomic data, such as population, GDP, and GDP structure were collected from the China City Statistical Yearbook. GDP is adjusted to 2005 constant prices to eliminate the effects of price change. We use the provincial GDP deflator for cities' data that were collected from the National Bureau of Statistics of China.[16]

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.oneear.2020.12.004.

ACKNOWLEDGMENTS

B.C. was supported by the National Natural Science Foundation of China (71673107), and Y.Z. was supported by the National Natural Science Foundation of China (71704029) and the Humanities and Social Science Foundation of the Ministry of Education of China (16YJCZH162). K.H. was partly supported by the Czech Science Foundation under the project VEENEX (GA ČR no. 16-17978S).

AUTHOR CONTRIBUTIONS

Y.S. and K.H. designed the study. Y.S. led the project, calculated the results, and drafted the manuscript. B.C. calculated the emissions with contribution from D.L. S.F. performed the analysis of the environmental Kuznets curve. Y.Z. contributed a lot in the round of revision and performed the policy analysis. K.H., S.F., and Y.Z. revised the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

Received: April 11, 2020
Revised: June 23, 2020
Accepted: December 15, 2020
Published: January 11, 2021

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