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Infrastructure Shapes Differences in the Carbon Intensities of Chinese Cities

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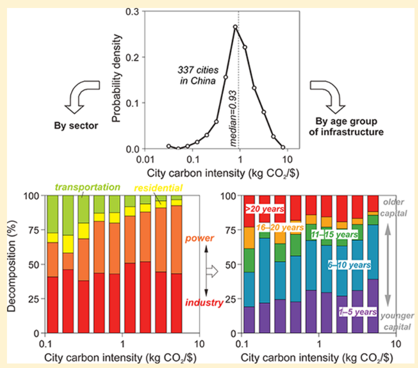
Supporting Information

ABSTRACT: The carbon intensity of economic activity, or CO_2 emissions per unit GDP, is a key indicator of the climate impacts of a given activity, business, or region. Although it is well-known that the carbon intensity of countries varies widely according to their level of economic development and dominant industries, few studies have assessed disparities in carbon intensity at the level of cities due to limited availability of data. Here, we present a detailed new inventory of emissions for 337 Chinese cities (every city in mainland China including 333 prefecture-level divisions and 4 province-level cities, Beijing, Tianjin, Shanghai, and Chongqing) in 2013, which we use to evaluate differences of carbon intensity between cities and the causes of those differences. We find that cities' average carbon intensity is 0.84 kg of CO_2 per dollar of gross domestic product (kgCO_2 per \$GDP), but individual cities span a large range: from 0.09 to 7.86 kgCO_2 per \$GDP (coefficient of variation of 25%). Further analysis of economic and technological drivers of variations in cities' carbon intensity reveals that the differences are largely due to disparities in cities' economic structure that can in turn be traced to past investment-led growth. These patterns suggest that "carbon lock-in" via socio-economic and infrastructural inertia may slow China's efforts to reduce emissions from activities in urban areas. Policy instruments targeted to accelerate the transition of urban economies from investment-led to consumption-led growth may thus be crucial to China meeting both its economic and climate targets.



■ INTRODUCTION

Since 2006, China has emitted more CO_2 per year than any other country;[1,2] in 2013, Chinese emissions reached 9.1 Gt CO_2,[3] or 27% of the global total. The rapid increase in Chinese emissions since 2000 reflects sharp increases in the nation's economic output and energy use, along with persistently high carbon intensity due to its reliance on coal.[4−6] These drivers are particularly evident in industrializing provinces in midwestern China, where improvements in industrial efficiency were outpaced by surging energy demand.[7,8] Although Chinese emissions have leveled off (or decreased slightly) between 2013−2016 because of a decline in coal use,[9,10] it remains unclear if this stabilization reflects a nascent but permanent decoupling of emissions from economic growth or if Chinese emissions will rise again when the global economy fully recovers from the Great Recession of 2007−2008. The latest literature[11,12] indicates that China's coal use and CO_2 emissions rose again in 2017, which drove global emissions up for the first time in four years.

Under the Paris Agreement, China has pledged reductions in carbon intensity, to 60−65% below 2005 levels by 2030. In the interim, China's 13th five-year plan aims for an 18% reduction in carbon intensity below 2015 levels by 2020—equivalent to a 46% reduction from 2005 levels. These goals represent an ambitious restructuring of the Chinese economy that curbs emissions without undermining economic growth.[13]

Perhaps one of the greatest barriers to the improved carbon intensity goal is the ongoing urbanization of China.[14−17] Rural-to-urban migration has been a major contributor to the nation's economic development, and the Chinese government is planning for 200 million new urban dwellers between now and 2030, increasing the fraction of Chinese living in cities from 56% to approximately 70%.[18] However, along with gains in income and living standards come increases in energy use and

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a

Sector	Power	Industry		Residential		Transportation	
Sub-sector	/	Major sectors	Others	Urban	Rural	Onroad	Nonroad
Incoming Resolution	Lat/Lon	Lat/Lon	Province	Province	Province	City	Province
Numbers	5775	88202	31	31	31	337	31
Spatial Allocation Proxies	/	/	Industrial GDP	Urban population	Rural population	/	Multi proxies
Final Resolution	Lat/Lon	Lat/Lon	City	City	City	City	City
Emission Shares	38%	44%	2%	3%	3%	7%	3%

CO_2 emissions of 337 cities in China

b

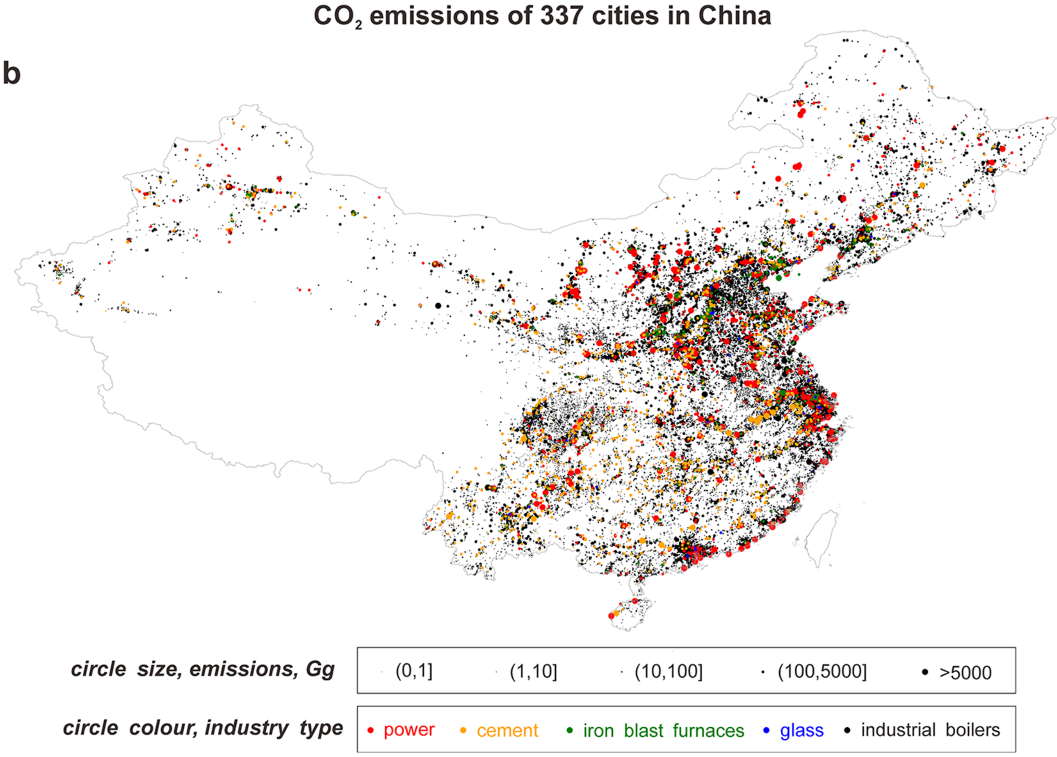

Figure 1. Processing details of the city-level inventory of Chinese CO_2 emissions. Table (a) shows emission source sectors, data sources, incoming/outgoing resolution, and emission shares. Map (b) shows the location, CO_2 emissions (sizes), and industry types (colors) of all the point sources (~100 000) estimated in this paper.

consumption related to these new urban residents, which could drive up the country's CO_2 emissions.[19] In recognition of this trade-off, in 2012 China began pilot projects in 36 cities meant to demonstrate a low-carbon pathway of urban growth, and the number of these pilot cities will soon be expanded to 100.[20] There is also an increasing number of integrated assessment model studies aimed at translating national emissions targets to regional, local, and sector-specific levels including in cities.[21−26] However, a lack of detailed data has prevented comprehensive analysis of carbon intensity across existing cities, hindering the potential to assess the factors[27−30] that systematically contribute to low carbon intensity.

Here, we present and analyze a new database of city-level emissions in China as of 2013, the latest year for which detailed data sources are available. The new data set contains all of the 337 cities in mainland China, including 333 prefecture-level divisions (i.e., 286 prefecture-level cities and 47 other prefecture-level divisions) and 4 province-level cities (Beijing, Tianjin, Shanghai, and Chongqing). Details of methods and data sources are available in the Methods. In summary, we first compiled and fused data from official statistics on energy,[31] industrial output,[5,6] and emissions[32,33] to estimate CO_2 emissions from nearly 100 000 discrete sources, including 5775 electric generators, 1971 cement factories, 1355 iron- and steel-making furnaces, 273 glass kilns, and industrial boilers at 84 603 factories. The on-road mobile emissions were estimated using a city-level emission model.[32] This emission inventory data has an unprecedented level of details for individual

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emitting sites and sectors compared to previous data gathered at country scale or for very few cities.[34−36] We then evaluated the determinants of cities' carbon intensities according to two main variables: economic structure, or the composition and outputs of various sectors of the city economy, and carbon emissions per unit of output by each industry sector. At the same time, we decomposed cities' GDP into the share related to capital investments (including both real estate and fixed industrial assets like machinery but excluding any agricultural investments) and the share related to all other production types (usually dominated by service sectors). Finally, for each source of emissions we assessed the date at which each emitting equipment was built and decommissioned, geographical locations, production capacity, combustion technology, annual product activity, fuel type, and fuel use; these data were used to evaluate the management- and technology-gaps in each city as well as targeted opportunities for decreasing the cities' carbon intensities.

■ DATA AND METHODS

Emission Model Framework. CO_2 emission inventories are usually developed on the basis of energy balance statistics. The concept of energy balance is a complete statistical accounting of all energy products entering, transforming, existing, and being used in the economy. However, using the energy balance based method to account for city-level emissions is not feasible in China, because the city-level energy balance tables are very scarce. Thus, we develop a new approach (Figure 1a) to estimate annual citywide CO_2 emissions by industrial unit, sector, and subsector, and total these using the administrative boundary of each city. Our CO_2 emissions inventory includes anthropogenic sources of burning fossil fuels and producing cement. Nearly 100 000 discrete power and industrial units are covered in our database (Figure 1b), and 16 fuels are tracked in the emission model framework (see Supporting Information (SI) Table S1). We estimate activity data for these emission sources and assign source-specific emission factors (i.e., carbon emission rate per unit fuel use) to calculate CO_2 emissions. Four primary data sets are used to provide activity data for each infrastructure and each source (i.e., socioeconomic statistics, MEP database, ES database, and MEIC database, see references in SI Table S2 for details). Emission factors are calculated by the product of fuel carbon content, calorific values, and oxidation rate.[3] When summarized to city totals, emissions related to the use of grid-supplied electricity, heat, and steam within the city territory but produced outside are not included in the city that consumes these energy but included in the city where these energy are produced. The inventory developed in this study is a territorial-based emission inventory.[37,38] We aggregate emission sources into four source sectors of power, industry, transportation, and residential to summarize emission estimate methods in the following text. More details of our method are given in SI Texts S1 and S2.

Power Sector. This source sector includes both grid-connected facilities and industrial autoproducers (i.e., captive power) in territory of cities. Our estimate relies on the MEP database using the method of our previous work.[33] The MEP database contains information about the date each generating unit came online and retired, geographical locations, generating capacity, combustion technology, annual power generation, fuel type, and fuel consumption. 5775 fossil-fuel generators were running in 2013 and therefore included into our CO_2 emissions database. We scale annual fuel consumption of these generators consistent with the total fuel use by power sector in national statistics.[31] The magnitude of scale factors are close to one (e.g., 0.97 and 0.96 for coal and natural gas, respectively), that indicates the facility level statistics in MEP database are well constrained by macroeconomic data. For emission factors, we use the data of 491 gC kg^{-1} coal, 838 gC kg^{-1} oil, and 590 gC m^{-3} natural gas,[3] respectively.

Industry Sector. Industry encompasses a wide range of activities, including all facilities and equipment used for producing, processing goods, and materials. Emissions are produced from fossil fuel burning as well as calcination of limestone in cement production. Three databases are harmonized and combined through a data fusion approach to create a unified estimate of industry emissions. We begin by using the MEP database to compile the activity information on carbon-intensive industries, which are composed of 1971 cement clinker production facilities, 1355 iron and steel making furnaces, and 273 glass kilns. Next, we cross-check these data with plant-level energy statistics from the ES database, adjust and add basic information where necessary (e.g., fuel use, operation time, and locations). Besides, where the ES includes factories not in the MEP, we retain such data that our emissions data represents an integration of all industries. Consequently, another 84 603 factories are supplemented to the industry database. These factories contain large numbers of small boilers and small kilns, those accounted for 27% of burning coal in the industry sector. Last, we use the MEIC data to fill in the missing fuel types in MEP and ES data, because these two databases include only coal, fuel oil, natural gas, and coke. The other transformed fossil fuels used by industries are derived from the MEIC data at province scale. Therefore, the industry sector represents a mixture of data sources from both pointwise estimates and province-level estimates. We sum all the industry activities and scale them consistent with national statistics by fuel and industry type.[5,31] Emission factors are taken from literatures and the MEIC database. For the provincial estimates that are not geocoded, emissions are downscaled from province to city using city-level GDP[6] (Table S3) related to industrial activities.

Transportation Sector. The transportation sector includes emissions from both onroad and nonroad sources. The onroad mobile emissions are estimated using the city-level emission model built in our previous work,[32] comprising vehicle stock model, vehicle age distribution model, fuel economy database,[39] and traffic volume database.[40] City vehicle numbers are obtained from city statistics,[6] and then multiplied by age distributions, annual vehicle miles traveled, and fuel consumption per mile to calculate total fuel use specific to city/vehicle class/vehicle age/fuel type. We adopt a vehicle miles ratio on intercity roads to take account of intercity traffic.[40] Carbon emission factors are based on the carbon content of gasoline and diesel fuel used in China, i.e., 855 gC kg^{-1} and 870 gC kg^{-1}, respectively. Emissions from nonroad sources in the transportation sector are taken directly from the MEIC data, which include construction, agricultural, and farming machinery. The province-level emissions are allocated from province to city using additional spatial proxies (Table S3).

Residential Sector. Residential emissions come from the combustion of fossil fuels in residential and commercial activities, primarily for heating and cooking. We utilize residential urban/rural emissions from the MEIC data, where province-level estimates are built for different fuel and

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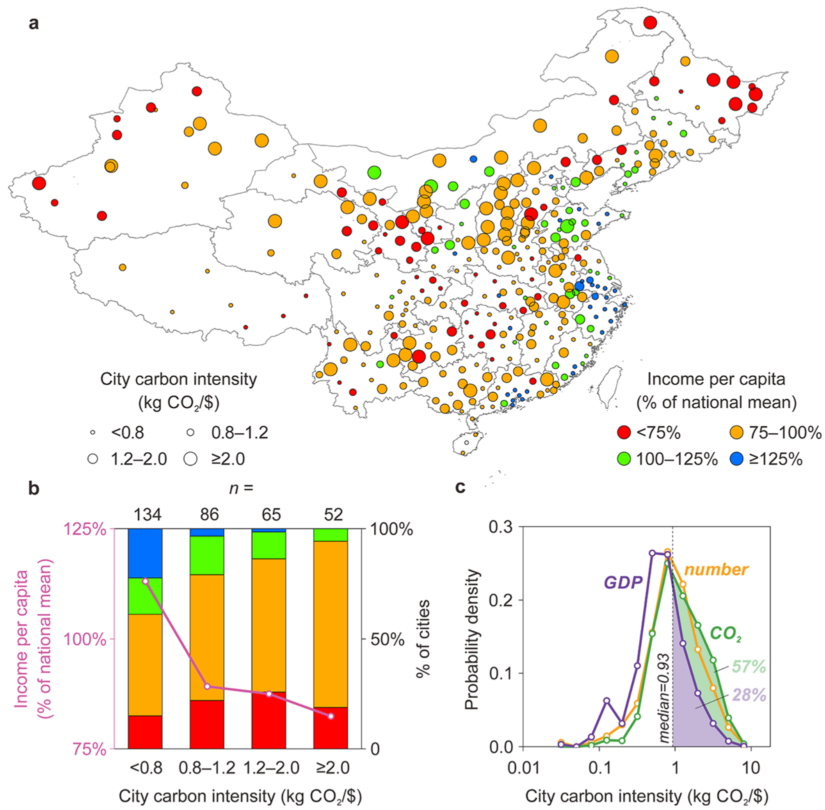

Figure 2. Overview of economy and carbon emissions in China cities. Map (a) shows the location, carbon intensity (sizes), and income per capita (colors) of 337 cities in 2013. The curve (pink) in b shows the average income per capita with different carbon intensities, and bars in b show corresponding shares of income per capita (colors) of cities. Curves in c indicate probability density functions of city numbers (yellow), emissions (green), and GDP (purple).

combustion device types. The amount of fossil fuel use is updated to the year of 2013 using the latest statistics data.[31] Spatial downscaling of residential emissions are performed through use of population densities[41] specific to urban/rural extent[42] for each city.

Uncertainty Analysis. Monte Carlo uncertainty analysis is performed by estimating the 95% confidence interval of the CO_2 emissions for each city. We collect uncertainty information on activity data, emission factors, and other estimation parameters for each component part, and aggregate the component uncertainties to the total estimate of city emissions.[37,43,44]

The uncertainty analysis is conducted by source sector. For power and industry sectors, we estimate the uncertainties of emissions for each industrial unit. The activity rates are assumed to follow a normally distributed pattern with coefficient of variations (CV) ranging from 10% to 20% according to data sources and industry types. For onroad transportation, the emission uncertainties are estimated at the city level. The fuel use of each city is assumed to follow a normally distributed pattern, with a CV of 15% for passenger vehicles and of 30% for trucks. The CV for trucks is higher because such vehicles are more used for intercity transport that could involve larger uncertainties in city emissions estimate. For the other emission sources, they all come from the MEIC database, which calculates the province's emission totals and distributes to each city using proxies. Considering the spatial allocation method may not accurately reflect the true value, we assume that the city emissions derived from MEIC have a uniform distribution within a range of ±30% to ±50% to reflect the large uncertainties. For all the emission sources, the CO_2 emission factors follow a normal distribution with the CV of 10% for coal and of 5% for oil and natural gas. All the parameters mentioned above with their probability distributions are placed in a Monte Carlo framework, and 100 000 trials are performed to estimate the 95% confidence interval of city CO_2 emissions.

RESULTS

China's average carbon intensity in 2013 was 0.84 kgCO_2/\$GDP. However, among the 337 Chinese cities we analyzed, the variability in carbon intensities in the same year followed a log-normal distribution that spanned nearly 2 orders of magnitude: from 0.09 to 7.86 kgCO_2/\$ (a 25% coefficient of variation). The cities with the highest carbon intensities tend to have low per capita income levels (SI Figures S1−S3), and are often located in central and western provinces (Figure 2a and b). The cities with carbon intensities greater than the median (0.93 kgCO_2/\$) account for 57% of the country's CO_2 emissions but only 28% of the country's GDP (Figure 2c), with per capita incomes that are 14% lower than the national average.

In 2013, 64% of China's GDP was tied to capital investments that consist of investing in real estate and in industries. Across cities in the same year, however, this investment share was as low as 18% and as high as 89%, with greater shares in cities with higher carbon intensities (Figure 3a and b; SI Figure S4). The greater a city's carbon intensity, the lower the share related to real estate (hashed blue areas in Figure 3a and b; SI Figure S4), and the higher the share related to industrial capitals tends to

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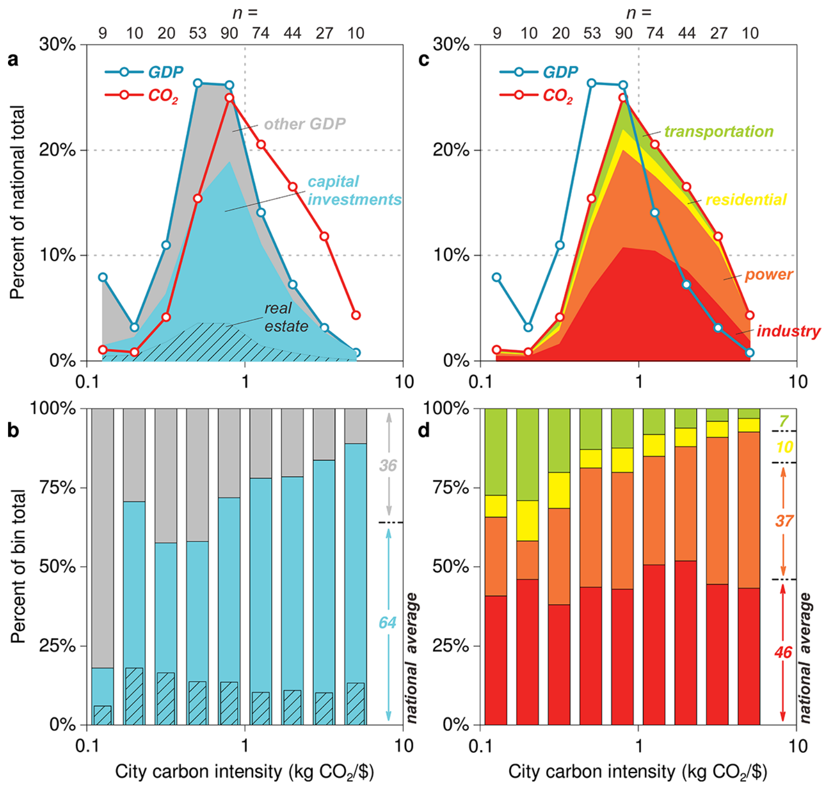

Figure 3. Decomposition of city GDP and emissions. (a) Decomposition of city GDP into capital investment (light blue) and others (gray). The data for each city come from statistical yearbook.[6] (b) Percentages of capital investments in GDP by city carbon intensity classes. (c) Breakdown of carbon emissions by sectors of industry (red), power (orange), residential (yellow), and transportation (green). (d) Percentages of emissions from different sectors by city carbon intensity. Each bar represents a value range of carbon intensities that spans between 10^x and $10^{x+0.2}$, where x refers to −1, −0.8, −0.6, −0.4, ..., and 0.8. It is the same for Figures 4−6.

be (solid blue areas in Figure 3a and b; SI Figure S4). In cities with low carbon intensities (e.g., < 0.32 kgCO_2/$), real estate accounted for ∼20% of GDP, and industrial capital and other (service) GDP contributed roughly 40% each (Figure 3b). By contrast, for carbon-intensive cities, real estate investments accounted for only ∼10% while investments flowing to industrial capital represented 65−80% of GDP (Figure 3b).

In turn, these structural differences in cities' economic structure generally translate in differences in the sources of CO_2 emissions. In total, 46% of cities' emissions are produced by industrial activities, 37% by power generation in cities' territory, 10% by transportation, and 7% by the residential sector in our estimates. Figure 3c and d (as well as SI Figure S5) show that in carbon-intensive cities, the industry and power sectors comprise a larger portion of emissions than the national average: 85−90% of all emissions. Conversely, the share of industry and power emissions drops to 60% in low-carbon cities, but transportation and residential emission shares rise to 30% and 10%, respectively, reflecting the central role of service economy in those cities (Figure 3c and d; SI Figure S5).

In addition to the structural roots of cities' carbon intensities differences, our analysis found systematic differences in the technologies used by various industries in different cities. Figure 4 shows that there is an increase in the ratio of emissions per physical unit of products (expressed as a ratio to the national average) as a function of cities' carbon intensity. The relationship is evident in almost all of the industries we assessed: power, cement, iron, and glass, as well as for industrial boilers operating in many different industries (Figure 4). More detailed, facility-level analysis reveals relationships among combustion technology, fuel type, production capacity, and year of construction, but also a surprising range of intensities across cities and sectors that share similar technological characteristics (Figure 4; SI Figures S6 and S7). This suggests that suboptimal operations management (i.e., operations worse than the original design performance due to a low level of maintenance management abilities) also plays a role in making higher carbon intensities through more emissions per physical unit of products.

Analyzing the distribution of emissions by source and class of technology, we identify facilities whose carbon intensities (defined as emissions per physical unit of products) exceed the average of facilities that burn the same fuel, use the same technology, and have similar operating capacity. We defined classes of "super-emitting" facilities according to how much their carbon intensity exceeds the average of similar facilities: by more than 2σ, by more than 1σ but less than 2σ, and above average but $<1\sigma$. Figure 5a shows the relative age of superemitting facilities as related to cities' carbon intensity: across the different sectors, most superemitting facilities were found in cities with greater carbon-intensities, and there were few superemitting units in cities with the lowest carbon intensities. Perhaps surprisingly, the highest-emitting facilities are not necessarily older than facilities with mean emissions, probably because there are simply not many facilities in China that have been operating more than 20 years (Figure 5a; red shading in Figure 6a).

Figure 5b and c show the magnitude of the reductions in carbon intensity and absolute emissions, respectively, that could be achieved if the superemitting facilities with emissions more

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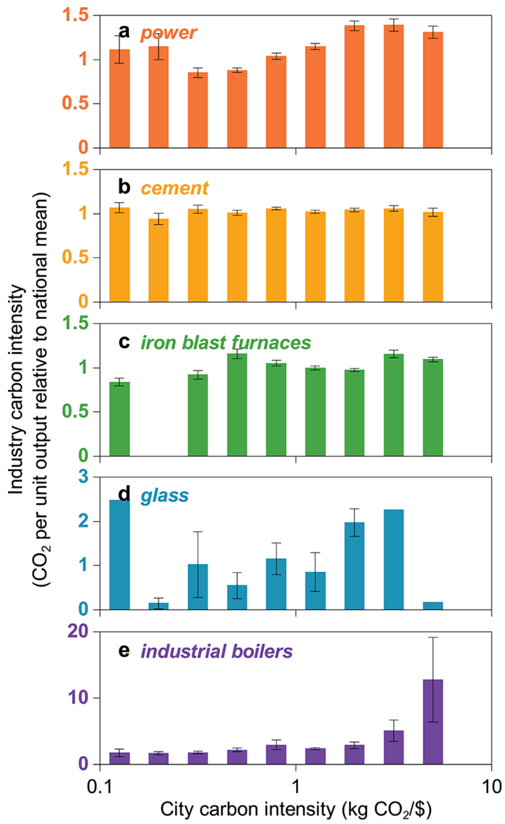

Figure 4. Carbon emissions per physical unit of products. The industrial products are estimated based on electricity and heat generation for power (a), on clinker production for cement (b), on pig iron production for iron blast furnace (c), on flat glass production for glass (d), and on energy output for industrial boilers (e). The carbon emissions per unit output (*y*-axis) is normalized by national mean. Each column with 95% confidence interval error bar represents the mean of a group of facilitates (the numbers are listed in SI Table S4) located in cities within a specific range of carbon intensities. Error bars are not shown if the number of industrial units is less than 5.

than 2σ greater than the mean were targeted for improvement and their carbon intensities brought down to the average of similar facilities. In more carbon-intensive cities hosting superemitting sites, intensities would decline roughly twice as much as in less carbon-intensive cities, by 4−5% (Figure 5b). Moreover, the emissions avoided by targeting these super-emitters would total 0.34 Gt CO_2 across China (3.7% of the country's emissions, see Figure 5c). If the carbon intensity of all "super-emitting" facilities were brought down to the current average (Figure 5b), then the cities with the greatest carbon intensities would see those intensities decline by 8−10%, and China's emissions would fall by 0.67 Gt CO_2 (7.3%, see Figure 5c). Yet because the variance in cities carbon intensities is primarily related to economic structure, targeting these superemitting facilities would not substantially narrow the disparity in the carbon intensities across cities. More discussions on possible changes in future are presented in SI Text S3.

DISCUSSION

Uncertainty and Validation. The uncertainty of city CO_2 emissions is estimated at the range of −3.7−3.5% to −35.8−34.5% depending on emission conditions (SI Figure S8). The overall uncertainties are significantly smaller than the variability of 2 orders of magnitude among city carbon intensities. The cities with larger percent of power and industry emissions tend to have lower uncertainties, and carbon intensities of these cities are usually much higher. For example, the cities where 75% emissions come from power and industry sectors tend to have an uncertainty range of ±5% to ±10%. They account for 83% of the country's CO_2 emissions but only 70% of the country's GDP. The results suggest that our city emissions database has a good estimate on carbon intensive cities, and the accuracy of our data is mainly attributed to pointwise estimates of power and industrial emissions, which contribute 81% of China's CO_2 emissions in 2013.

We also search from statistical yearbooks of the 337 city governments and retrieve complete energy balance tables for 20 cities. The city-level energy balance represents energy products and their flow occurring physically within the territory of cities. These statistics of city-level energy balance are independent with the data used in our inventory, thus are appropriate to evaluate our city emissions estimates. Energy consumption of the 20 cities account for 5.7% of national totals in 2013. We recalculate CO_2 emissions for these 20 cities using the energy balance data and the same emission factors as used in our inventory. The results suggest that the amount of CO_2 emissions are broadly consistent with our estimates (SI Figure S9 and Table S5). The consistency of emissions estimates lends confidence to the city-level emissions database developed in this paper. We also compare our results with emissions estimates by Cai et al.,[45] who calculates CO_2 emissions from 288 cities in China for the year of 2012. The comparison results (SI Figure S10) show that these two data sets are broadly consistent (Pearson's r is 0.89) although they are compiled for different years (2013 and 2012) using different methods.

Policy Implication. Capital investment has been a key driver of fast economic growth in China over the last 20 years, and investment has frequently been used as a policy tool to maintain growth. For example, at the end of 2008, a 4 trillion Yuan (∼US$ 570 billion) economic stimulus program was launched to boost the economy after the global financial crisis. These funds were primarily invested in infrastructure, spurring iron, and cement industries as well as growth in the (predominantly coal-based) power sector. Although these industries succeeded in maintaining China's economic growth during the crisis, they also effectively locked-in the energy- and carbon-intensive economic structure in many cities, and resulted in the large disparities in carbon intensities we observe across Chinese cities. Now, as economic growth has slowed and the government tries to transition from investment-led growth to consumption-led growth (discussed in SI Text S4), progress is hampered in some regions by the locked-in capital. Figure 6 illustrates the nature of the challenge: in cities with the greatest carbon intensities, 60−70% of power and industrial emissions in 2013 were produced by infrastructure that is less than 10 years old (blue and purple shading in Figure 6b). Given that service lifetimes of such infrastructure are commonly 30−40 years, these young facilities represent a dilemma: either fail to achieve emissions reduction goals or suffer economic losses related to their early retirement. This lock-in dilemma is further exacerbated by the fact that, China's most carbon-intensive cities also tend to be its poorest (Figure 2; SI Figures S2 and S3), such that it presents challenges not only for China's climate goals but also for efforts to reduce income inequality.[46]

Our findings suggest that the emissions reductions necessary for China to meet its 2030 climate targets will not be

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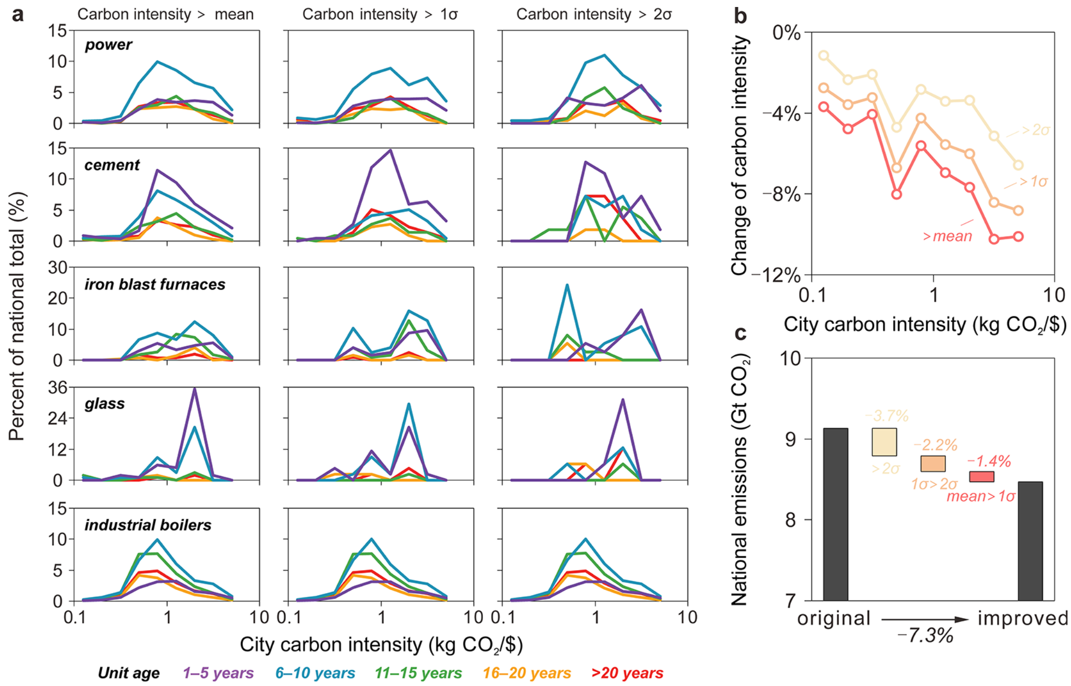

Figure 5. Potential reduction of carbon emissions through technology-driven efficiency gains. (a) Distribution of number of superemitting facilities by source type and unit age as a function of carbon intensity of the cities where each facility is located. The superemitters are defined as those with carbon emissions per physical unit of products greater than 2σ (right), 1σ (middle), or the mean (left). (b) Curves show the estimated reduction ratio of carbon intensity that could be achieved if the superemitting units of industry and power sources were updated with efficiency improvements to be brought to the sector mean. (c) Carbon emissions that could be avoided if the superemitters were replaced or improved as discussed above.

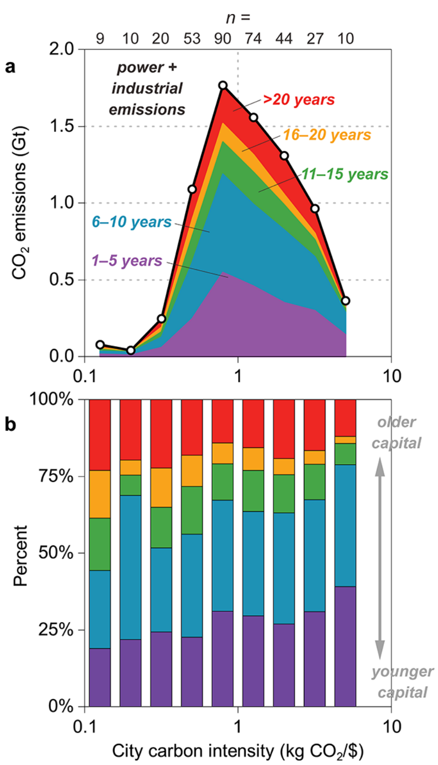

Figure 6. Age structure of power and industrial emissions. (a) Breakdown of carbon emissions by five age groups, with the youngest units located at the bottom and oldest ones at the top. (b) Percentages of emissions from each age group by city carbon intensity.

distributed uniformly across cities. Extreme inequalities in emissions intensities and per capita incomes will require mitigation strategies tailored to each city's economic structure and infrastructure. The industrial cities may make cost-effective cuts in total emissions targeting supper emitters (SI Table S6), which only need to improve maintenance management abilities and operate close to their original design performance. It is a suitable policy instrument given the industrial cities are relatively "poor" regions. Gradually tightening carbon intensity targets can help remove supper-emitting facilities, and balance climate goals and economy in these "Industrial" oriented cities. The "Service" oriented cities have low carbon intensities and high income per capita due to low CI activities in the service economy. Compared with industrial intensive cities, the "Service" oriented cities can reduce their carbon intensities easily with a service sector surge even without a reduction in absolute emissions. Therefore, absolute caps rather than intensity targets should be used to maximize emissions reductions in "Service" oriented cities. Progressive emissions caps may be feasible to achieve incremental improvements.

Carbon trading may be a cost-effective policy instrument[47,48] to link cities with different climate targets and opportunities for emissions reductions, as they could provide economic incentives for city-to-city transfer and deployment of low-carbon technologies, benefiting efficiency improvement and accelerating economic restructuring.[49] Compared to command and control policies, the market-based instruments create financial incentives for polluters to emit less until it is cheaper to buy emissions allowances on a market than to cut emissions further. Consequently the emitters that can mitigate emissions in cheapest ways will reduce the most. The super-emitting facilities have the potential to cost-effectively improve the overall performance by means of upgrade and retrofit, which will help reduce emission intensities in carbon-intensive cities. These are examples of policies that might address the large disparity in carbon intensity among China's cities. It is clear, however, that the huge differences in cities' carbon intensity revealed by our study will demand careful policies to ensure that China meets its economic and climate goals.

Future Work. The method developed in this study can be used to monitor city CO_2 emissions over time, which is crucial to assess compliance with carbon intensity targets. Tracking city changes at the level of individual facilities and economic sectors extends our ability to accurately understand emission trends and their drivers, especially in rapidly emerging cities. This is a potentially useful way to track the effectiveness of mitigation policy and to verify that cities make their promised carbon intensity cuts, which lay a foundation for the cap-and-trade program. To achieve this goal, considerable improvements are needed in getting reliable sources of facility level data that have improved resolution and near real-time updates. At the same time, when massive amounts of data are becoming more accessible, the emission accounting method will see further improvement in particular the following three aspects.

The city emissions estimated in this study refer to territorial-based emissions. If we take the emissions embodied in trade into account, or use consumption-based estimates, then China carbon emissions will be redistributed over cities. The cities that import electricity and industrial products lead to higher estimates of carbon emissions, whereas the opposite is true for exporting cities. Given that cities with low carbon intensities in territorial-based estimates are mostly likely the import market, the disparity in carbon intensities across cities shown in this study will be narrowed if consumption-based emissions are used. But even so, the importing cities still tend to have lower carbon intensities, because they produce final products and services that capture most of the value of goods traded. Furthermore, the policy implication inferred by consumption-based emissions might show that targeting supper-emitting facilities in carbon intensive cities will have cobenefits for reducing carbon intensities in importing cities. At the current stage the available data do not allow quantitative analysis until supply chains of products can be tracked between cities.

The emissions of methane (CH_4), the second most important greenhouse gas after CO_2, are not considered in our study, because the data we relied on are not available to count CH_4 emissions. Anthropogenic sources of CH_4 contain mainly leakage from the natural gas system, rice cultivation, and the raising of livestock, which are quite different from the combustion sources of CO_2. Therefore, the cities within the natural gas supply chain are expected to create CH_4 emissions from natural gas production and use, and the cities that have large agricultural output also lead to CH_4 emissions. Carbon intensities of these cities are underestimated in this study due to the omission of CH_4 accounting, which highlights the need for city level CH_4 emissions inventories in future.

The emissions reduction policies analyzed in this study mainly focus on superemitting facilities. It represents a short-time measure that can cost-effectively improve the overall performance by means of upgrade and retrofit with a balance between climate goals and the economy. Urban form planning introduces long-term measures[16,17] that structure city carbon emissions on long time scales, differing from short-term measures like removing superemitters. The relationship between urban form and CO_2 emissions can be built using our new database for Chinese cities. The analysis results can support policy recommendations with both short- and long-term measures to mitigate climate change. Quantification analysis of how these policies affect China's emissions, which involve extra work on emission projections and scenario analysis, will help in understanding how to achieve China's climate targets in the future.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.7b05654.

> Details of emissions estimation method (Text S1) and key assumptions (Text S2); possible changes of city carbon intensities in future (Text S3); investment- and consumption-led growth (Text S4); statistical relationships between city carbon intensity and different variables (Figures S1−S5); carbon emissions per unit output for power (Figure S6) and industry sectors (Figure S7); uncertainty analysis of city CO_2 emissions (Figure S8); validation of city CO_2 emissions (Figures S9−S10; Table S5); details of city emission model (Table S1−S3); number of industrial facilities for each bar in Figure 4 (Table S4); and emissions reductions due to super emitter policies (Table S6) (PDF)

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Notes

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