Local Strategies for China's Carbon Mitigation: An Investigation of Chinese City-Level CO_2 Emissions

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Abstract

This paper provides a systematic analysis that identifies the driving forces of carbon dioxide (CO_2) emissions of 286 Chinese prefecture-level cities in 2012. The regression analysis confirms the economic scale and structure effects on cities' CO_2 emissions in China. If China's annual economic growth continues at the rate of 7%, CO_2 emissions will increase by about 6% annually. In addition, climate conditions, urbanization and public investment in R&D are identified as important driving forces to increase the CO_2 emissions of Chinese cities. While an increment of the urbanization rate by 1% increases the CO_2 emissions by about 0.9%; An increase in R&D investment by 1% can help reduce CO_2 emissions by 0.21%. As cities in our study vary greatly based on their industry composition, development stage and geographical location, the patterns of their CO_2 emissions are also variable. Our study improves the comprehensiveness and accuracy of previous carbon accounting method by distinguishing the scope 1 and scope 2 CO2 emissions and establishing a high spatial resolution dataset of CO2 emissions (CHRED). The analysis covers almost all Chinese prefectural cities and derives useful implications for China's low carbon development.

Keywords: CO_2 emissions; Carbon accounting; Local strategy; Urban development; China
JEL codes: O53, Q54, Q56, R11

1. Introduction

In 2014, the Intergovernmental Panel on Climate Change (IPCC) warned that greenhouse gas emissions are contributing significantly to climate change, which has been proven a major threat for all countries on the planet (IPCC, 2014). As the world's largest emitter of carbon dioxide (CO_2), China is highly vulnerable to climate change and environmental degradation and has taken "more and more concerted and aggressive actions against climate change" in recent years (The Guardian, 2016). In its ratification of the 2016 Paris agreement, China agreed to cut its carbon emissions per unit of GDP by 60-65% by 2030. Now that the Paris agreement has been set to enter into force, turning these political commitments into concrete action is a more difficult mission to accomplish.

A particular challenge lies in the potential conflicts between China's rapid urbanization and the urgent need for local climate change mitigation. As estimated by the International Energy Agency (IEA), in 2008, urban areas in the world account for more than 71% of energy-related greenhouse gases (GHG) and it could increase to 76% by 2030 (IEA, 2008). Particularly in China, rapid urbanization contributes to 84% of commercial energy usage. The 35 largest cities in China, which contain 18% of the population, contribute 40% of China's energy uses and CO2 emissions. (Dhakal, 2009; Ouyang and Lin, 2016; Zheng et al., 2010). As a consequence, local environmental pollution and global climate change have profoundly damaged the health and lives of citizens in Chinese cities such as Beijing and Tianjin (Chen et al., 2013; Ebenstein et al., 2015). As urban populations continue to grow, the huge demand for buildings and transport could also have a large impact on local carbon emissions. In addition to direct carbon emissions, cities may induce significant indirect carbon emissions by importing energy and displacing industrial production to areas outside of their borders (Feng et al., 2014).

Nevertheless, while cities are a major source of the climate change problem, they are also at the core of the solution. As pointed out by Glaeser (2011), urbanization increases citizens' per-capita income because cities facilitate learning, trade and specialization. With higher incomes and tax revenues, governments can provide more infrastructure and better public services to fight climate change and protect citizens from harm. In China, provinces are generally too large and counties have little political power; therefore, cities are the most well-suited units for effective management of local CO_2 emissions. To conciliate the conflicts between city and climate change, and achieve the goal of sustainable urbanization, national climate policy should be further decomposed to the city level and well tailored to the local condition. This is particularly difficult in a large country with significant geographical and social-economic diversity like China, because it requires very detailed carbon accounting for each city and comprehensive understanding of local climate strategies. Without this knowledge, China can hardly make its climate targets credible or turn its commitments into effective local action. Although this is well recognized, due to data constraints, most studies on China's carbon emissions and climate policies are done at the national or provincial level (Guan et al., 2009; Jalil and Mahmud, 2009; Li, 2010; Zhang and Lin, 2012). A few studies use household survey data to infer carbon emissions for some Chinese cities (Zheng et al., 2010). Still, more work needs to be done on the basic carbon accounting and climate policy analysis for all of Chinese prefecture level cities. There is no doubt that this work will provide valuable information and scientific basis for more effective climate policy design, which are important to Chinese policy decision-makers. It is also important for other international stakeholders, who are in the expectation of China to move forward current international negotiation for climate change mitigation in the absence of the U.S.

With this understanding in mind and to fill the gap, this paper aims to establish the most disaggregated carbon accounting at the Chinese prefectural city level and provide a comprehensive analysis of the driving forces of CO_2 emissions. Unlike previous studies, which use population data or nighttime light data to indirectly approximate the spatial distribution of CO_2 emissions (Doll et al., 2000; Wang and Ye, 2016), we construct a high spatial resolution CO_2 emissions dataset based on detailed point sources and other supporting data. The point sources includes almost all the industrial emission sources in China, which comes from First China Pollution Source Census (FCPSC) and subsequent data updates from our latest survey (Cai et al., 2016; Wang et al., 2014).

This bottom-up approach is simple and accurate, and the reliability of data and the actual spatial resolution are much higher than approximations. Moreover, we also improve previous carbon accounting methods, e.g., road traffic emissions are calculated by taking road traffic volume and road density into account. Emissions from rural areas are based on remote sensing interpretation of rural residential data and the distribution of population density data. These improvements in carbon accounting make our local CO_2 emissions data estimates much more accurate, which is a starting point for further investigation of China's local climate policies. Moreover, the study offers a new perspective from which to examine different driving forces and strategies available to Chinese cities to manage their local carbon emissions. There is no one best approach; the appropriate strategy must be adapted to local conditions and carbon emissions patterns.

We firstly calculate the CO_2 emissions of 286 Prefecture Level Cities, distinguishing direct (scope 1) and indirect (scope 2) CO_2 emissions in a detailed carbon accounting. In a second step, we conduct a simple but rigorous econometric regression analysis to deepen our understanding of the economic patterns and driving forces of both direct and indirect CO_2 emissions of Chinese cities[1]. In contrast to previous decomposition studies, our econometric analysis tests not only classic drivers of CO_2 emissions, e.g., the economic scale and economic structure effects, but also takes into account more comprehensive climatic and socio-economic factors, e.g., climate conditions, population density, urbanization rates, Foreign Direct Investments (FDI) and R&D investment, which have direct implications for the policy design of local climate change mitigation. Lastly, we divide cities into groups according to their industry composition, development stage and geographic location, in order to determine the effective strategies specific to heterogeneous local conditions.

For an overview of the results, our econometric analysis confirms previous findings of the scale and structural effects in CO_2 emissions (He and Wang, 2012; Li, 2010). In particular, we identify climate conditions, urbanization and public investment in R&D as major driving factors of CO_2 emissions in China. Moreover, we also detect some opposite effects by distinguishing between direct and indirect CO_2 emissions. Last but not the least, our analyses illustrate the great heterogeneity in emission patterns among cities and shed light on the appropriate strategies specific to local conditions. The overall results are consistent and robust, which may derive pertinent and precise policy implications for the on-going low-carbon city development in China

[1] The economic pattern of CO_2 emissions refers to the relationship between economic development and CO2 emissions, which varies according to the local conditions.

The rest of the paper is organized as follows. Section 2 describes the detailed data sources we used for the carbon accounting and provides an overview of the level of CO_2 emissions of 286 Chinese prefecture level cities. Section 3 explains our empirical estimation of the driving forces of CO_2 emissions of these cities. Section 4 discusses the main results and policy implications for local climate mitigation. Finally, Section 5 concludes the paper.

2. Data

We combine various and consolidated data sources for our analysis. First, we follow the common method of city CO_2 emissions accounting to consider scope 1 (direct) and scope 2 (indirect) CO_2 emissions (UNEP, 2010; WRI, 2014). Direct CO_2 emissions include emissions from the combustion of fossil fuels and industrial processes (production of clinker, lime, and iron and steel). CO_2 emissions from land-use change and forestry are not within the scope of this study. The direct CO_2 emissions data is derived from China's High Resolution Emission Gridded Data (CHRED), which is based on point emission sources and other supporting data. CHRED provides detailed anthropogenic emissions of China's greenhouse gases on a high-resolution spatial grid. Detailed information about CHRED can be found on our website (http://www.cityghg.com/) and in previous publications (Cai et al., 2016; Cai and Zhang, 2014; Wang et al., 2014). In this paper, we construct an aggregated prefectural level city CO_2 emissions dataset in 2012 based on the 1 km gridded CO_2 emissions data derived from CHRED 2.0[2].

Indirect CO_2 emissions are defined as the CO_2 emissions due to city's imported electricity. The imported electricity is calculated by the difference between a given city's electricity generation and its total electricity consumption. In China, while the data of electricity consumption is easily obtained from the statistical yearbook (cf. China City Statistical Yearbook, 2013), the data of city electricity production is non available. Therefore,

[2] The CHRED 2.0 contains only data of 2012, that's why we can construct city level carbon emissions data in 2012 and remains on cross sectional analysis in this paper. But the CHRED project is on going. The analysis can be extended for several time periods when data will be available.

we have to rely on the basic data of electricity generation of all Chinese power plants to calculate the city's electricity generation. In collaboration with the China Electricity Council, we obtain detailed data of power plants' electricity generation and their address information. By identifying each power plant's geographical location and the boundary of cities, we can locate all power plants to cities and finally calculate the total electricity generation of each city through spatial analysis model. Once we have the city electricity generation data, we can calculate the city's electricity importation and multiply it by the average emission factor of regional electricity grids (NDRC, 2014) to calculate the indirect CO_2 emission. Figure 1 illustrates the calculation of CO_2 emissions for 286[3] Chinese prefectural level cities in 2012[4].

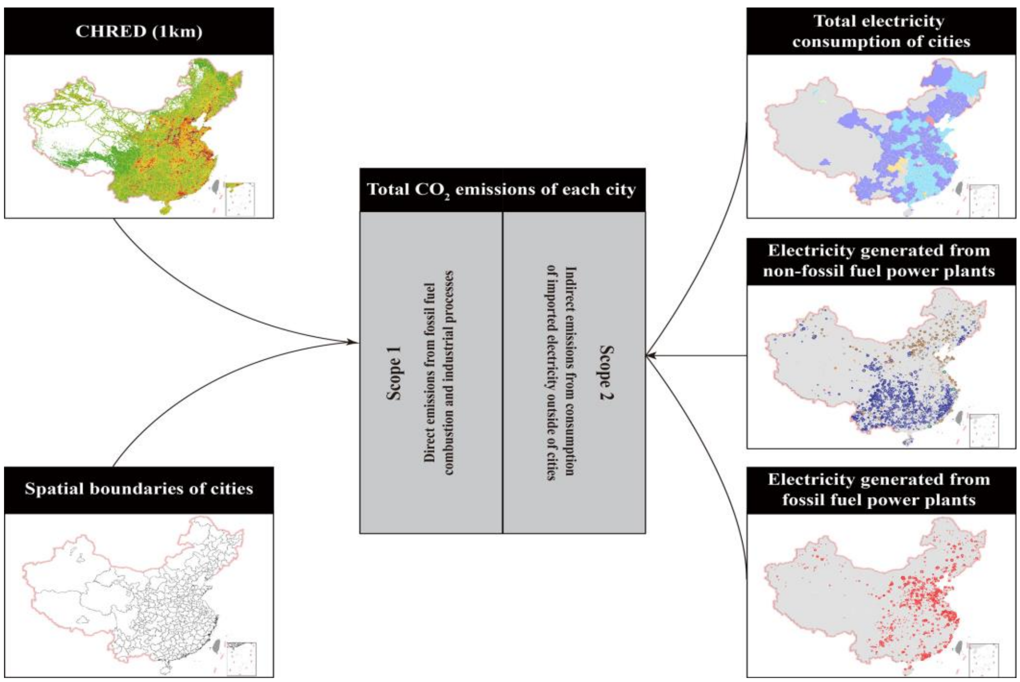

Figure 1. Schema of calculation of CO_2 emissions of Chinese cities

Second, to investigate the driving forces underlying the city CO_2 emissions, we complement the CO_2 emissions dataset with additional socio-economic data derived from

[3] In 2012, there were 285 prefecture-level cities and 4 municipalities in China. However, due to the problem of missing data, we have dropped three cities (i.e., Sansha, Zunyi and Wuhai) and include 286 cities (including municipalities) with complete data for the analysis (see Table A1 in the Appendix for the complete list of cities).
[4] According to our calculation method, there is possible overlap of total CO_2 emission between cities, because the electricity imports of one city maybe part of the electricity production of another city. Therefore, the aggregation of total CO_2 emission to national level is problematic, which is not the purpose of the paper.

other sources. For instance, the city demographic data is derived from the *6th China Population Census*; other socio-economic data is majorly derived from the *2013 China City Statistical Yearbook.* For climate conditions, we calculate the Heating Demand Day (HDD18) and the Cooling Demand Day (CDD26) for each city according to the Chinese national standard for the design of energy saving buildings (*JGJ 997—2010*). Readers can find more details about the variables in the Appendix. Table A2 provides detailed information about the variable definition and data sources. Table A3 provides the descriptive statistics and Table A4 is a correlation matrix of the variables.

3. Empirical model

In order to deepen our understanding of the driving forces of CO_2 emissions in our 286 Chinese cities and identify relevant climate change mitigation strategies, we conduct an econometric regression analysis using a Log-Linear Model as follows:

$$E_i = \alpha + \beta GDP_i + \gamma GDP_i^2 + \delta Structure_i + \tau X_i + \varepsilon_i \qquad (1)$$

The Log-Linear Model is a basic form of Multi-Linear Regression (MLR) model that is widely used for analysis of influence factors (Greene, 2008). The model relies on basic assumption to estimate a linear relationship between dependent variable and covariates. By taking the form of natural logarithm, the distribution of the disturbance is close to a Normal distribution, so that the model could be estimated by the Ordinary Least Square (OLS) method. The estimated coefficients have good statistical properties and are easy to interpret, which enable us to determine the sign and the magnitude of each influence factor. On the left hand side of the equation, the dependent variable E_i is the logarithm of per capita CO_2 emissions in city *i*. Specifically, we break down the total emissions into direct CO_2 emissions and indirect CO_2 emissions, as explained in the previous section. As such, we investigate the driving forces of each city's total CO_2 emissions, direct emissions and indirect emissions, respectively.

On the right hand side, we firstly follow the Environmental Kuznets Curve (EKC) literature to test the relationship between economic growth and CO_2 emissions (Grossman and Krueger, 1991). The EKC hypothesis states that pollution increases with economic growth, but at a certain turning point, pollution will decrease with economic growth. The inverted U-shaped relationship has been extensively tested on various pollutants such as CO_2, SO_2 and NOx using cross-country data (Cole et al., 1997; Selden and Song, 1994; Stern and Common, 2001). In our study, we include the first and second order of per capita Gross Domestic Product (GDP) to test the existence of EKC in the CO_2 emissions of Chinese cities. If the coefficient β is significantly positive and γ is significantly negative, the EKC hypothesis is true. Otherwise, there is a classic economic scale effect in carbon emissions.

Next for the $Structure_i$ variable, we use the labor shares in three sectors, i.e., agriculture, service and industry, to capture the effect of economic structure in cities' CO_2 emissions. Theoretically, one would expect that higher shares of the agriculture and service sectors in the economy would reduce CO_2 emissions. By contrast, one would expect the share of industrial sector to increase CO_2 emissions. We test a vector of climatic and socio-economic factors X_i for comprehensive driving forces of CO_2 emissions, which include climate conditions, population density, age of population, education level, urbanization rate, Foreign Direct Investment (FDI) and public expenditure in R&D. All of these covariates are taken from relevant literature on carbon emissions. Inclusion of additional covariates could test our model specification and ensure the robustness of our results. Furthermore, these covariates have significant economic meaning and could derive useful policy implications for local carbon mitigation.

Climate condition is associated with a household's energy demands for indoor cooling and heating (Creutzig et al., 2015). In cities with extreme climate conditions, households need to use more heating and cooling utilities, which consume more fossil energy and electricity and emit more CO_2. For instance, Glaeser and Kahn (2010) found that household carbon emissions are 78 percent higher in Memphis than in San Diego. Therefore, we use a logarithm of the sum of Heating Degree Day (HDD) and Cooling Degree Day (CDD) to measure the climate condition in cities, expecting the coefficient to be positive.

Population density is another important determinant of carbon emissions. In the U.S., people who live in cities with higher population density use more public transportation than private cars, which leads to less consumption of gasoline and lower carbon emissions per household (Glaeser and Kahn, 2010). If this relationship is true in China, public policies for the development of mega metropolitan cities like Shanghai and Shenzhen could be justified. We test this factor and expect the population density to be negatively associated with CO_2 emissions.

Age of population is also taken into account in our analysis. As surveyed by Liddle (2014), previous studies in OECD countries used cross-country data sets and focused on aggregated energy consumption and carbon emissions. They have uncovered that the relationship between age structure and carbon emissions is complex and nonlinear. For instance, Liddle and Lung (2010) uncovered a positive elasticity of carbon emissions for young adults and a negative elasticity for older adults. Menz and Welsch (2012) also estimated differential age effect on carbon emission and concluded that the ongoing demographic change in OECD countries will imply rising carbon emissions in the future. To capture this potential complex and non-linear relationship between age and CO_2 emissions, we include the first and second order of the average population age in our model. The expected signs should be positive for the first-order term and negative for the second-order term.

Education is considered as vital for climate change mitigation. In developed as well as developing countries, education is regarded as a factor in driving the convergence of carbon dioxide growth (Romuald, 2011). As the level of education in cities rises, a change in household consumption should be more likely to occur, which could reduce CO_2 emissions. In our model, we use the average education year of the city population to capture the potential effect of education on CO_2 emissions. The expected sign is negative.

Rapid urbanization is regarded as a major driving force of CO_2 emissions in developing countries (Elliott and Clement, 2014; Liddle, 2014; Sheng and Guo, 2016). On the one hand, the rapid urbanization induced by large scale rural to urban migration creates a demand for residential energy consumption and housing construction, which should increase CO_2 emissions from fossil fuel combustion and industrial production such as cement and steel. On the other hand, urbanization promotes construction of public infrastructures such as roads, public transit and collective heating systems, which will have positive long-term implications for energy consumption and CO_2 emissions. To capture the different aspects of urbanization, we use two different measures in our study. One measure is the share of urban inhabitants in total population, which captures the urbanization rate of the population. The other measure is the share of land used for urban construction. This measure captures more of the infrastructure construction aspect. We check the potential effects of different aspects of urbanization on cities' CO_2 emissions to better understand the sustainable process of urbanization.

As Foreign Direct Investment (FDI) is increasing in China, it may have important implications for China's CO_2 emissions. As suggested by the Pollution Haven Hypothesis (PHH), developing countries may compete for polluting FDIs with their lax environmental regulation, so that FDIs contribute to local pollution (Chung, 2014; Kivyiro and Arminen, 2014). However, studies also show that the FDI may promote technology transfer from developed to developing countries, which is vital for climate change mitigation (Zhu et al., 2016). For our study, we include the FDI in our model to test its potential effect on cities' CO_2 emissions, where the coefficient could be positive or negative.

R&D is regarded as another critical factor for climate change mitigation. New clean production technology is a fundamental solution to the trade-off between economic growth and environmental protection (Ang, 2009). From this perspective, local R&D activities and clean technology transfer should be considered in the analysis. Due to data constraints, we use the public expenditure for education and research as a proxy of local R&D activities to test the effect. We expect R&D may have a positive impact on the reduction of cities' CO_2 emissions.

Finally, to complete the model, we include α as the intercept and ε_i is the disturbance term which is assumed to be independent and identically distributed (i.i.d). As China is a large country with great regional heterogeneity, different cities may face different local conditions and exhibit different economic patterns of CO_2 emissions. Therefore, local strategies for climate mitigation should be adapted to various local conditions. For a demonstration, we follow the conventional division method in the literature to classify

Chinese cities into groups according to three types, i.e., industry composition, development stage and geographical location. The industry composition indicates the specialization of cities, the development stage indicates economic development level and the geographical location indicates geographical features of cities. These classifications are based on the common sense but tailored to the Chinese reality to illustrate the heterogeneity in local mitigation strategies of Chinese cities. Table 1 gives details of the classifications and Figure A1 in the Appendix illustrates the divisions on the map. By contrasting the estimation results of different groups, we are able to identify the appropriate strategies for local climate change mitigation.

Table 1. City classifications

Type	Division	Criteria
Industry composition	Industrial cities	Cities with share of secondary industry in GDP ≥50%
	Service based cities	Cities with share of tertiary industry in GDP ≥50%
	Other cities	Other cases
Development stage[5]	Developed cities	First and second tier cities
	Developing cities	Third and fourth tier cities
	Less developed cities	Fifth and sixth tier cities
Geographical location	Eastern cities	Cities belong to provinces of Beijing, Tianjin, Shanghai, Hebei, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
	Central cities	Cities belong to provinces of Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan
	Western cities	Cities belong to provinces of Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang
	Northeast cities	Cities belong to provinces of Liaoning, Jilin, Heilongjiang

[5] Classification by *China Business Weekly* and reports of the National Bureau of Statistics on city housing prices survey.

4. Results

4.1 Graphical evidence of CO_2 emissions in Cities

Before presenting the econometric results, we firstly derive some preliminary evidence about our cities' CO_2 emissions from figures. Figure 2 provides an overview of China's total CO_2 emissions. On average, the CO_2 emissions by Chinese cities were about 36 million metric tons in 2012. As one can note, most Chinese cities emit moderate CO_2 levels below the national average. Cities with high CO_2 emissions are generally concentrated in the north, northeast and the coastal areas of China. For instance, cities with the highest CO_2 emissions are Beijing, Tianjin, Tangshan, Ordos, Shanghai and Suzhou, which exceeded 150 million metric tons (Mt) annually in 2012. Low CO_2 emission cities are generally located in less developed regions, such as the South, Southwest and Northwest of China. The exception case is Chongqing, which emits 192 Mt CO_2, ranking third highest CO_2 emitter in China.

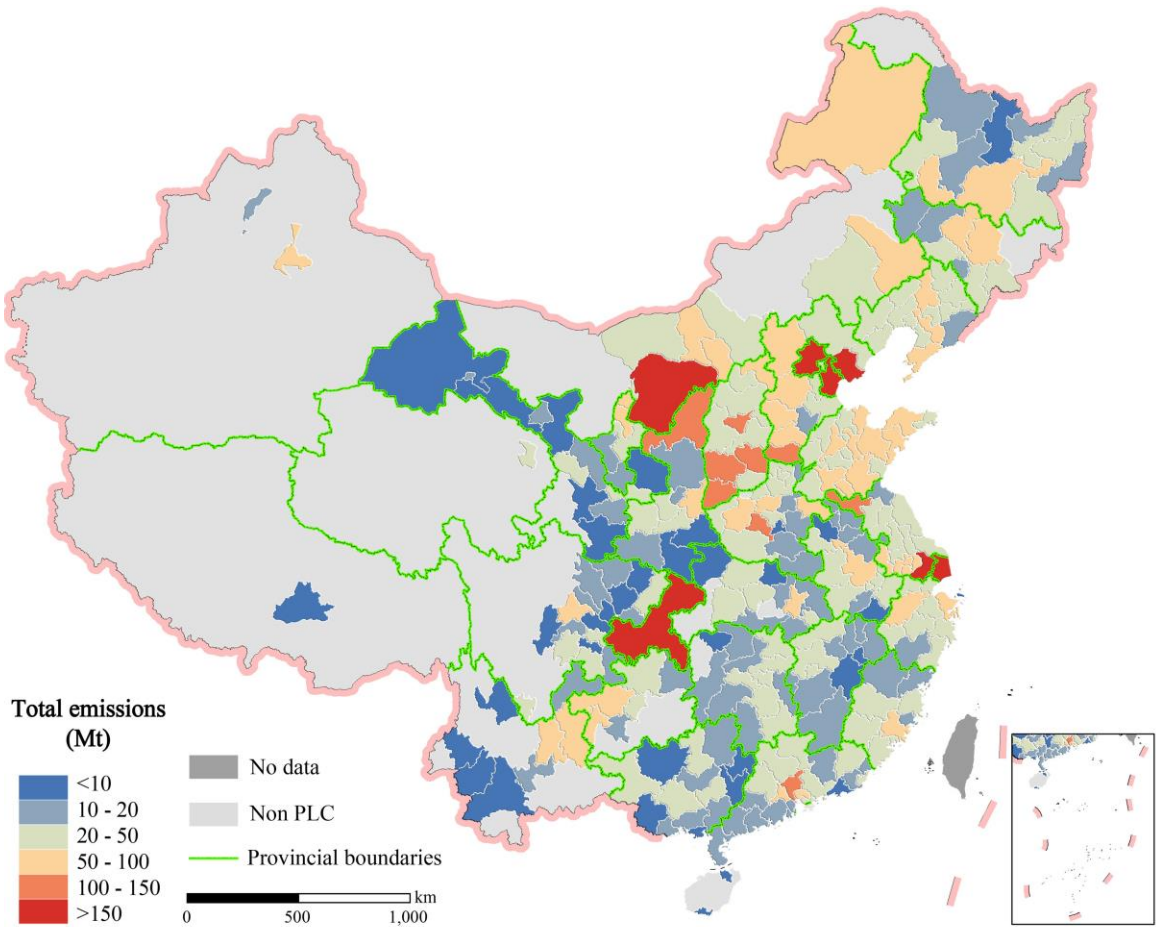

Figure 2. Distribution of total CO_2 emissions of Chinese prefectural level cities

Note: The PLC stands for prefectural level city.

We then plot per capita CO_2 emissions on per capita GDP to investigate the relationship between economic development and the CO_2 emissions (Figure 3a-3c). As expected, economic development drives up CO_2 emissions in China. However, different cities exhibit distinct patterns. Figure 3a distinguishes cities by their industry composition and shows that CO_2 emissions are positively correlated with economic growth. Yet, the slopes of the fitted lines are different, i.e., while the fitted line is upward for industrial cities (red line), it is flat for service-based cities (blue line). This highlights the industry composition as an important determinant of low carbon development in China.

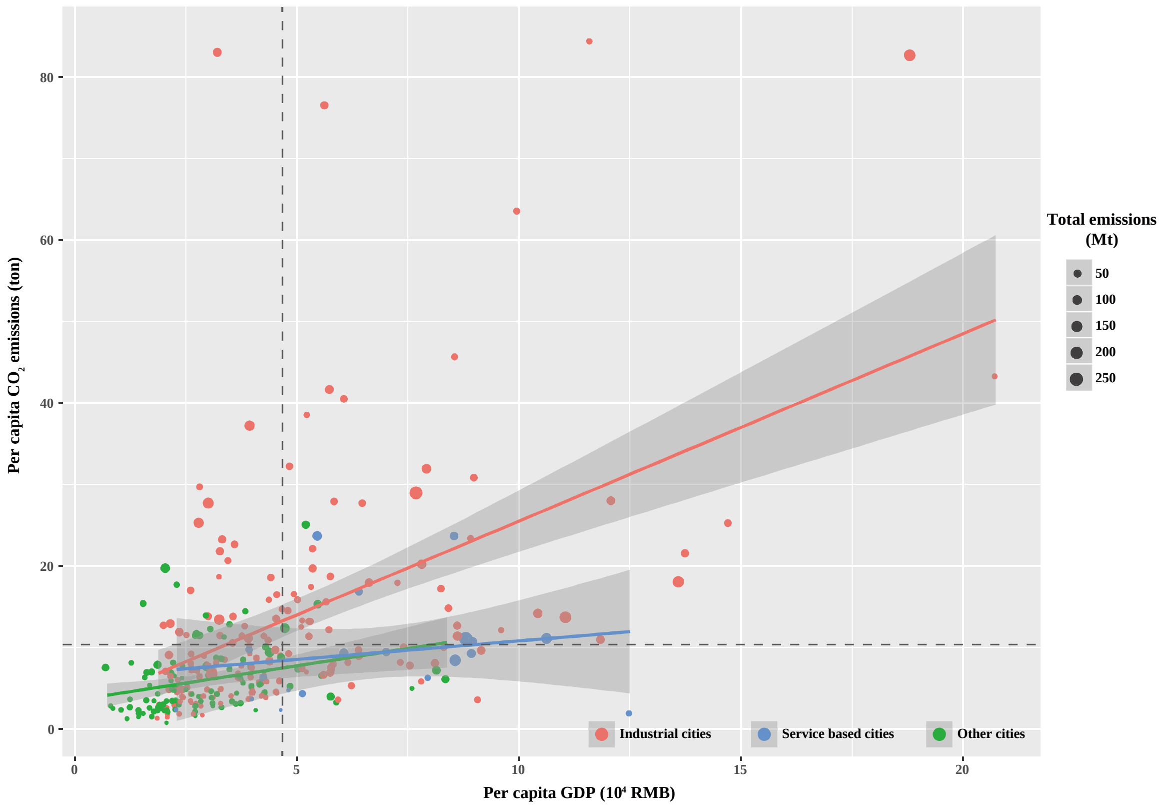

Figure 3a. Correlation of CO_2 emissions and economic growth (by city industry composition)

Note: Dots refer to cities and grey areas refer to the 95% significance level. The dash lines indicate the national mean level.

Figure 3b distinguishes cities according to their development stage, i.e., developed cities, developing cities and less-developed cities. As one can note, less-developed cities (blue spots) in the low development stage are found in two extreme cases of CO_2 emissions. While most of them remain on low level of CO_2 emission, some of them have the highest level of CO_2 emission. However, for most developed cities (red spots), they remain on the low level of CO2 emission compared to the national mean level. The slope of fitted lines decrease as the level of development increases, i.e., developed cities have the flattest fitted line and great potential for low-carbon economic development.

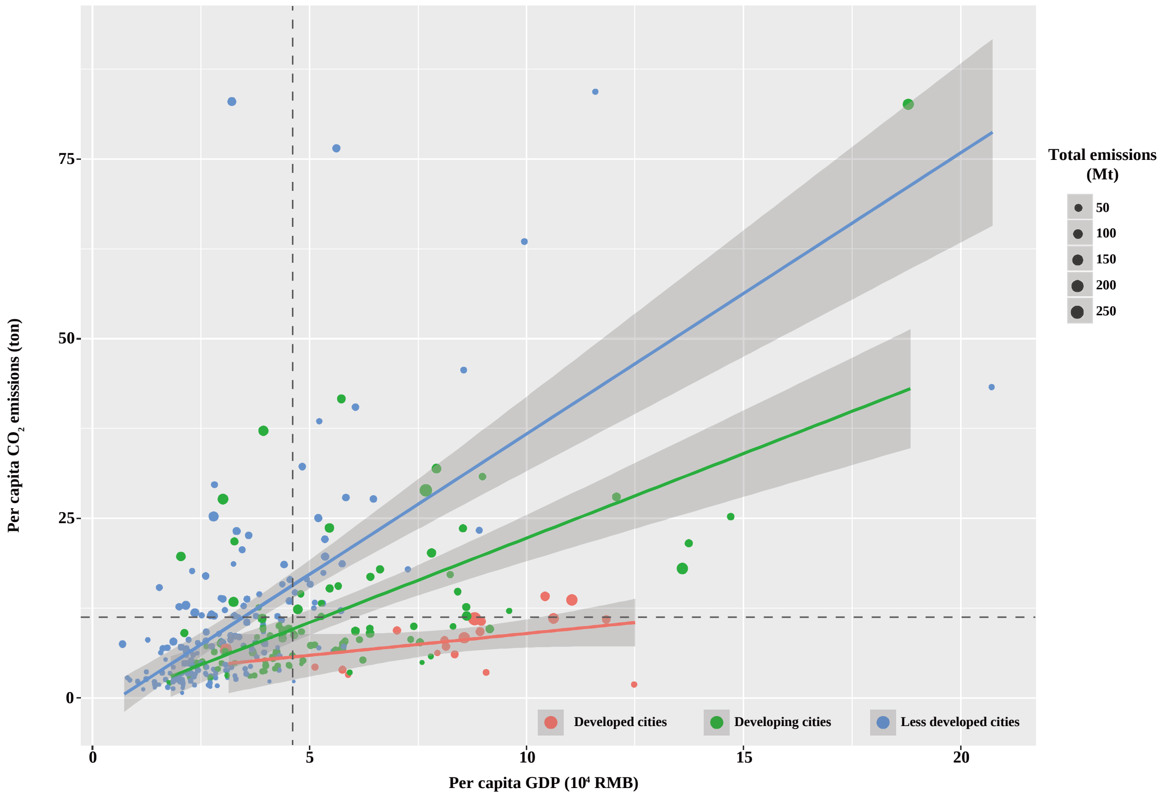

Figure 3b. Correlation of CO_2 emissions and economic growth (by city's development stage)

Note: Dots refer to cities and grey areas refer to the 95% significance level. The dash lines indicate the national mean level.

Figure 3c distinguishes cities by their geographical location, i.e., eastern, central, western and northeastern China. We find that cities in western China (blue spots) have low levels of economic development, whereas the CO_2 emissions in some western cities are high compared to the national mean level. Cities in the center and northeast have intermediate levels of economic development and CO_2 emissions. Although cities in the east of China (red spots) have advanced economic development relative to the national mean level, they also include cities with the lowest CO_2 emissions. The pattern of fitted lines is just in line with previous graphical patterns. In China, most eastern cities are developed cities and the service industry is much important there. Therefore, these two driving forces may explain the low carbon development in the eastern cities. Still, other potential explanations such as age structure should also be investigated by more rigorous regression analysis, to which we now turn.

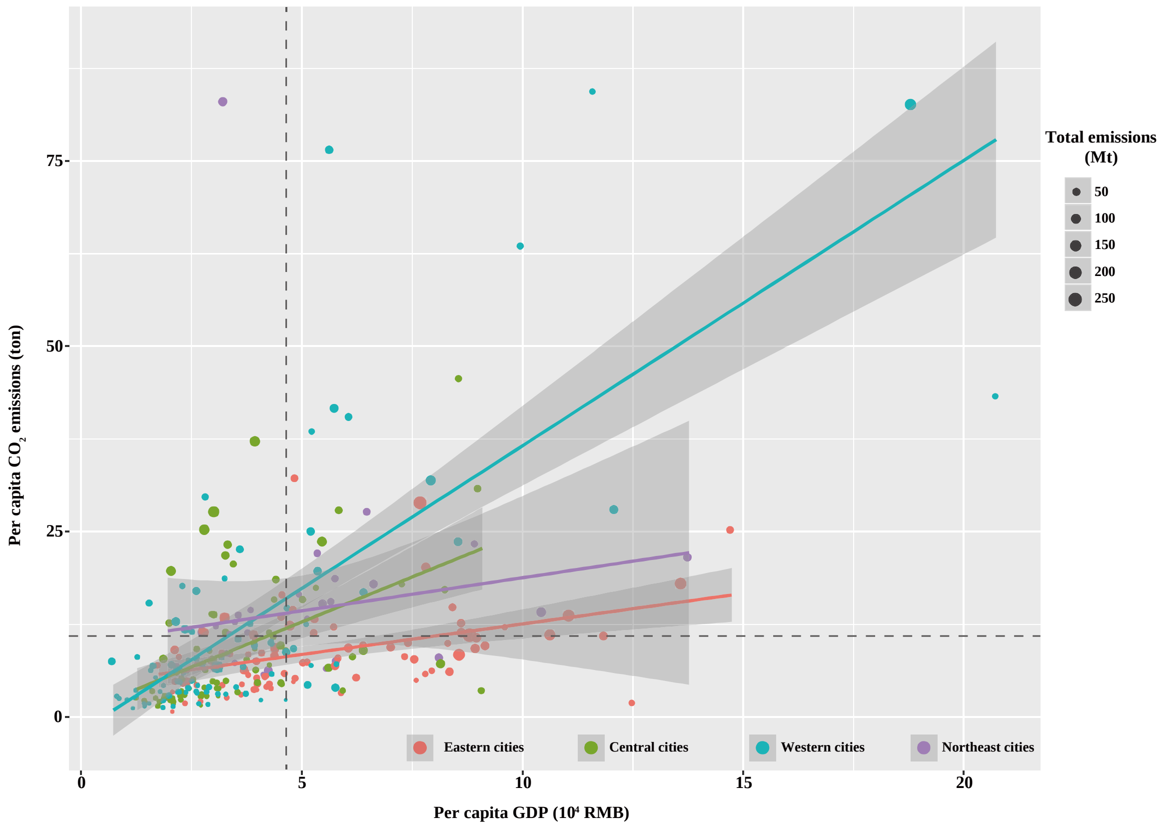

Figure 3c. Correlation of CO_2 emissions and economic growth (by geographical location)

Note: Dots refer to cities and grey areas refer to the 95% significance level. The dash lines indicate the national mean level.

4.2 Econometric results: Driving forces of city CO_2 emissions

For the econometric regression analysis, equation (1) is estimated with the Ordinary Least Square (OLS) method by assuming that error term ε_i satisfies the Independent and Identically Distribution (I.I.D.). Given the presence of regional development policies, cities'

CO_2 emissions may be clustered at the provincial level[6]. We therefore correct for the robust standard error with clusters by province. The cross-sectional estimates provide an overall picture for the whole country and help identify the most relevant driving forces of CO_2 emissions. To ensure the correct model specification, we follow a step-by-step approach to progressively include the control variables and check the robustness of the estimates. The results are presented in Table 2.

Table 2. Driving forces of Chinese prefectural city CO_2 emissions

	(1)	(2)	(3)	(4)	(5)	(6)
Y: lnCO_2 emission	Total		Direct		Indirect	
lnGDP_percapita	0.643*	0.848**	0.784**	0.952**	-1.755	-1.719
	(0.332)	(0.309)	(0.338)	(0.361)	(1.548)	(1.675)
lnGDP_percapita_sq	0.0294	-0.0504	-0.0186	-0.0898	0.909	0.938
	(0.114)	(0.0897)	(0.118)	(0.108)	(0.588)	(0.609)
Share_Agriculture	0.542	-2.246***	0.709	-2.440***	-3.717*	3.790
	(0.644)	(0.599)	(0.681)	(0.630)	(2.016)	(2.593)
Share_Service	-0.968*	-1.230***	-1.181**	-1.555***	2.623	3.609*
	(0.505)	(0.306)	(0.566)	(0.344)	(2.084)	(1.977)
lnClimate_condition		0.615***		0.621***		-0.120
		(0.0790)		(0.0885)		(0.484)
lnPop_density		-0.0831		-0.134*		0.964***
		(0.0672)		(0.0732)		(0.285)
lnAge		48.47		43.37		-92.08
		(54.24)		(58.42)		(273.4)
lnAge_sq		-7.030		-6.329		13.33
		(7.529)		(8.116)		(38.48)
lnEducation		-1.079		-0.787		2.588
		(1.032)		(1.156)		(3.912)
Urban_pop		0.936**		0.822		-2.462
		(0.449)		(0.519)		(2.559)
Urban_construction		-0.00241		-0.00228		-0.00961
		(0.00360)		(0.00365)		(0.0155)
lnFDI		-0.0213		-0.0161		-0.110
		(0.0280)		(0.0288)		(0.0924)
lnR&D		-0.211***		-0.220***		0.485
		(0.0482)		(0.0542)		(0.348)
Constant	8.501***	-74.91	8.403***	-66.38	2.954*	155.6

[6] There are three major regional development policies in China: the Western Development policy, the Rising of Central China policy and the Northeastern Revitalization policy.

	(0.471)	(97.76)	(0.495)	(105.2)	(1.647)	(484.4)
Observations	286	286	286	286	286	286
R-squared	0.341	0.591	0.324	0.563	0.038	0.099

Note: Results from OLS estimations. Robust Standard Errors in parentheses, SE is clustered by province for all estimations. *** p<0.01, ** p<0.05, * p<0.1.

We firstly check the results of total CO_2 emissions. In column 1 of Table 2, we estimate the basic model without including control variables. It turns out that economic growth is a major driving force of China's prefectural city CO_2 emissions. The coefficient of GDP per capita is positive and significant at the 10% level. However, the second order of GDP per capita is non-significant, implying a monotonic increasing relationship between economic growth and CO_2 emissions for the whole country. In terms of economic structure[7], the share of the service sector is negative and significant at the 10% level, implying that economic structural changes can effectively reduce CO_2 emissions.

In column 2, we include other control variables. As one can note, the coefficient of GDP per capita remains significant and robust. Keeping all other factors constant, if China's annual economic growth continues at the rate of 7%, CO_2 emissions should increase by about 6% annually. This result is in line with previous studies and confirms the large economic scale effect of China's CO_2 emissions (Li, 2010). Furthermore, climate conditions and urbanization are two significant driving forces of China's CO_2 emissions. China is a country highly vulnerable to climate change, and abnormal climate conditions are becoming increasingly frequent. These worsening climate conditions in turn increase CO_2 emissions of cities, which in turn accelerate climate change in a perpetual vicious circle, which calls for immediate action to mitigate and adapt to climate change. China's ever-increasing urban population significantly increases CO_2 emissions. Ceteris paribus, a 1% increment of the urbanization rate will increase the city CO_2 emissions by about 0.9%. The rapid expansion of China's urban population means a collective lifestyle change characterized by significant increases in energy consumption, which translate into increased CO_2 emissions. The significant urbanization effect on CO_2 emissions highlights the great challenge that China faces to meet its climate change commitments.

[7] The share of secondary industry is dropped due to the perfect collinearity.

Nevertheless, the Chinese government has different strategy options to tackle the challenge. The first strategy is to change the economic structure of certain cities. As revealed by our results, a large share of agriculture and service sectors in the economy will significantly reduce CO_2 emissions. More precisely, increasing the share of agriculture and tertiary sectors by 1% may reduce CO_2 emissions by 2.25% and 1.23%, respectively. The second strategy is to increase public expenditures in R&D. A 1% investment in R&D may reduce CO_2 emissions by 0.21%. In light of our results, the policy implication is clear. The Chinese government should continue to encourage the development of the agricultural and tertiary sectors by investing more public resources in related R&D activities. These investments could have a direct impact on the mitigation of CO_2 emissions. Moreover, new and clean technologies generated by R&D activities could further upgrade the industry and have long-term implications for reducing CO_2 emissions.

Next, we distinguish between direct and indirect CO_2 emissions and check the results, respectively. In column 4, the results for direct CO_2 emissions are similar to those of total emissions. In addition to previous results, we find that population density has a significant effect in reducing direct CO_2 emissions. This result is in line with the findings of Glaeser and Kahn (2010). In the U.S., cities with higher population density tend to produce lower CO_2 emissions. This evidence then justifies the development of megacities such as Shanghai and Shenzhen in China. However, we also note that high population density significantly increases indirect CO_2 emissions (column 6). If a city's population density increases by 1%, it should reduce the city's direct CO_2 emissions by 0.13%, but it should also increase indirect CO_2 emissions by 0.94%. This result is striking, and it is plausible that energy consumption in megacities does not actually decrease but is rather offset by the import of electricity from other cities. Take Beijing for example. As it has become an international megacity, many local polluting steel and chemical plants were urged to move out of Beijing and relocated to the neighboring province of Hebei (Xia et al., 2015) in order to reduce fossil fuel energy consumption and pollution. As a result, direct energy consumption was driven down in Beijing but increased in Hebei province. Consequently, the relocation of pollution and CO_2 emissions does not resolve environmental problems but rather raises the concern of environmental inequality. Therefore, we advocate close collaboration among cities in their environmental policy design and carbon mitigation strategies; the coordinated development of cities with intensive infrastructure networks seems to be the most suitable and effective strategy in increasing sustainability and reducing total CO_2 emissions

4.2 Heterogeneous local strategies for carbon mitigation

To check heterogeneous local strategies for carbon mitigation, we divide the full sample into subsamples and redo the same regression analysis. First, we divide cities into three groups based on industry composition, i.e., industrial cities (163), service-based cities (18), and other cities (105). The results are presented in Table 3.

Table 3. CO_2 emission patterns by city industry composition

	(1)	(2)	(3)
City type	Industry	Service	Others
Dependent Var.		ln total CO_2 emissions	
lnGDP_percapita	1.222**	7.413*	0.545
	(0.561)	(3.733)	(0.509)
lnGDP_percapita_sq	-0.156	-2.132*	-0.0465
	(0.161)	(1.097)	(0.201)
Share_Agriculture	-0.652	-6.123**	-2.061**
	(0.770)	(2.072)	(0.764)
Share_Service	-1.216***	6.908*	-0.459
	(0.387)	(3.597)	(0.644)
lnClimate_condition	0.670***	0.267	0.515***
	(0.0982)	(0.438)	(0.0792)
lnPop_density	-0.0514	0.255	-0.256***
	(0.0982)	(0.327)	(0.0745)
lnAge	79.69	947.2***	-6.336
	(51.69)	(292.2)	(92.75)
lnAge_sq	-11.36	-132.0***	0.503
	(7.178)	(40.50)	(12.93)
lnEducation	-1.870	-17.55*	-0.613
	(1.164)	(8.888)	(1.425)
Urban_pop	0.997*	9.845*	1.664**
	(0.541)	(5.087)	(0.757)
Urban_Construction	-0.00267	0.0915	0.00107

	(0.00343)	(0.0618)	(0.00770)
lnFDI	-0.0339	0.616**	0.00697
	(0.0304)	(0.285)	(0.0195)
lnR&D	-0.197**	-1.272**	-0.0769
	(0.0830)	(0.501)	(0.0745)
Constant	-130.0	-1,658***	21.22
	(93.45)	(514.6)	(167.3)
Observations	163	18	105
R-squared	0.604	0.938	0.441

Note: Results from OLS estimations. Robust Standard Errors in parentheses, SE is clustered by province for all estimations. *** p<0.01, ** p<0.05, * p<0.1.

The patterns of CO_2 emissions are distinct across cities with different types of industry composition. Economic growth, climate conditions and urbanization are major driving forces of CO_2 emissions of industrial cities. The best mitigation strategy for these cities, therefore, is to enlarge the share of the service sector and increase investment in R&D. For service-based cities, as economic growth continues and the age structure changes, CO_2 emissions will firstly increase then decrease, which confirms the EKC turning point in these cities. However, it should note that urbanization and FDI are major factors that may increase CO_2 emissions, whereas development of the agriculture sector and investment in R&D and education can effectively reduce CO_2 emissions. Therefore, more balanced economic structure and high-tech development are appropriate mitigation strategies to sustain the economic growth and achieve low carbon development in service-based cities. In other cities where climate conditions and urbanization are two major driving forces of CO_2 emissions, development of the agriculture sector and increasing population density appear to be more appropriate strategies.

Second, we divide cities into three groups according to their development stage, i.e., developed cities (18), developing cities (96) and less-developed cities (172). The results are presented in Table 4.

Table 4. Patterns of CO_2 emission by Chinese city development stage

	(1)	(2)	(3)
City type	Developed	Developing	Less developed
Dependent Var.		ln total CO_2 emissions	

lnGDP_percapita	-4.427	0.590	0.849**
	(7.212)	(0.609)	(0.396)
lnGDP_percapita_sq	1.212	0.0979	-0.0549
	(1.631)	(0.151)	(0.151)
Share_Agriculture	16.76	-2.635	-2.437***
	(32.57)	(2.112)	(0.631)
Share_Service	3.884	-0.561	-1.397***
	(2.644)	(0.554)	(0.387)
lnClimate_condition	1.240*	0.640***	0.547***
	(0.691)	(0.151)	(0.0822)
lnPop_density	0.307	-0.00405	-0.0614
	(0.274)	(0.0711)	(0.0923)
lnAge	1,021**	54.91	-10.08
	(355.6)	(51.81)	(81.14)
lnAge_sq	-142.8**	-8.082	1.209
	(49.99)	(7.202)	(11.33)
lnEducation	-18.90*	-0.580	-1.047
	(9.963)	(1.518)	(1.275)
Urban_pop	14.32**	0.00550	1.622**
	(6.346)	(0.547)	(0.720)
Urban_construction	0.0215	-0.00159	-0.00277
	(0.0236)	(0.00505)	(0.00447)
lnFDI	-0.0617	-0.0117	-0.0370
	(0.393)	(0.0546)	(0.0284)
lnR&D	-0.787*	-0.290**	-0.0610
	(0.409)	(0.132)	(0.0647)
Constant	-1,778**	-84.36	27.66
	(610.7)	(92.42)	(145.9)
Observations	18	96	172
R-squared	0.933	0.585	0.625

Note: Results from OLS estimations. Robust Standard Errors in parentheses, SE is clustered by province for all estimations. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In China, developed cities such as Beijing, Shanghai, Guangzhou and Shenzhen have a high level of socio-economic development and have received political priority by the central government. Developing cities like Suzhou, Zhengzhou and Dongguan, have lower political priority but high economic growth rates. As revealed by the results in Table 4, cities in different development stages have different emission patterns. For instance, rapid economic growth in developed or developing cities does not significantly increase CO_2 emissions, whereas it significantly drives up CO_2 emissions in less developed cities. While urbanization seems to be a driving force of CO_2 emissions in the developed and less developed cities in our study, it is not significant in the developing cities. Interestingly, while extremity in climate conditions increases CO_2 emissions in all cities, it has the largest impact in developed cities, where people are wealthier and may use more energy under extreme climate conditions. This result thus calls for more efficient public facilities and collective strategies for residents' adaptation to climate change. Governments in different cities have different carbon mitigation strategies. For developed cities, aging and more educated populations facilitate local carbon mitigation and public investment in R&D is a major mitigation strategy of local government. For developing cities, only public investment in R&D has proved significant in reducing CO_2 emissions, while the most efficient solution for less developed cities would be to focus on changes in economic structure by increasing the share of agriculture and tertiary sectors.

Third, as the distribution of population and industry is highly uneven across China, geographical location may have important implications for the CO_2 emissions of cities. We thus divide cities into eastern (86), central (80), western (86) and northeast (34) groups according to their geographical location. The results are presented in Table 5.

Table 5. Patterns of Chinese city CO_2 emissions by geographical location

	(1)	(2)	(3)	(4)
Region	East	Central	West	Northeast
Dependent Var.		ln total CO_2 emissions		
lnGDP_percapita	0.526***	1.069*	0.924*	1.196*
	(0.109)	(0.505)	(0.439)	(0.335)
lnGDP_percapita_sq	0.0300	-0.0805	-0.0994	-0.260
	(0.0732)	(0.123)	(0.141)	(0.123)
Share_Agriculture	-5.540	-0.660	-3.083	-2.178***
	(3.678)	(1.926)	(2.633)	(0.124)
Share_Service	-0.166	-0.724	-1.701***	-4.583***
	(0.419)	(0.605)	(0.452)	(0.446)
lnClimate_condition	0.429***	1.367***	0.627***	-0.608
	(0.0782)	(0.171)	(0.107)	(1.148)
lnPop_density	-0.0558	0.00901	-0.0770	0.125
	(0.0506)	(0.117)	(0.137)	(0.162)
lnAge	132.9**	78.78	-19.30	600.7
	(49.45)	(155.3)	(85.37)	(320.6)

lnAge_sq	-18.56**	-11.34	2.250	-82.69
	(6.888)	(21.66)	(12.05)	(43.21)
lnEducation	1.235	-0.690	-2.547	3.835
	(0.845)	(2.677)	(1.506)	(3.454)
Urban_pop	-0.0610	1.849	1.726*	-0.204
	(0.666)	(1.074)	(0.932)	(0.240)
Urban_construction	-0.00376	-0.00615*	-0.000831	-0.0122
	(0.00529)	(0.00295)	(0.0148)	(0.00675)
lnFDI	-0.00733	-0.0914	0.00206	-0.180
	(0.0339)	(0.0632)	(0.0239)	(0.100)
lnR&D	-0.283**	-0.282	-0.143*	-0.0773
	(0.112)	(0.169)	(0.0749)	(0.128)
Constant	-231.8**	-133.8	50.74	-1,080
	(88.66)	(278.6)	(149.7)	(595.9)
Observations	86	80	86	34
R-squared	0.562	0.629	0.687	0.822

Note: Results from OLS estimations. Robust standard errors in parentheses, SE is clustered by province for all estimations. *** p<0.01, ** p<0.05, * p<0.1.

Cities in the eastern region, such as Beijing and Tianjin, have received early political priority for reform and opening up, and their citizens are generally wealthy compared to those in other parts of the country. A significant feature of eastern cities is the aging population, which helps reduce CO_2 emissions. Local governments should invest more public resources in R&D, which has the largest effect on local CO_2 emissions of these more affluent cities. For cities in central China such as Wuhan and Zhengzhou, economic growth and climate conditions are major driving factors of their CO_2 emissions. A particular mitigation strategy of central cities would be to invest in urban construction of public infrastructure. The development of infrastructure may meet the demands of the large populations of the central region and effectively reduce CO_2 emissions. Cities such as Xi'an and Chengdu in the western region have received policy focus since 2000. In China's western development campaign, economic growth and urbanization have become urgent development objectives of western cities. As a result, pursuit of economic growth and rapid urbanization has sacrificed the environment and significantly driven up CO_2 emissions. Moreover, climate conditions threaten to accelerate carbon emissions. Development of the service sector and public investment in R&D would be appropriate policy options. Finally, cities such as Shenyang and Harbin in the northeast region are historical bases for heavy industry development. Their economic growth has contributed most to CO_2 emissions. Therefore, the declining heavy industrial economy should contribute to carbon mitigation. At the same time, as land and natural resources are abundant in the northeast region, economic structural changes to the agriculture and service sectors would be appropriate strategies to revive the economy and shift to low-carbon development in the northeast region.

5. Conclusion and policy implications

In developing countries like China, urbanization is a necessary pathway to economic prosperity. To build more low-carbon and climate-resilient cities, accurate knowledge about cities' carbon emissions is the first step for carbon mitigation action at the local level. To this end, this paper constructs a reliable carbon accounting for 286 Chinese prefectural level cities in 2012 and provides a systematic econometric analysis of the key driving forces of CO_2 emissions and local carbon mitigation strategies in China. Our contributions to the literature are threefold. First, the bottom-up approach improves previous carbon accounting methods and establishes a more comprehensive and reliable high spatial resolution CO_2 emissions dataset. Second, we distinguish the scope 1 and scope 2 CO_2 emissions, which is unique and more accurate. Third, our systematic analysis covers almost all Chinese prefectural level cities and provides solid evidences for the heterogeneous strategies of carbon mitigation according to local conditions. The findings complement current literature and provide useful implications of tailored policy design for China's low carbon development.

According to our calculations, the average Chinese city CO_2 emissions were about 36 million metric tons in 2012. The distribution is highly uneven across the country with significantly higher emissions in the northern and coastal regions. Using linear regression analysis, we find that on the one hand, economic growth, rapid urbanization and the worsening climate conditions are major factors that increase Chinese cities' CO_2 emissions. On the other hand, fundamental economic structural change and public investment in R&D

can effectively reduce CO_2 emissions. While increasing population density may reduce direct CO_2 emissions, it also increases indirect CO_2 emissions.

As cities differ greatly in their industry composition, development stage and geographical location, corresponding local strategies for carbon mitigation are also different. Therefore, we recommend that national climate policies should be tailored to take into account distinct local conditions. For instance, climate policies should favor tertiary sector in industrial cities, but agricultural sector in service-based cities to achieve balanced economic structure. In developed cities, more public resources should be allocated to education, R&D activity, and more public facilities; whereas in less developed cities, a fundamental change in economic structure to the agricultural and tertiary sectors are more appropriate. Lastly, since cities in different geographical locations have different priorities and constraints, climate policies should stimulate their economic specialization and favor alternative pathways to the low-carbon development.

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References

Ang, J.B., 2009. CO_2 emissions, research and technology transfer in China. Ecological Economics 68, 2658-2665.

Cai, B., Wang, J., He, J., Geng, Y., 2016. Evaluating CO_2 emission performance in China's cement industry: an enterprise perspective. Applied Energy 166, 191-200.

Cai, B., Zhang, L., 2014. Urban CO_2 emissions in China: Spatial boundary and performance comparison. Energy Policy 66, 557-567.

Cai B, Wang J, Yang S, Mao X, Cao L. Carbon dioxide emissions from cities in China based on high resolution emission gridded data. Chinese Journal of Population Resources and Environment. 2017;15:58-70.

Chen, Y., Ebenstein, A., Greenstone, M., Li, H., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. Proceedings of the National Academy of Sciences 110, 12936-12941.

Chung, S., 2014. Environmental regulation and foreign direct investment: Evidence from South Korea. Journal of Development Economics 108, 222-236.

Cole, M.A., Rayner, A.J., Bates, J.M., 1997. The environmental Kuznets curve: an empirical analysis. Environment and development economics 2, 401-416.

Creutzig, F., Baiocchi, G., Bierkandt, R., Pichler, P.-P., Seto, K.C., 2015. Global typology of urban energy use and potentials for an urbanization mitigation wedge. Proceedings of the National Academy of Sciences 112, 6283-6288.

Dhakal, S., 2009. Urban energy use and carbon emissions from cities in China and policy implications. Energy policy 37, 4208-4219.

Doll, C.H., Muller, J.-P., Elvidge, C.D., 2000. Night-time imagery as a tool for global mapping of socioeconomic parameters and greenhouse gas emissions. AMBIO: a Journal of the Human Environment 29, 157-162.

Ebenstein, A., Fan, M., Greenstone, M., He, G., Yin, P., Zhou, M., 2015. Growth, pollution, and life expectancy: China from 1991–2012. The American Economic Review 105, 226-231.

Elliott, J.R., Clement, M.T., 2014. Urbanization and carbon emissions: a nationwide study of local countervailing effects in the United States. Social Science Quarterly 95, 795-816.

Feng, K., Hubacek, K., Sun, L., Liu, Z., 2014. Consumption-based CO_2 accounting of China's megacities: The case of Beijing, Tianjin, Shanghai and Chongqing. Ecological Indicators 47, 26-31.

Glaeser, E., 2011. Triumph of the city: How our greatest invention makes us richer, smarter, greener, healthier, and happier. Penguin.

Glaeser, E.L., Kahn, M.E., 2010. The greenness of cities: carbon dioxide emissions and urban development. Journal of urban economics 67, 404-418.

Greene, H. 2008. "Econometric Analysis (6-Th Ed.)." Prentice-Hall, New Jersey.

Grossman, G.M., Krueger, A.B., 1991. Environmental impacts of a North American free trade agreement. National Bureau of Economic Research.

Guan, D., Peters, G.P., Weber, C.L., Hubacek, K., 2009. Journey to world top emitter: An analysis of the driving forces of China's recent CO_2 emissions surge. Geophysical Research Letters 36.

He, J., Wang, H., 2012. Economic structure, development policy and environmental quality: An empirical analysis of environmental Kuznets curves with Chinese municipal data. Ecological Economics 76, 49-59.

International Energy Agency, 2008. World Energy Outlook 2008, IEA, Paris.

IPCC, 2014. Climate change 2014: Mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change., Cambridge University Press, Cambridge, UK.

Jalil, A., Mahmud, S.F., 2009. Environment Kuznets curve for CO_2 emissions: a cointegration analysis for China. Energy Policy 37, 5167-5172.

Kivyiro, P., Arminen, H., 2014. Carbon dioxide emissions, energy consumption, economic growth, and foreign direct investment: Causality analysis for Sub-Saharan Africa. Energy 74, 595-606.

Li, M., 2010. Decomposing the change of CO_2 emissions in China: a distance function approach. Ecological Economics 70, 77-85.

Liddle, B., 2014. Impact of population, age structure, and urbanization on carbon emissions/energy consumption: evidence from macro-level, cross-country analyses. Population and Environment 35, 286-304.

Liddle, B., Lung, S., 2010. Age-structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption-related environmental impacts. Population and Environment 31, 317-343.

Menz, T., Welsch, H., 2012. Population aging and carbon emissions in OECD countries: Accounting for life-cycle and cohort effects. Energy Economics 34, 842-849.

NBS, 2010. The sixth population census of China, National Bureau of Statistics, Beijing, China.

NDRC, 2014. Average CO_2 emission factors for regional power grids in China in 2011 and 2012, National Development and Reform Commission, Beijing, China.

Ouyang, X., Lin, B., 2016. Carbon dioxide (CO_2) emissions during urbanization: A comparative study between China and Japan. Journal of Cleaner Production.

Romuald, K.S., 2011. Education, convergence and carbon dioxide growth per capita: research paper. African Journal of Science, Technology, Innovation and Development 3, 65-85.

Selden, T.M., Song, D., 1994. Environmental quality and development: is there a Kuznets curve for air pollution emissions? Journal of Environmental Economics and management 27, 147-162.

Sheng, P., Guo, X., 2016. The long-run and short-run impacts of urbanization on carbon dioxide emissions. Economic Modelling 53, 208-215.

Stern, D.I., Common, M.S., 2001. Is there an environmental Kuznets curve for sulfur? Journal of Environmental Economics and Management 41, 162-178.

The Guardian, 2016. China ratifies Paris climate change agreement ahead of G20, London, UK.

UNEP, UNHABITAT,, World Bank, 2010. International Standard for Determining Greenhouse Gas Emissions for Cities.

Wang, J., Cai, B., Zhang, L., Cao, D., Liu, L., Zhou, Y., Zhang, Z., Xue, W., 2014. High resolution carbon dioxide emission gridded data for China derived from point sources. Environmental science & technology 48, 7085-7093.

Wang, Z., Ye, X., 2016. Re-examining environmental Kuznets curve for China's city-level carbon dioxide (CO_2) emissions. Spatial Statistics.

WRI, 2014. Local Governments for Sustainability. 2014. Global Protocol for Community-Scale Greenhouse Gas Emission Inventories (GPC). World Resources Institute, C40 Cities Climate Leadership Group, and ICLEI.

Xia, X.-H., Hu, Y., Chen, G., Alsaedi, A., Hayat, T., Wu, X., 2015. Vertical specialization, global trade and energy consumption for an urban economy: A value added export perspective for Beijing. Ecological Modelling 318, 49-58.

Zhang, C., Lin, Y., 2012. Panel estimation for urbanization, energy consumption and CO_2 emissions: a regional analysis in China. Energy Policy 49, 488-498.

Zheng, S., Wang, R., Glaeser, E.L., Kahn, M.E., 2010. The greenness of China: household carbon dioxide emissions and urban development. Journal of Economic Geography 11(5), 761-792.

Zhu, H., Duan, L., Guo, Y., Yu, K., 2016. The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: Evidence from panel quantile regression. Ecological Modelling 58, 237-248.

Appendix

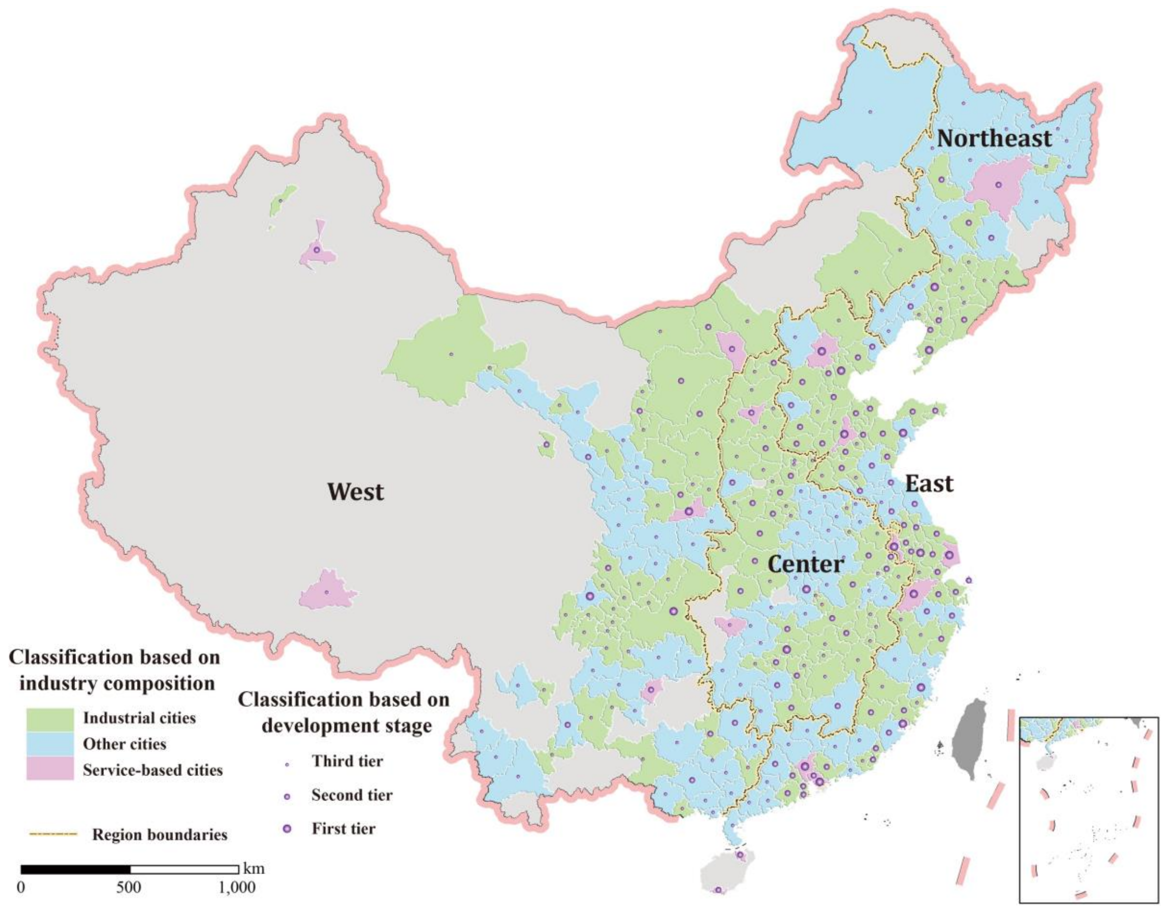

Figure A1. Spatial distribution of Chinese cities

Table A1. List of Chinese cities

Beijing	Linfen	Quzhou	Putian	Xiangtan	Meizhou	Yulin
Tianjin	Lvliang	Zhoushan	Sanming	Hengyang	Shanwei	Ankang
Shijiazhuang	Hohhot	Taizhou	Quanzhou	Shaoyang	Heyuan	Shangluo
Tangshan	Baotou	Lishui	Zhangzhou	Yueyang	Yangjiang	Lanzhou
Qinhuangdao	Karamay	Hefei	Nanping	Changde	Qingyuan	Jiayuguan
Handan	Chifeng	Wuhu	Longyan	Zhangjiajie	Dongguan	Jinchang
Xingtai	Tongliao	Bengbu	Ningde	Yiyang	Zhongshan	Baiyin
Baoding	Ordos	Huainan	Nanchang	Chenzhou	Chaozhou	Tianshui
Zhangjiakou	Hulunbeier	Ma'anshan	Jingdezhen	Yongzhou	Jieyang	Wuwei
Chengde	Bayannur	Huaibei	Pingxiang	Huaihua	Yunfu	Zhangye
Cangzhou	Wulanchabu	Tongling	Jiujiang	Loudi	Nanning	Pingliang
Langfang	Shenyang	Anqing	Xinyu	Guangzhou	Liuzhou	Jiuquan
Hengshui	Dalian	Huangshan	Yingtan	Shaoguan	Guilin	Qingyang
Taiyuan	Anshan	Chuzhou	Ganzhou	Shenzhen	Wuzhou	Dingxi
Datong	Fushun	Fuyang	Ji'an	Zhuhai	Beihai	Longnan
Yangquan	Benxi	Suzhou	Yichun	Shantou	Fangchenggang	Xining
Changzhi	Dandong	Lu'an	Fuzhou	Foshan	Qinzhou	Yinchuan
Jincheng	Jinzhou	Bozhou	Shangrao	Jiangmen	Guigang	Shizuishan
Shuozhou	Yingkou	Chizhou	Jinan	Zhanjiang	Yulin	Wuzhong
Jinzhong	Fuxin	Xuancheng	Qingdao	Maoming	Baise	Guyuan
Yuncheng	Liaoyang	Fuzhou	Zibo	Zhaoqing	Hezhou	Zhongwei
Xinzhou	Panjin	Xiamen	Zaozhuang	Huizhou	Hechi	Urumqi
Tieling	Suihua	Dongying	Xuchang	Laibin	Ziyang	Jiamusi
Chaoyang	Shanghai	Yantai	Luohe	Chongzuo	Guiyang	Qitaihe
Huludao	Nanjing	Weifang	Sanmenxia	Haikou	Liupanshui	Mudanjiang
Changchun	Wuxi	Jining	Nanyang	Sanya	Anshun	Heihe
Jilin	Xuzhou	Tai'an	Shangqiu	Chongqing	Bijie	Jiaxing
Siping	Changzhou	Weihai	Xinyang	Chengdu	Tongren	Huzhou
Liaoyuan	Suzhou	Rizhao	Zhoukou	Zigong	Kunming	Shaoxing
Tonghua	Nantong	Laiwu	Zhumadian	Panzhihua	Qujing	Jinhua
Baishan	Lianyungang	Linyi	Wuhan	Luzhou	Yuxi	Hebi
Songyuan	Huai'an	Dezhou	Huangshi	Deyang	Baoshan	Xinxiang
Baicheng	Yancheng	Liaocheng	Shiyan	Mianyang	Zhaotong	Jiaozuo
Harbin	Yangzhou	Binzhou	Yichang	Guangyuan	Lijiang	Puyang
Qiqihar	Zhenjiang	Heze	Xiangyang	Suining	Pu'er	Xianning
Jixi	Taizhou	Zhengzhou	Ezhou	Neijiang	Lincang	Suizhou
Hegang	Suqian	Kaifeng	Jingmen	Leshan	Lhasa	Changsha
Shuangyashan	Hangzhou	Luoyang	Xiaogan	Nanchong	Xi'an	Zhuzhou
Daqing	Ningbo	Pingdingshan	Jingzhou	Meishan	Tongchuan	Bazhong
Yichun	Wenzhou	Anyang	Huanggang	Yibin	Baoji	Hanzhong
Ya'an	Dazhou	Weinan	Guangan	Xianyang	Yan'an	

Source: own elaboration

Table A2. Variable Definition and Data Sources

Variable	Definition	Unit	Data Source
CO_2 emission	The city's total CO_2 emissions per capita (direct and indirect).	Metric ton	CHRED2.0, (Wang et al., 2014; Cai et al., 2017;)
Direct CO_2 emission	CO_2 emissions per capita released from sources of industry production, agricultural production, household energy consumption, transportation.	Metric ton	CHRED2.0, (Wang et al., 2014; Cai et al., 2017;)
Indirect CO_2 emission	CO_2 emission per capita calculated from electricity imported from outside the administrative border of the city.	Metric ton	Cai et al., 2017
GDP_percapita	Gross domestic production per capita of the city.	10,000 yuans	China City Statistical Yearbook, 2012
Share_agriculture	Share of labor in agriculture sector in the total labor of the city.	%	China City Statistical Yearbook, 2012
Share_service	Share of labor in tertiary sector in the total labor of the city.	%	China City Statistical Yearbook, 2012
Share_industry	Share of labor in secondary industry sector in the total labor of the city.	%	China City Statistical Yearbook, 2012
Climate_condition	The sum of Cooling Degree Days (CDD) and Heating Degree Days (HDD) during the year (in logarthm).	Days	Resource and Environment Science Data Center，Chinese Academy of Sciences. http://www.resdc.cn
Pop_density	Population per km2 of the city (in logarithm).	10,000 persons	China City Statistical Yearbook, 2012
Age	Average age ofpopulation in the city (in logarithm).	Years	The 6th Population Census of China, (NBS, 2010)
Education	Average education level of population in the city.	Years	The 6th Population Census of China, (NBS, 2010)
Urban_pop	Share of urban population in total population of the city.	%	The 6th Population Census of China, (NBS, 2010)
Urban_construction	Share of land for urban construction in the city.	%	China City Statistical Yearbook, 2012
FDI	Foreign direct investment actually used during the year in the city (in logarithm).	10,000 US dollars	China City Statistical Yearbook, 2012
R&D	Public expenditure in education and research activities (in logarithm).	10,000 yuans	China City Statistical Yearbook, 2012

Table A3. Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Total CO2 emission	286	10.869	12.089	0.783	84.409
Direct CO2 emission	286	10.165	11.856	0.783	83.129
Indirect CO2 emission	286	0.704	1.183	0	11.752
GDP percap	286	4.386	2.820	0.730	20.73
Share_agriculture	286	0.0307	0.0673	0	0.521
Share_industry	286	0.451	0.142	0.0809	0.831
Share_service	286	0.518	0.130	0.167	0.912
Climate_condition	286	2460	1353	250	7108
Pop_density	286	0.0443	0.0485	0.000565	0.519
Age	286	35.89	2.468	29.92	43.17
Education	286	8.946	0.822	6.550	11.71
Urban_pop	286	0.496	0.161	0.187	1
Urban_construction	286	9.569	10.94	0.190	75.26
FDI	286	81376	177014	0	1.502e+06
R&D	286	598588	709527	15720	8.286e+06

Table A4. Matrix of correlation between variables

	CO_2 emissions	Direct CO_2 emissions	Indirect CO_2 emissions	GDP_percap	Share_agriculture	Share_industry	Share_service	Climate_condition	Pop_density	Age	Education	Urban_pop	Urban_const	FDI	R&D
CO_2 emissions	1														
Direct CO_2 emissions	0.995	1													
Indirect CO_2 emissions	0.244	0.149	1												
GDP_percap	0.494	0.470	0.335	1											
Share_agriculture	-0.0099	-0.0062	-0.0386	-0.103	1										
Share_industry	0.321	0.313	0.146	0.464	-0.408	1									
Share_service	-0.346	-0.339	-0.140	-0.453	-0.0718	-0.881	1								
Climate_condition	0.359	0.361	0.0489	0.106	0.433	-0.187	-0.0199	1							
Pop_density	-0.132	-0.143	0.0894	0.301	-0.234	0.292	-0.198	-0.325	1						
Age	0.104	0.101	0.0499	0.217	0.107	0.142	-0.211	0.384	-0.196	1					
Education	0.288	0.275	0.196	0.639	-0.0172	0.351	-0.375	0.221	0.334	0.181	1				
Urban_pop	0.414	0.398	0.250	0.743	0.0534	0.454	-0.524	0.153	0.428	0.221	0.802	1			
Urban_construction	-0.0571	-0.0592	0.0100	0.140	-0.151	0.223	-0.166	-0.0501	0.353	-0.074	0.296	0.175	1		
FDI	-0.0151	-0.0288	0.134	0.466	-0.116	0.189	-0.147	-0.0413	0.404	0.140	0.442	0.432	0.187	1	
R&D	-0.0968	-0.110	0.114	0.321	-0.145	0.0683	0.0005	-0.0747	0.422	0.029	0.364	0.318	0.173	0.784	1