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Does urban concentration mitigate CO_2 emissions? Evidence from China 1998–2008[☆]

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ABSTRACT

We provide evidence of first increasing and then decreasing CO_2 emission intensity as the degree of urban concentration increases, based on data from 25 provincial regions in China over the period 1998–2008. This evidence is consistent with the environmentally desirable urban concentration argument identified in recent literature. Our findings indicate the importance of the spatial organization of activities and people in addressing regional CO_2 emissions.

1. Introduction

China has experienced an unprecedented rate of urbanization over the past three decades (Henderson, 2009; McKinsey Global Institute, 2009). Accompanying such rapid process, China's energy consumption and air pollution have increased substantially. In 2009, the total energy consumption of China was roughly 2.9 billion tons of standard coal and total CO_2 emissions was 7.7 billion tons (Du, Wei, & Cai, 2012). Is the urbanization process blamed for such significant environmental consequences? What urban development policies can contribute to the reduction of pollution emissions in the future? To answer these questions, this paper investigates the link between urbanization and CO_2 emission intensity using China's 25 provincial data over the time period of 1998 and 2008. Specifically, we examine urbanization through urban concentration — the spatial concentration of cities within a given region.

Urban spatial organization is one of the key factors that influence energy consumption, and thus CO_2 emissions. The high concentration of people and economic activities in some locations can lead to scale economies, proximity and agglomeration that may decrease energy use and associated pollution. Some studies find that increasing urban density may facilitate the mitigation of CO_2 emissions by significantly reducing energy consumption in urban areas (Glaeser & Kahn, 2010; Kamal-Chaoui & Robert, 2009;

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Newman & Kenworthy, 1989). However, these studies ignore the impact of changes in industrial composition, technological advance and institutional reform on the role played by urban spatial concentration in CO_2 emissions. Initial urban concentration may produce more air pollutants as the natural-resource-based or heavy industries are dominant. As clean technology adopts and industrial structure shifts towards light consumer industries or services, ongoing urban concentration tends to give rise to less pollution emissions per unit of economic activity. In the context of China, the adoption of clean technology may be closely related to the manufacturing's plants ownership status (Zheng & Kahn, 2013). The managers of Chinese state-owned enterprises (SOEs) are regarded as political officials, and they may have fewer incentives to reduce pollution under the old promotion criteria emphasizing output and profit targets. However, ownership reform prompted by local market development can push the local industrial structure towards 'green performance'. Thus, we argue that the interplay of scale economies, technological advance, ownership reform and industrial composition can lead to a non-linear relationship between the degree of urban concentration and CO_2 emissions.

A key issue in our analysis is the measure of urban concentration. We employ four measures as proxies for urban concentration within a region. The first is Zipf's coefficient, which provides an overall measure of spatial inequality for the entire distribution of an urban population. The second is the spatial Hirschman–Herfindahl Index (denoted by HHI) based on the sum of squared shares of every city in a regional urban population. The third is the urban primacy index measured as the share of the largest city in a regional urban population. Since the spatial HHI contains squared shares, they may be dominated by the largest share, and thus highly correlated with the urban primacy index. The last is the spatial Gini coefficient, which is used to calculate the spatial inequality of a population across cities within a region.

The paper starts with a simple STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model and investigates the fundamental sources of CO_2 emissions per unit of GDP in a region by incorporating the degree of urban concentration. It is found that CO_2 emissions in per unit of GDP increases with urban concentration, which conflicts with findings from other studies. We then employ a nonparametric method to investigate the relationship between CO_2 emissions per unit of GDP and urban concentration. The estimation result shows a robust pattern of first increasing and then decreasing CO_2 emissions per unit of GDP as urban concentration increases. Such bell-shaped relationship confirms that the effects of the interplay of scale economies, technological change, institutional reform and associated industrial composition on CO_2 emission intensity at different levels of urban concentration.

Our study contributes to several strands of studies. First, it enriches current literature on the economic efficiency of urban concentration. For example, Henderson (2003) has identified a non-monotonous impact of urban primacy on economic development, thus suggesting a range of values for optimal primacy levels below which urban concentration fosters rather than deters economic growth. Rather than focus on economic growth as Henderson did, we examine the environmental implications of urban concentration. Second, this paper is closely related to recent studies focusing on China's CO_2 emissions (Auffhammer & Carson, 2008; Du et al., 2012; He & Wang, 2012; Zheng & Kahn, 2013). These studies find that economic development, urbanization and industrial structure are the key driving forces behind CO_2 emissions in China. Moving beyond them, our paper investigates how the spatial concentration of economic activities affects CO_2 emission intensity using China's provincial level data as other variables are considered.

The analysis of the impact of urban concentration on pollution emission intensity in China carries significant policy implications. China's fast urbanization has not only brought about economic benefits but also introduced severe environmental challenges. Our findings suggest that policies to mitigate carbon dioxide emissions should include improving the efficiency of the spatial organization of cities, such as the adoption of better technique for environmental management.

The following sections are organized as follows: Section 2 provides the conceptual framework and measures of urban concentration. Section 3 presents data on CO_2 emissions and measures of urban concentration and other variables. Section 4 conducts the empirical analysis including both parametric estimations and nonparametric estimations. Section 5 briefly discusses the results and concludes.

2. Conceptual framework

To explore the relationship between CO_2 emission and urban concentration, we start with a simple STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model[1] which can be expressed as follows:

$$y_{it}^{z} = \mathrm{f}^{z}\left(\mathrm{P}_{it}, \mathrm{A}_{it}, U_{it,} X_{it}\right) + u_{it}^{z}, \tag{1}$$

where i and t index province and year, respectively. y is the environmental impact which in our case is CO_2 emission intensity. P is population size. A is per capital consumption. X is a vector of other relevant control variables and u is the error term. The vector U is the vector of z different measures of urban concentration in this analysis, which is to be defined precisely in the following paragraph. The STIRPAT model is then estimated in a semi-log-linear specification as the following:

$$y_{it}^{z} = \alpha_{z0} + \alpha_{z1}\log(\mathrm{P}_{it}) + \alpha_{z2}\log(\mathrm{A}_{it}) + \alpha_{z3}\mathrm{U}_{it} + X_{it}^{'}\beta_{z} + u_{zi}. \tag{2}$$

[1] STIRPAT model is originated from Enrich and Holdren (1971) and then reformulated by Dietz and Rosa (1994), which illustrates the impact of demographic and economic factors on the environment.

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The linear specification in Eq. (2) may be inadequate to study the effect of the degree of urban concentration on CO_2 emission intensity. The non-linearity in the link between them arises from a number of factors. First, most existing studies predict a monotonic relationship between carbon emissions and urban concentration (Glaeser & Kahn, 2010; Kamal-Chaoui & Robert, 2009; Newman & Kenworthy, 1989). They argue that the spatial concentration of economic activities in several cities can improve the efficiency of energy use because of scale economies, thus reducing CO_2 emission intensity. However, the environmental desirability of urban concentration also depends on the effect of industrial composition (Copeland & Taylor, 2004). Initial high relative concentration increases the demands for local resources and heavy industries, such as coal, iron, and steel. Thus the concentration of dirty industrial activities may initially produce more industrial wastes pollutants despite the benefits of scale economies. Due to technological change, the demands for these products tend to decline and the industrial structure may shift from dirty industries based on raw materials towards lighter consumer and service industries. The change in industrial mix will decrease pollution emissions per unit of economic activity as urban concentration continues to grow. At the same time, large concentration generated by economic growth might prompt pollution control and abatement measures beyond a sufficiently high urban size threshold, regardless of the level of economic development. Using cross-national data over the years 1976–1985, Shukla and Parikh (1992) provides the evidence that the positive association between air pollution and city size is not always robust and tends to diminish with economic development, indicating the role of industrial composition and technological advance in mitigating urban pollutant emissions. In the context of China, the adoption of clean technology is always affected by industrial ownership structure (Zheng & Kahn, 2013). The managers of SOEs in China are regarded as political officials. They have easy access to cheap land and natural resources and therefore face few incentives to adopt clean technology under the promotion criteria emphasizing output and profit targets. Thus the ownership reform associated with the increasing employment share of non-SOE firms should bring about a change in industrial mix as more clean technologies are adopted. The interaction of scale economies, industrial composition, technological advance, and ownership reform is likely to result in a non-linear relationship between the degree of urban concentration and the intensity of carbon emissions.

Eq. (2) can be modified to allow for flexible functional form regarding urban concentration as the following:

$$y_{it}^{z} = \alpha_{z0} + \alpha_{z1}\log(\mathrm{P}_{it}) + \alpha_{z2}\log(\mathrm{A}_{it}) + \alpha_{z3}g^{z}(\mathrm{U}_{it}) + X_{it}^{'}\beta_{z} + u_{zi}, \tag{3}$$

where $g^{z}(\mathrm{U}_{it})$ is expected to be a non-linear function of U_{it}.

The estimation of Eq. (3) can be implemented only when we have the measure of urban concentration. We consider four indices related to urban concentration. The first is the Zipf's coefficient. As proposed by Zipf (1949), city size distribution obeys the following form:

$$R = \alpha_0 S^{-\alpha_1}, \tag{4}$$

where R is the number of cities with population greater than S in a province, S is the population of cities, α_0 is the constant, and α_1 is Zipf's coefficient. Taking the natural log of both sides of Eq. (4) results in the empirical part of this rank-size rule:

$$\ln R = \alpha_0 - \alpha_1 \ln S. \tag{5}$$

When $\alpha_1 \cong 1$, Zipf's law is satisfied. The interpretation of the magnitude of α_1 is that α_1 becomes larger as the city size distribution becomes more even. Thus, the larger the estimate of α_1, the lower the degree of urban concentration.

Our second measure of urban concentration is the spatial Hirschman–Herfindahl Index (HHI) based on the sum of squared shares of each city in a province, which is defined as:

$$HHI = \sum_{k=1}^{n}\left(\frac{S_k}{TS}\right)^2, \tag{6}$$

where S_k is the population of city k, TS is total population in a province, and n is the number of cities within the sample province. The magnitude of the spatial HHI is positively associated with the degree of inequality of the city size distribution. Since the spatial HHI contains squared shares, they are likely to be dominated by the largest share if it is a large number.

Our third measure of urban concentration is the urban primacy index, which is measured as the population share of the largest city in a province. In general the larger the urban primacy index, the more unequal the city size distribution. This is a crude measure but is widely utilized as a measure of urban concentration (Ades & Glaeser, 1995; Henderson, 2003). The limitation of this measure is that it largely ignores the size distribution of cities smaller than the largest.

The last is the spatial Gini coefficient. To calculate this Gini, we first calculate the population share of each city in a province ($\frac{S_k}{TS}$). The Lorenz curve associated with the spatial Gini coefficient ranks $\frac{S_k}{TS}$ across cities in ascending order and plots the cumulative share of population on the y-axis and against the order going from 1 to k on the x-axis. This Gini is equal to the area between the Lorenz curve and the 45° line. If all cities were of equal size in terms of population, the plotted line would be the 45° line. The greater the area, the 'less equal' is the spatial distribution of a population across cities.

3. Data

3.1. CO_2 emissions across regions in China

According to the 4th Assessment Report (IPCC, 2010), global warming is largely due to CO_2 emissions caused by human activities, especially the use of fossil fuels. It is estimated that in 2004 95.3% of the total volume of CO_2 emissions was generated from the use of fossil fuels. However, the official data on province-level CO_2 emissions over time in China is not available. Zhang (2000) considers coal as an equivalent proxy for CO_2 emissions. Auffhammer and Carson (2008) use waste gas emissions to proxy for CO_2 emissions across provinces. Different from their studies, we calculate provincial CO_2 emissions in a direct way: on the basis of the 2006 IPCC Guidelines for National Gas Inventories (IPCC, 2006), we calculate provincial CO_2 emissions generated from all types of fossil fuel consumption, e.g. coal, oil, heating and electricity. In our calculation, both CO_2 emissions from the fossil fuel consumption within a province and those from the fossil fuel consumption due to secondary energy imported from other provinces, i.e. heating and electricity, are considered. The calculation of provincial CO_2 emissions from fossil fuel consumption data is presented as follows:

$$\mathrm{CO}_i^t = \sum\nolimits_j \mathrm{CO}_{ij}^t = \sum\nolimits_j E_{ij}^t EF_j K_j M * A, \tag{7}$$

where CO_i^t (ton) is the total volume of CO_2 emissions of province i in year t; CO_{ij}^t (ton) is the volume of CO_2 emissions caused by the use of fossil fuel j in province i in year t; E_{ij}^t (ton) is the volume of fossil fuel j consumption in province i in year t; EF_j (kt/TJ) is the emission factor of fossil fuel j; K_j (kgCal/ton) is the net calorific value of fossil fuel j; M is the ratio between the weight of one CO_2 molecule and that of C (44/12); and finally, A is the conversion rate between kgCal/ton and kt/TJ. Our calculations consider not only fossil fuels consumed as primary energy sources such as gasoline and natural gas, but also fossil fuels used for secondary energy sources including heating and electricity.

In terms of CO_2 emissions from heating consumption, our calculation is done in two steps: first, we calculate fossil fuels for heat consumption using the data from the energy input–output sheet in the annual China Energy Statistical Yearbooks; second, we use the formula (7) to calculate CO_2 emissions arising from heating consumption.

Calculations of fossil fuels consumed for electricity use are more complex. China's electric network is divided into six sub-nation networks – North China, Northeast China, East China, Central China, South China and Northwest China – each of which covers several provinces. On the one hand, electricity in one region could be ‘imported from’ or ‘exported to’ other regions within the same sub-nation network. For instance, 30% of electricity in Beijing in 2008 was ‘imported’ from nearby provinces. On the other hand, the fossil fuel structure varies across sub-nation networks. Thus it would be problematic if we were to use the energy input–output sheet of one province to calculate its fossil fuel consumption for electricity or if we were to use a single emission factor to calculate CO_2 emissions for all provinces stemming from electricity consumption.

We calculate provincial CO_2 emissions due to electricity consumption according to the following steps: the first step is to calculate the total volume of electricity at the sub-nation network level by aggregating electricity consumption across provinces belonging to the same sub-nation network; second, we calculate the total volume of CO_2 emissions from fossil fuels for electricity consumption for each province according to Eq. (7), and then sum them across provinces within the same sub-nation network; third, we calculate the emission factor of electricity at the sub-national level by dividing the total CO_2 emissions (the summation in the second step) by the total volume of electricity (the summation in the first step); finally, we calculate the provincial CO_2 emissions by multiplying the sub-nation emission factor of electricity with the total volume of electricity. Our calculations show that CO_2 emissions due to electricity use account for a large share in the total volume of CO_2 emissions. In Beijing, for instance, 45% of total CO_2 emissions are contributed by electricity-related fossil fuel consumption. Therefore, the inclusion of fossil fuel use due to electricity consumption is essential to the calculations of CO_2 emissions, and its omission would lead to biased results, such as in Zhang (2000).

The data for fossil fuel consumption and net calorific value are collected from the China Energy Statistical Yearbooks for 1999–2009. These yearbooks report the consumption volumes of all fossil fuels including raw coal, cleaned coal, washed coal, briquettes, coke, crude oil, gasoline, kerosene, fuel oil, LPG, natural gas, and the consumption volumes of heating and electricity across provincial regions in China between 1998 and 2008. We set our conversion A, as $4186.8 * 10^{-9}$. The emission factors for a variety of fossil fuels (EF_j) refer to the default value provided by the IPCC (2010). Eight main fossil fuels and their corresponding emission factors are summarized in Table 1.

Table 1
Emission factors for eight fossil fuels.

Fossil fuel	Emission factor (kt/TJ)	Fossil fuel	Emission factor (kt/TJ)
Raw coal	1.825	Fuel oil	3.157
Coke	2.721	Crude oil	2.973
Gasoline	2.907	Natural gas	2.114
Kerosene	3.049	Diesel oil	3.097

Data source: the China's Energy Statistical Yearbook for 1999–2009.

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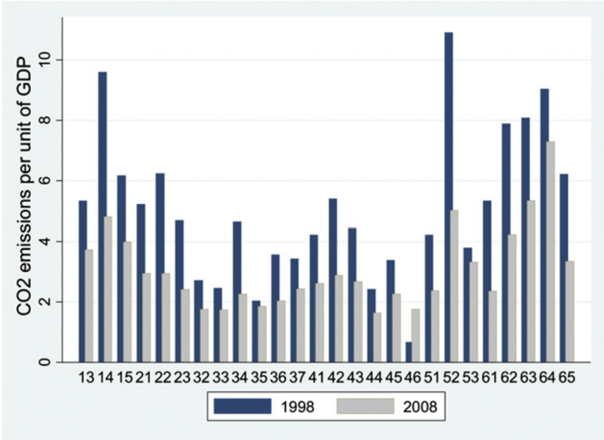

Fig. 1. Cross-province CO_2 emissions per unit of GDP in 1998 and 2008. Notes: 13 — Hebei, 14 — Shanxi, 15 — Inner Mongolia, 21 — Liaoning, 22 — Jilin, 23 — Heilongjiang, 32 — Jiangsu, 33 — Zhejiang, 34 — Anhui, 35 — Fujian, 36 — Jiangxi, 37 — Shandong, 41 — He'nan, 42 — Hubei, 43 — Hunan, 44 — Guangdong, 45 — Guangxi, 46 — Hainan, 51 — Sichuan, 52 — Guizhou, 53 — Yunnan, 61 — Shananxi, 62 — Gansu, 63 — Qinghai, 64 — Ningxia, 65 — Xinjiang. The unit of CO_2 emissions per unit of GDP is tons per Yuan. Data source: the China Energy Statistical Yearbook for 1999–2009, and the China Compendium of Statistics 1949–2009.

Fig. 1 presents the emissions of CO_2 per unit of GDP (tons per Yuan) across regions in China in 1998 and 2008.[2] We obtain provincial GDP data from the China Compendium of Statistics 1949–2008 compiled by the National Bureau of Statistics of China. On the one hand, there is a decreasing trend in emissions of CO_2 per unit of GDP between 1998 and 2008. The exception is Hainan Province. On the other hand, CO_2 emissions per unit of GDP are found to vary across regions. In line with the data from 1998, CO_2 emissions per unit of GDP were the lowest among the coastal provinces. The central provinces are grouped around the middle, and the interior provinces such as Ningxia and Guizhou lie at the upper end of CO_2 emission intensity. These patterns also hold for the data from 2008.

3.2. Urban concentration measures and other variables

We construct four urban concentration measures across provinces for the years of 1998 to 2008 using urban population data.[3] In China, cities are classified into two groups according to their administrative status: county-level cities and prefecture-level cities.[4] Our use of 'cities' refers to both prefecture-level and county-level cities.[5] The urban population data for the prefecture-level cities are collected from the Urban Statistical Yearbook of China for 1999–2009, and the urban population data for the county-level cities are collected from the China County Statistical Yearbook for 1999–2009.

Table 2 contains summary statistics for the measures of urban concentration using urban population data. Zipf's coefficient, defined as α_1 in Eq. (5), is constructed from Zipf's Law across cities within a province. Zipf's coefficient is larger as the city size distribution becomes more even. The mean value of Zipf's coefficient is about 0.914. However, there are considerable variations in the level of Zipf's coefficients across provinces over time as shown by the standard deviation. The second urban concentration measure is the sum of squared shares of each city across provinces — the spatial HHI. According to Table 2, the mean value of the spatial HHI is around 0.140, indicating that the largest cities are not dominant in the city size distribution across provinces in China. The third measure in our paper relates to the urban population share of the largest city in a province — the urban primacy index. Despite a higher value of urban population share of the largest city in some regions as shown by the maximum value of 0.920, the mean value of this index is around 0.252, suggesting the low degree of urban concentration across provinces over time. Our final measure of urban concentration is the spatial Gini coefficient. As noted above, this coefficient takes a value of 1 if all provincial urban population is concentrated in one city and declines in value with an increase in urban population for other cities. The mean value of the spatial Gini coefficient is 0.500. The low value of the standard deviation indicates that most provinces

[2] In our sample, four Municipalities, Beijing, Shanghai, Tianjin, and Chongqing, are excluded because they have no prefecture-and-below-level cities within their jurisdictions. Tibet is also excluded due to missing data.

[3] In terms of published population data at the regional level in China, there are four categories. They are population in the whole region, population in an urban area, nonagricultural population in the whole region, and nonagricultural population in an urban area. Previous studies such as Henderson and Wang (2007) use nonagricultural population to measure urban size. Different from them, we use urban population data since it contains a huge amount of migrant population. We thank one of our referees for this idea.

[4] The prefecture-level cities are administered by provinces and some of them are further defined as sub-provincial-level cities. The county-level cities are controlled by the prefecture-level cities and some are controlled directly by the province.

[5] In our analysis, cities with an urban population of less than 60,000 are excluded from the sample.

Table 2
Summary statistics for urban concentration indices (pooled data).

	Non-agricultural population (275 observations)			
	Mean	Standard deviation	Min	Max
Zipf's coefficient	0.914	0.229	0.449	2.819
Spatial HHI	0.140	0.148	0.053	0.854
Urban primacy index	0.252	0.154	0.095	0.920
Spatial Gini coefficient	0.500	0.090	0.153	0.642

Data source: the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

in China have more even city size distribution patterns, which is consistent with the results after employing the other three measures.

Data for population size, nonagricultural GDP share, and per capita GDP at the provincial level are available from the China Compendium of Statistics 1949–2008. We present the summary statistics for all three variables in Table 3.

4. Empirical analysis

4.1. Parametric estimation

We present the empirical results in the sequential manner starting with a simple STIRPAT model as in Eq. (2). To isolate the effect of the degree of urban concentration, we control for other factors that may determine the emission intensity of CO_2 at the provincial level. The set of explanatory variables includes local population size, local per capita GDP, and nonagricultural GDP share. Since a panel data structure with 25 provinces and 11 years is employed, we also control for both province and year dummies to capture, respectively, the time-invariant unobserved effects and the stochastic shocks that common to all regions.

We estimate the simple STIRPAT specification outlined in Eq. (2) using a two-way fixed effects model. We examine the four measures of urban concentration respectively. Table 4 reports the parametric regression results. The urban concentration is found to be statistically significant with positive sign for all four measures. The coefficient of population size is positive but not significant in all the regressions, which is consistent with previous studies. The per capita GDP has the expected negative sign in all four regressions but not statistically significant. The nonagricultural GDP share has the negative sign but not statistically significant in all regressions, indicating the positive role played by industrial restructuring in mitigating the carbon emission intensity. The results in Table 4 suggest the simple STIRPAT model does not perform well in identifying the effect of urban concentration on emission intensity. Whichever measure is considered, the estimated positive coefficient of urban concentration regressed on the emissions of CO_2 per unit of GDP is not consistent with extant studies. Moreover, this finding may not capture the effect of industrial restructuring, a result of technological advance and ownership reform, on CO_2 emission intensity. Because of the key influence of industrial composition change, the relationship between the degree of urban concentration and CO_2 emissions per unit of GDP may be non-linear. In the following section, we explore this possibility using nonparametric estimation technique.

4.2. Nonparametric estimation

We proceed to investigate the link between the degree of urban concentration and CO_2 emissions per unit of GDP using Eq. (3). Because the form of the function representing their relationship is unknown, we use a nonparametric method, which attempts to infer the regression surface from the data. We employ a robust locally weighted scatterplot smoothing (Lowess) method proposed by Imbs and Wacziarg (2003). Specifically, suppose we have a data sample, indexed by $n = 1,\ldots,N$, of independent and dependent variable pairs, say (y_n,x_n). For each observation n, we run a weighted least-squares regression of y on variable x using a subsample of data centered around, which is called the midpoint. This procedure is repeated using each observation in the sample at the midpoint, thereby tracing out a curve describing the non-parametric relationship between y

Table 3
Summary statistics for provincial characteristics.

	Mean	Standard deviation	Min	Max
Population size (in logs)	8.285	0.725	6.220	9.202
Nonagricultural GDP share	0.839	0.057	0.691	0.953
Per capita GDP (in logs)	9.170	0.585	7.761	10.645

Data source: the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

Table 4
STIRPAT model and CO_2 emissions per unit of GDP.

	Measures of urban concentration			
	Inversed Zipf's coefficient	Spatial HHI	Urban primacy index	Spatial Gini coefficient
Urban concentration	2.895***	12.623***	9.779***	10.878***
	(0.719)	(4.063)	(2.978)	(3.315)
Population size (in logs)	0.182	2.706	3.821	1.175
	(0.481)	(4.949)	(4.997)	(4.878)
Per capita GDP (in logs)	−0.497	−0.022	−0.122	−0.605
	(1.626)	(1.652)	(1.646)	(1.645)
Nonagricultural GDP share	−6.482	−2.456	−0.143	−2.887
	(0.716)	(7.379)	(7.381)	(7.357)
Intercept	5.332	−16.938	−27.636	11.483
	(40.079)	(41.349)	(41.888)	(40.535)
Province fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Number of Obs	275	275	275	275

Notes: Standard errors are in parentheses. ***, **, and * denote 1%, 5% and 10% significance, respectively. The dependent variable is CO_2 emissions per unit of GDP (tons per Yuan). Data sources: the data for CO_2 emissions per unit of GDP are from the China Energy Statistical Yearbook for 1999–2009 and the China Compendium of Statistics 1949–2009; The data for the four measures of urban concentration are from the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

and x. We set y as CO_2 emissions per unit of GDP and x to represent the measure of urban concentration. We implement the Lowess procedure as follows. At the first step, we define the bandwidth H (the amount of data around x_n that is used in each regression) as the size of the overlapping intervals of x. We also choose interval increments of x, labeled as Δ.[6] The larger the interval increment, the smaller is the number of regressions. Given the bandwidth and increment, the data are divided into M subsamples. Then, we run a simple fixed-effects linear regression of CO_2 emissions per unit of GDP on the measure of urban concentration with a rectangular weighting scheme. Finally, for each of these regressions we compute a fitted value, evaluated at the midpoint of the interval of the measure of urban concentration, and plot these fitted values to construct the nonparametric curve linking CO_2 emissions per unit of GDP and urban concentration. We also compute 95% confidence intervals by calculating the standard error of the predicted value of CO_2 emissions per unit of GDP, and plot these confidence bands around the fitted curve.

According to Imbs and Wacziarg (2003), two additional issues in terms of this methodology deserve noting. The first is that each local regression includes both province and year fixed effects for all regions in the local sample.[7] To compute the predicted value of CO_2 emissions per unit of GDP at the midpoint, we average over the estimated fixed effects to obtain an average value of the fixed effect for each subsample. As a result, the plotted nonparametric curve reflects the link between CO_2 emissions per unit of GDP and urban concentration for an average region. The second is that the group of regions in each local regression changes over the whole sample. Therefore, both the average estimated fixed effects and the slope of the coefficient will be different at each midpoint. The plotted curve thus reflects both within-region and between-region variation.

We run this Lowess procedure proposed by Imbs and Wacziarg (2003) on a panel data set with 25 provinces over the period of 1998 and 2008 in China to estimate the link between CO_2 emissions per unit of GDP and urban concentration. We look at four measures of urban concentration, the inversed Zipf's coefficient, the spatial HHI, the urban primacy index, and the spatial Gini coefficient, respectively. Figs. 2–6 plot the estimates along with the 95% confidence intervals. The solid line represents the central estimate, while the dashed line and the dotted line are the 95% confidence interval's lower bound and upper bound, respectively. According to Fig. 2, there is a nonlinear relationship between CO_2 emissions per unit of GDP and the inversed Zipf's coefficient. The estimate has a tight 95% confidence interval for much of the range of the inversed Zipf's coefficient. CO_2 emission intensity first increasing and then decreasing as urban concentration rises can be explained as the ecological consequence of the industrial mix change: the upward part of the curve captures the relatively larger role of the industrial structure based on raw materials or dirty technology, which increases CO_2 emission intensity as urban concentration rises; the downward part of the curve is evidence of industrial restructuring or adoption of clean technology, which mitigates CO_2 emissions per unit of GDP as urban concentration continues to grow. There is a similar bell-shaped link between CO_2 emission intensity when applied to the other three urban concentration measures, the spatial HHI (see Fig. 3), the urban primacy index (see Fig. 4), and the spatial Gini coefficient (see Fig. 5). In addition, the 95% confidence interval is found to be wide at the lower values for the spatial Gini coefficient.

To further demonstrate the robustness of the results, we run the standard Lowess procedure in Stata on panel data, in which the bandwidth is 0.8 and the weighting scheme is a tricube weighting function. Figs. 6–9 display the Lowess estimates computed using data for all 25 provinces. A bell-shaped curve is apparent for all four measures of urban concentration: CO_2 emissions per

[6] Given the range of the data, we set $\Delta = 0.005$ for the inversed Zipf's coefficient and spatial HHI coefficient, $\Delta = 0.01$ for the urban primacy index, and $\Delta = 0.02$ for the spatial Gini coefficient.
[7] The other regional characteristics variables are not included since they are not significant as illustrated in Table 4.

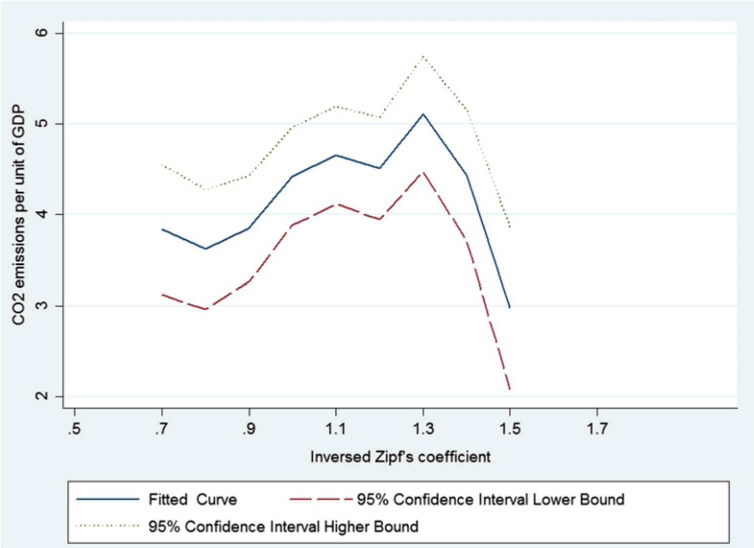

Fig. 2. Imbs and Wacizarg (2003)'s Lowess estimates of the link between CO_2 emissions per unit of GDP and urban concentration (The inversed Zipf's coefficient). Notes: This graph presents Imbs and Wacizarg (2003)'s Lowess estimates of the relationship between CO_2 emissions per unit of GDP and urban concentration measured as the inversed Zipf's coefficient for 11-year panel data (275 observations). The unit of CO_2 emissions per unit of GDP is tons per Yuan. Data sources: the data for CO_2 emissions per unit of GDP are from the China Energy Statistical Yearbook for 1999–2009 and the China Compendium of Statistics 1949–2009; the data for the inversed Zipf's coefficient are from the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

unit of GDP first increase and then decrease as the level of urban concentration rises. These results are similar to those using Lowess procedures in Imbs and Wacziarg (2003).

5. Discussion and conclusion

Urban concentration impacts economic growth but also has significant environmental consequences. Using provincial level data in China we empirically analyzed how urban concentration affects CO_2 emissions per unit of GDP. In particular, we rely on

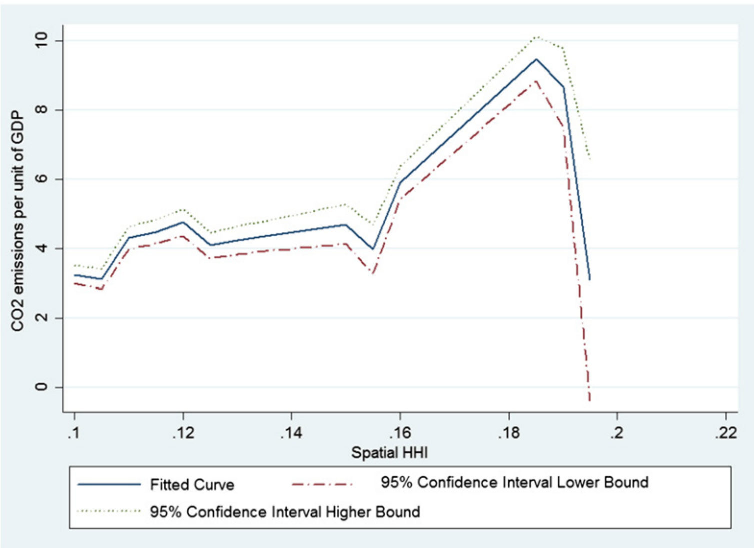

Fig. 3. Imbs and Wacizarg (2003)'s Lowess estimates of the link between CO_2 emissions per unit of GDP and urban concentration (The spatial HHI). Notes: This graph presents Imbs and Wacizarg (2003)'s Lowess estimates of the relationship between CO_2 emissions per unit of GDP and urban concentration measured as the spatial HHI for 11-year panel data (275 observations). The unit of CO_2 emissions per unit of GDP is tons per Yuan. Data sources: the data for CO_2 emissions per unit of GDP are from the China Energy Statistical Yearbook for 1999–2009 and the China Compendium of Statistics 1949–2009; the data for the spatial HHI are from the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

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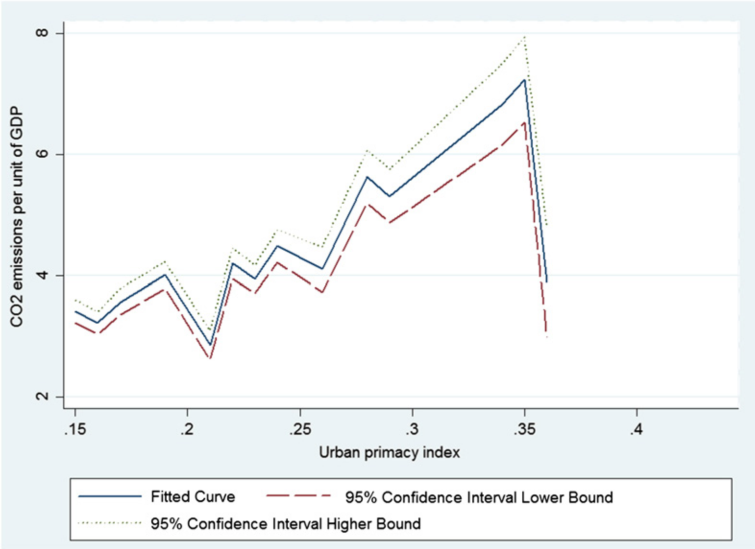

Fig. 4. Imbs and Wacizarg (2003)'s Lowess estimates of the link between CO_2 emissions per unit of GDP and urban concentration (The urban primacy index). Notes: This graph presents Imbs and Wacizarg (2003)'s Lowess estimates of the relationship between CO_2 emissions per unit of GDP and urban concentration measured as the urban primacy index for 11-year panel data (275 observations). The unit of CO_2 emissions per unit of GDP is tons per Yuan. Data sources: the data for CO_2 emissions per unit of GDP are from the China Energy Statistical Yearbook for 1999–2009 and the China Compendium of Statistics 1949–2009; the data for the urban primacy index are from the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

the nonparametric method derived from robust locally weighted scatter plot smoothing (Lowess). The main empirical results show a bell-shaped relationship between CO_2 emission intensity and the degree of urban concentration. The findings in our analysis, on the one hand, provide empirical evidence for the nature of industrial restructuring on air pollution: pollutant emissions may decline as the industrial structure shifts toward more clean technology or as large concentration generated by urban growth prompts pollution control and abatement measures beyond a sufficient threshold of city size. On the other hand, our analysis contributes to the literature on the ecological consequences of urbanization. The environmental effect of urbanization is one of the most popular topics in both environmental and urban economics and has prompted numerous studies on the

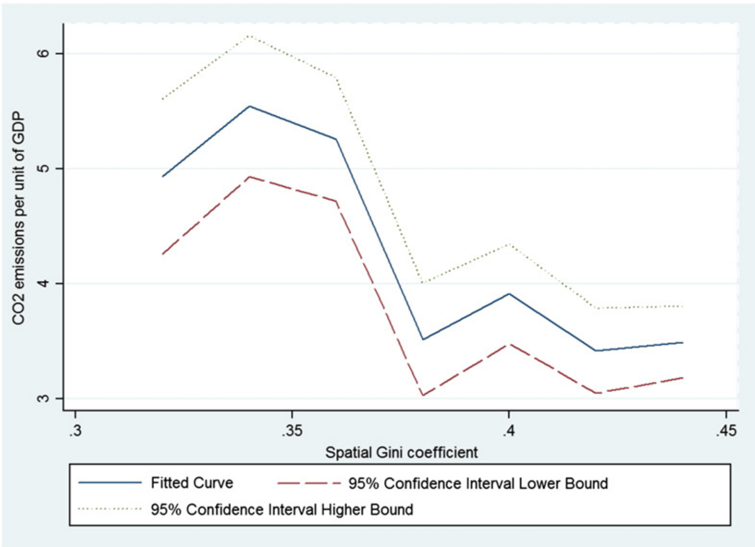

Fig. 5. Imbs and Wacizarg (2003)'s Lowess estimates of the link between CO_2 emissions per unit of GDP and urban concentration (The spatial Gini coefficient). Notes: This graph presents Imbs and Wacizarg (2003)'s Lowess estimates of the relationship between CO_2 emissions per unit of GDP and urban concentration measured as the spatial Gini coefficient for 11-year panel data (275 observations). The unit of CO_2 emissions per unit of GDP is tons per Yuan. Data sources: the data for CO_2 emissions per unit of GDP are from the China Energy Statistical Yearbook for 1999–2009 and the China Compendium of Statistics 1949–2009; the data for the spatial Gini coefficient are from the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

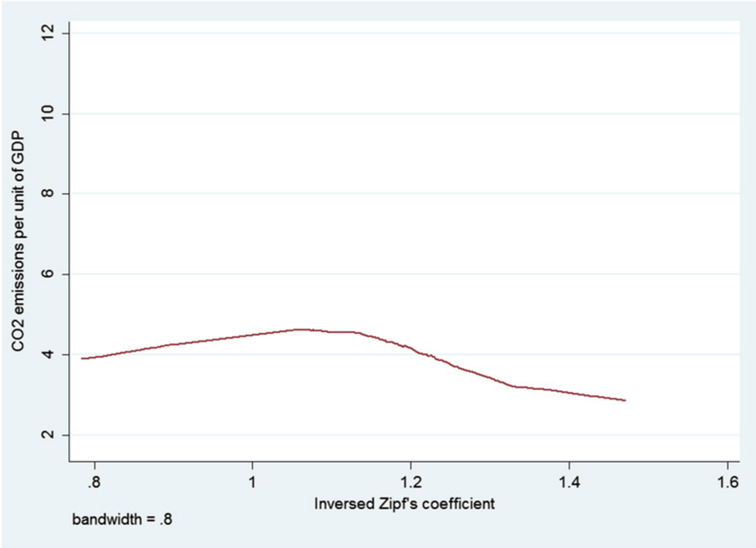

Fig. 6. Standard Lowess estimates of the link between CO_2 emissions per unit of GDP and urban concentration (The inversed Zipf's coefficient). Notes: This graph presents the Stata's standard Lowess estimates of the relationship between CO_2 emissions per unit of GDP and urban concentration measured as the inversed Zipf's coefficient for 11-year panel data (275 observations). The unit of CO_2 emissions per unit of GDP is tons per Yuan. Data sources: the data for CO_2 emissions per unit of GDP are from the China Energy Statistical Yearbook for 1999–2009 and the China Compendium of Statistics 1949–2009; the data for the inversed Zipf's coefficient are from the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

experience of developed countries (for example, Glaeser & Kahn, 2010). Our paper traces the evolution path of pollution emission intensity as urban concentration increases in China, supplementing our understanding of the ecological print of urbanization in developing economies.

Our work suggests some recommendations for urban planners and policy makers. The bell-shaped relationship between urban concentration and the intensity of pollution emissions suggests that spatial concentration is not always ecologically friendly. Policies seek to mitigate the impacts of pollutant products by curbing the concentration of economic activities in several big cities are not necessarily the most effective, or may even be entirely ineffective. Such mitigation is best undertaken with a variety of

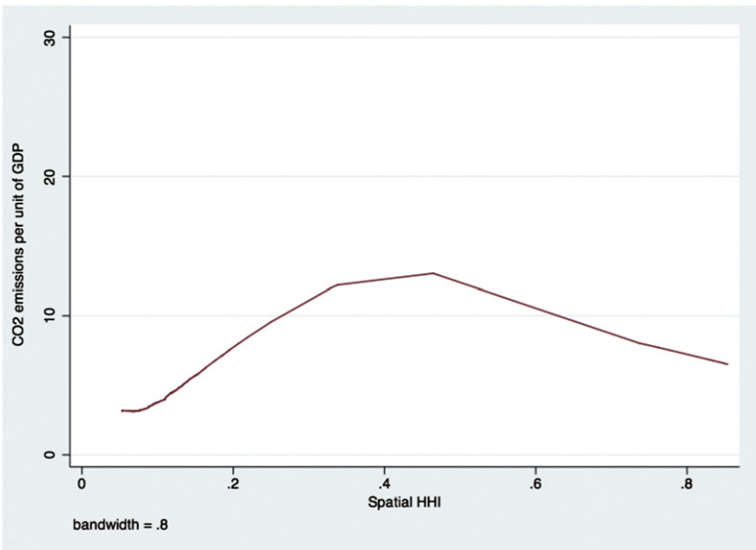

Fig. 7. Standard Lowess estimates of the link between CO_2 emissions per unit of GDP and urban concentration (The spatial HHI). Notes: This graph presents the Stata's standard Lowess estimates of the relationship between CO_2 emissions per unit of GDP and urban concentration measured as the spatial HHI for 11-year panel data (275 observations). The unit of CO_2 emissions per unit of GDP is tons per Yuan. Data sources: the data for CO_2 emissions per unit of GDP are from the China Energy Statistical Yearbook for 1999–2009 and the China Compendium of Statistics 1949–2009; the data for the spatial HHI are from the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

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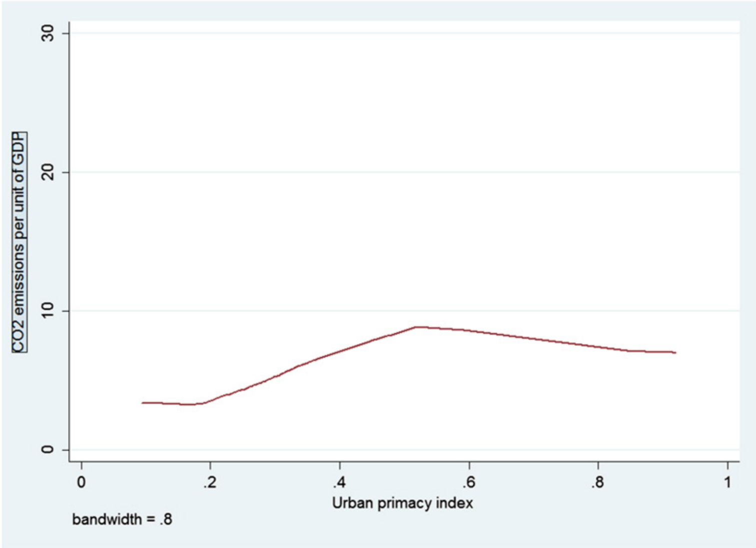

Fig. 8. Standard Lowess estimates of the link between CO_2 emissions per unit of GDP and urban concentration (The urban primacy index). Notes: This graph presents the Stata's standard Lowess estimates of the relationship between CO_2 emissions per unit of GDP and urban concentration measured as the urban primacy index for 11-year panel data (275 observations). The unit of CO_2 emissions per unit of GDP is tons per Yuan. Data sources: the data for CO_2 emissions per unit of GDP are from the China Energy Statistical Yearbook for 1999–2009 and the China Compendium of Statistics 1949–2009; the data for the urban primacy index are from the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

economic instruments associated with industrial composition change. For example, shutting down heavily polluted industries and nudging the industrial structure in big cities towards clean industries or service industries could be tried in order to reduce pollution emissions per unit of economic activity. Adopting better techniques for environmental management also decreases pollution for large urban concentration. In China, promoting ownership reform and increasing non-SOE share in the economy is also an option to push regions close to 'green performance'.

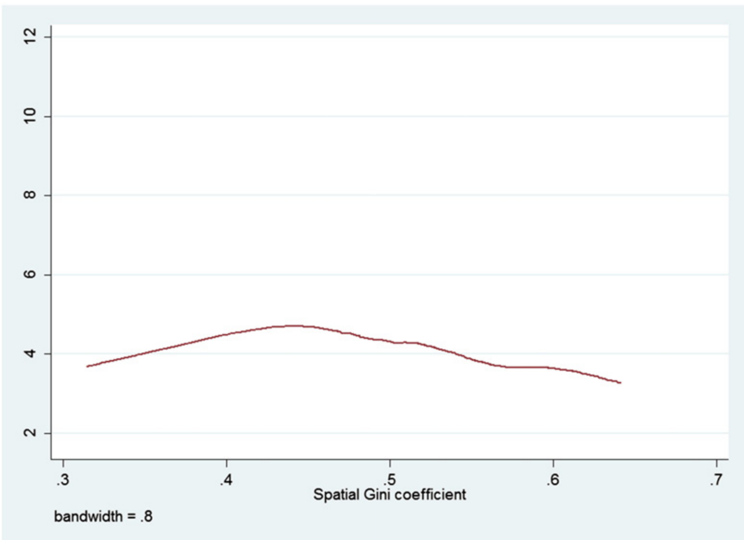

Fig. 9. Standard Lowess estimates of the link between CO_2 emissions per unit of GDP and urban concentration (The spatial Gini coefficient). Notes: This graph presents the Stata's standard Lowess estimates of the relationship between CO_2 emissions per unit of GDP and urban concentration measured as the spatial Gini coefficient for 11-year panel data (275 observations). The unit of CO_2 emissions per unit of GDP is tons per Yuan. Data sources: the data for CO_2 emissions per unit of GDP are from the China Energy Statistical Yearbook for 1999–2009 and the China Compendium of Statistics 1949–2009; the data for the spatial Gini coefficient are from the Urban Statistical Yearbook of China for 1999–2009 and the China County Statistical Yearbook for 1999–2009.

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