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Heterogeneity in the relationship between carbon emission performance and urbanization: evidence from China

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Abstract

Global change caused by carbon emissions alone has become a common challenge for all countries. However, current debates about urbanization and carbon emissions generally do not take into account the heterogeneities in urbanization and economic development levels. The goal of this study is to revisit the urbanization–emissions nexus by considering such heterogeneities in the Chinese context. The results reveal that there is significant heterogeneity in the total factor carbon emission performance index across provinces. Specifically, the relationship between carbon emission performance and urbanization reflects a U-shaped curve. Urbanization is found to have a stronger inhibiting effect on carbon emission performance when economic development levels improve. The results suggest that tailoring policies to each region's conditions, promoting investments in energy-saving and emissions-reducing technologies, and improving the use of public transportation could be mitigation strategies for global change that lead to low-carbon urbanization.

Keywords Urbanization heterogeneity · Economic development heterogeneity · Carbon emission performance · Non-radical direction function · Threshold effect

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1 Introduction

Amid the development of a globalized economy, global change has gradually become a new challenge facing all countries. Worldwide carbon mitigation efforts have been launched through the United Nations Framework Convention on Climate Change Kyoto Protocol (Kyoto Protocol) (UNFCCC 1998) and the United Nations Framework Convention on Climate Change 21st Conference of the Parties, Paris, France (Paris Agreement) (UNFCCC 2015). Although carbon emissions are generally believed to relate closely to urbanization, the exact nature of this relationship has been debated. The objective of this study is to contribute to this discussion by analyzing the urbanization–carbon emissions relationship considering heterogeneity in urbanization and economic development levels in China. We examine specifically how this relationship differs depending on each area's urbanization stage and economic development level. We believe that the heterogeneity in this relationship can help explain the contradictory findings in the literature.

China is selected for this study for two salient reasons. First, it is the most populous nation in the world and thus engenders extensive demand for both economic growth and energy consumption (Duan et al. 2019). As China has become the largest energy consumer and carbon emitter in the world (Wang et al. 2019), improving carbon emission performance is increasingly important for achieving sustainable development in China and the world. The Chinese government has promised to reduce the nation's carbon intensity (carbon emissions per unit gross domestic product) by 40% to 45% by 2020 and by 60% to 65% by 2030 relative to its 2005 level. These ambitious goals have posed a significant challenge for the Chinese government (Gao 2016; He 2015), which has called for further studies on the emissions dynamics involved. Second, Chinese cities are playing an increasingly important role in emissions. Research shows that 85% of China's carbon emissions come from cities (Mi et al. 2016). China is now at an accelerated stage of urbanization, with rates reaching as high as 58.52% in 2017. Rapid urbanization represents not only a change in the urban structure and rural population but also a shift that can alter the economic structure (Cheng et al. 2018), the energy consumption mix (Fan et al. 2006), and consumer behavior (Cai et al. 2018; Poumanyvong and Kaneko 2010). Specifically, the gradual transition of China's economic structure from a reliance on primary industry to a reliance on secondary and tertiary industries can bring about changes in the energy demand, which have a comprehensive impact on carbon emissions (Zhang et al. 2017). Moreover, energy-related structural changes influence carbon emissions (Fang et al. 2018). For example, an increase in the non-fossil fuel share in the energy mix is the primary driver of total energy consumption reduction (Yang and Yu 2017), while a substantial reduction in energy intensity is an effective means of achieving carbon emission-reduction targets (Huang et al. 2019). In addition, rapid urbanization influences residents' consumption habits. In the enjoyment model, it can increase carbon emissions (Ji and Chen 2017). Studying the relationship between carbon emission performance and urbanization in China can help us assess whether China can realize its mitigation targets as its urbanization continues. This is the motivation for this study.

Although many studies have used various methods and approaches to investigate the relationship between carbon emission performance and urbanization in China, these have several limitations. First, most studies have quantified the relationship between carbon emission performance and urbanization in China without considering the relevant heterogeneities due to differences in either urbanization stage or economic development level. Second, most studies measure carbon emission performance in China using variables, such as per capita

carbon emissions or total carbon emissions, which only partially reflect carbon emission performance. Third, many studies use emission factors published by the United Nations Intergovernmental Panel on Climate Change (IPCC 2006) and the energy inventory released by the National Energy Agency, which are not sufficiently accurate to calculate total energy consumption and total carbon emissions.

Using stochastic impacts by regression on population, affluence, and technology (STIRPAT) and panel threshold models, this study investigates the relationship between urbanization and carbon emission performance by considering the heterogeneities in urbanization and economic development levels in China. We contribute to the literature in two ways. First, we innovate by considering heterogeneities due to differences in urbanization stages when exploring the relationship between carbon emission performance and urbanization, drawing on the S-curve concept proposed by Northam (1979). This approach avoids regression errors due to neglecting the relevant heterogeneities. Second, we consider how the economic development level impacts the urbanization–emissions relationship. This approach is particularly important given that economic development in the eastern coastal areas of China is more advanced than it is in China's inland areas due to the areas' priority development strategy. Such rapid development and urbanization may contribute to carbon emissions. Additionally, this study offers policy implications for China that are applicable as well to other developing countries undergoing rapid urbanization.

2 Literature review

As nations face the challenge of meeting carbon emission mitigation targets, research has focused increasingly on the relationship between urbanization and carbon emissions. Our study relates broadly to three strands in the literature as follows: (1) the relationship between carbon emission performance and urbanization, (2) the measurement of carbon emission performance, and (3) applications of the STIRPAT model.

Looking at the first strand of literature, there is no consensus regarding the relationship between urbanization and carbon emissions. Some scholars regard urbanization as an incentive for increasing carbon emissions (Parikh and Shukla 1995; Poumanyvong and Kaneko 2010; Wu et al. 2017; York et al. 2003). However, other scholars find no evidence that urbanization promotes carbon emissions unidirectionally. For example, Liddle and Lung (2010), Sadorsky (2014), and Rafiq et al. (2016) argue that the correlation between total carbon emissions and urbanization is not significant. In addition, some scholars no longer regard urbanization and carbon emissions as having a simple linear relationship. For example, Li and Lin (2015) examine this relationship from the perspective of different income levels. Moreover, Salim and Shafiei (2014) find an inverted U-shaped relationship between carbon emissions and urbanization, which depends on the urbanization stage in the OECD country.

Amid the growing pace of urbanization, scholars are paying increasing attention to the relationship between urbanization and carbon emissions in China. Ouyang and Lin (2017) studied the relationship between urbanization and carbon emissions in India, China, and Japan. Zhang and Cheng (2009) and Zhang and Xu (2017) found a positive correlation between urbanization, energy consumption, and carbon emissions in China from a national perspective. Ding and Li (2017) used the LMDI decomposition method and found significant regional differences in the influence of urbanization on carbon emissions. Wang and Zhao (2018) showed that urbanization suppressed per capita carbon emissions in urbanized regions but had

a positive impact in other regions and at the national level. As the literature on this grows, scholars are no longer limited to studying how changes in urban and rural population structures affect national carbon emissions; namely, the research has become more comprehensive. From the perspective of land urbanization and financing, Zhang and Xu (2017) found that the rate of land urbanization played a weak role in reducing carbon emissions. Fan et al. (2017) employed the Divisia decomposition method to explore the impact of urbanization on China's residential carbon emissions from the perspective of collection and decomposition. In addition, scholars, such as Zhu et al. (2017), have studied the relationship between urbanization and carbon emissions in China from the regional perspective.

In the second strand of the literature, many studies have discussed methods for measuring carbon emission performance. Watanabe and Tanaka (2007) argue that analyzing carbon emission performance from the single-factor perspective ignores the substitution between factors and cannot produce an accurate measurement. Therefore, many scholars have employed data envelopment analysis (DEA) to measure carbon emission performance from the perspective of multiple indicators. For example, studies have used the Shephard production technology (Shephard 1970) to measure carbon emission performance, but do not address the weak disposability of undesirable outputs. Chung et al. (1997) proposed the directional distance function to overcome the shortcomings of the output-oriented distance function (Shephard 1970). Färe et al. (2007) later used this method to measure the environmental efficiency of coal-fired power generation companies. However, as Fukuyama and Weber (2009) argue, the direction distance function is a radial measurement method. Thus, when the slack variable is not zero, the radial measurement will overestimate the efficiency value, resulting in biased results. Non-radial measures of efficiency have been advocated frequently as ways to measure energy and environmental performance because of their advantages (Chang and Hu 2010; Zhou and Ang 2008; Zhou et al. 2007). For this reason, our study uses a non-radial directional distance function (Zhou et al. 2012) in constructing a total factor carbon emission performance index (*TCPI*) to avoid the bias caused by radial measurements when the slack variable is not zero.

The literature review shows that most studies on measuring carbon emission performance are focused on total carbon emissions and total energy consumption. Oda et al. (2019) studied the gridded carbon dioxide emissions inventory from the perspective of errors and uncertainties to characterize the biases in spatial disaggregation by emission sector across different scales. Jarnicka and Żebrowski (2019) studied greenhouse gas emission inventories from the perspective of uncertainty improvement over time. However, official data on China's total annual carbon emissions have not been released. Most scholars have used the carbon emissions energy inventory and emission factors published by the IPCC for their calculations. As the carbon emission factors published by the IPCC are not accurate (Liu et al. 2015), the carbon emission analyses that use them are also not accurate. Furthermore, the accuracy of the energy inventory has been questioned due to frequent revisions and inconsistencies in the published data (Korsbakken et al. 2016; Wang 2011; Zheng et al. 2018). Shan et al. (2016) used emission factors that were more in line with China's situation (Liu et al. 2015) and adopted the apparent energy consumption method to calculate provincial carbon emissions in China from 2000 to 2012. On this basis, Shan et al. (2018) proposed an energy inventory and calculated carbon emissions from 1978 to 2015 for 30 Chinese provinces and China overall. This was followed by the IPCC's emission accounting methods and geographical management requirements. Liu et al. (2015) and Shan et al. (2016, 2018) provided a reliable source of data for accounting of carbon emissions and energy consumption in China. Therefore, this study

uses the data provided by the China Emission Accounts and Datasets (CEADs) to recalculate China's total energy consumption and carbon emissions. The CEADs' emission factors are derived from accurate combustion tests on 602 raw coal samples taken from China's top 100 coal mining areas, combined with a revised carbon content, net calorific value, and oxidation rate. This carbon emissions calculation method is considered to be more in line with China's energy characteristics (Liu et al. 2015; Shan et al. 2018).

The third literature stream focuses on the IPAT and STIRPAT models, which have been used widely in studies on the environmental impact of human activities such as carbon emissions. The IPAT (I=P*A*T) model attributes the environmental impact (I) of human activities to population (P), wealth (A), and technology (T) (Ehrlich and Holdren 1971). Dietz and Rosa (1994, 1997) improved on the traditional IPAT model and proposed a STIRPAT model. STIRPAT has been used widely in studies involving carbon emission measurement (e.g., Wang et al. 2017; Yeh and Liao 2017; Zhang et al. 2017) because its model assumptions are more relaxed and it allows hypothesis testing. We choose the *TCPI* as a proxy variable for environmental impact (I) to measure the relationship between carbon emission performance and urbanization, while also taking into account heterogeneities in urbanization and economic development levels using STIRPAT and panel threshold models.

3 Methodology and data

3.1 Measuring TCPI

Assume there are $n(n = 1, 2, …, N)$ units, input vector $x = \left(x_1^t, x_2^t, x_3^t, …, x_N^t\right), x \in R_+^N$, desirable output vector $y = \left(y_1^t, y_2^t, y_3^t, …, y_M^t\right), y \in R_+^M$, and undesirable output vector $b = \left(b_1^t, b_2^t, b_3^t, …, b_I^t\right), b \in R_+^I$ for the period $t(t = 1, 2, …, T)$. The production technologies (T) can be expressed as follows:

$$T = \{(x, y, b) : x \ can \ produce(y, b)\} \tag{1}$$

As described in Färe et al. (1989), if outputs satisfy the assumption of strong disposability, undesirable outputs are the same as desirable outputs, which can be freely disposed of. Therefore, we must assume that the outputs are weak disposability, expressed as (a). In addition, T must satisfy the null-jointness assumptions, expressed as (b):

(a) If $(x, y, b) \in T$ and $0 \le \theta \le 1$, then $(x, \theta y, \theta b) \in T$.
(b) If $(x, y, b) \in T$ and $b = 0$, then $y = 0$.

Here, (a) implies that the reduction of undesirable outputs is not free but a proportional reduction in desirable outputs, while (b) implies that the undesirable outputs are unavoidable during the production process.

Following Zhou et al. (2012), we define the non-radial directional distance function as follows:

$$\overrightarrow{D}(x, y, b, g) = sup\{\omega^T \beta : ((x, y, b) + g \times diag(\beta)) \in T\} \tag{2}$$

where g is the explicit directional vector, in which T will be scales. For our purposes, $g = (-g_x, g_y, -g_b)$ indicates that desirable outputs will increase and undesirable outputs will decrease. $\omega = \left(\omega_m^x, \omega_s^y, \omega_j^b\right)^T$ is a normalized weight vector that is relevant to the numbers of inputs

and outputs.$\beta = \left(\beta_m^x, \beta_s^y, \beta_j^b\right)^T \geq 0$ denotes the vector of scaling factors. We can compute the value of $\overrightarrow{D}(x, y, b, g)$ by solving the following DEA-type model:

$$
\begin{aligned}
\overrightarrow{D}(x, y, b, g) = &\ max\ \omega_m^x \beta_m^x + \omega_s^y \beta_s^y + \omega_j^b \beta_j^b \\
s.t.\ &\sum_{n=1}^{N} z_n x_{mn} \leq x_m - \beta_m^x g_{xm}, m = 1, \ldots, M, \\
&\sum_{n=1}^{N} z_n y_{sn} \geq y_s + \beta_s^y g_{ys}, s = 1, \ldots, S, \\
&\sum_{n=1}^{N} z_n b_{jn} = b_j - \beta_j^b g_{bj}, j = 1, \ldots, J, \\
&z_n \geq 0, n = 1, \ldots, N \\
&\beta_m^x, \beta_s^y, \beta_j^b \geq 0
\end{aligned}
\tag{3}
$$

We can adjust the direction vector g according to different goals. If $\overrightarrow{D}(x, y, b, g) = 0$, the measured decision unit is on the valid frontier of best practice in the g direction. Inputs are capital (K), labor (L), and energy (E); desirable output is gross regional product (Y); undesirable output is carbon emissions (C). We set $g = (-x, y, -b) = (-K, -L, -E, Y, -C)$ and the normalized weight vector $\omega = (1/9, 1/9, 1/9, 1/3, 1/3)$. Following Zhou et al. (2012), we construct the TCPI by calculating the linear programming (3), as shown in formula (4):

$$
TCPI = \frac{\left(C - \beta_c^* C\right) / \left(Y + \beta_Y^* Y\right)}{C / Y} = \frac{1 - \beta_C^*}{1 + \beta_Y^*}
\tag{4}
$$

Furthermore, $0 \leq \beta \leq 1$ and TCPI is a standardized index between zero and unity. If TCPI is equal to unity, it means that the unit is located at the frontier of best practice.

3.2 Panel threshold model

The IPAT model proposed by Ehrlich and Holdren (1971) attributes the environmental impact (I) of human activities to population (P), wealth (A), and technology (T). In this model, the population factor (P), the wealth factor (A), and the technical factor (T) are mutually independent (Alcott 2010). Assuming that other factors remain unchanged, the impact can be analyzed only by changing one of the factors (Shi 2003). To overcome the limitations of the traditional IPAT model, Dietz and Rosa (1994, 1997) proposed stochastic impacts by performing regressions on the STIRPAT model, which has been widely applied in the recent literature such as Wang et al. (2019). After taking logarithms, the model is as follows:

$$
LnI_{it} = Lna_{it} + bLnP_{it} + cLnA_{it} + dLnT_{it} + Ln\varepsilon_{it}
\tag{5}
$$

Here, TCPI is a proxy variable for the environmental impact (I), and urbanization rate (URB) and population density (POP) represent the population factor (P). Following previous studies (Kais and Sami 2016; Liddle 2013; Wu et al. 2017), we select per capita GDP (PGDP) to represent affluence (A). Technological factors (T) are reflected by R&D intensity (RD). Thus, the STIRPAT model can be expressed as

$$\ln TCPI_{it} = \beta_0 + \beta_1 \ln URB_{it} + \beta_2 \ln POP_{it} + \beta_3 \ln PGDP_{it} + \beta_4 \ln RD_{it} + e_{it} \qquad (6)$$

where β_0 is a constant; β_1, β_2, β_3, and β_4 are coefficients; and e is a random error term.

According to Northam's (1979) S-curve, the relationship between carbon emission performance and urbanization varies according to the urbanization stage and economic development level. Therefore, we take urbanization rate (URB) and economic development level (PGDP) as threshold variables using Hansen's (1999) panel threshold model. Specifically, we use the panel threshold model to estimate the endogenous threshold parameters. The other parameters of each group are estimated only once, unlike the procedure for a grouped exogenous sample. The specific form is

$$\ln TCPI_{it} = \eta_0 + \eta_1 \ln POP_{it} + \eta_2 \ln PGDP_{it} + \eta_3 \ln RD_{it} + \eta_4 \ln URB_{it} I(URB \leq \gamma) \\ + \eta_5 \ln URB_{it} I(URB > \gamma) + \sigma_{it} \qquad (7)$$

$$\ln TCPI_{it} = \varphi_0 + \varphi_1 \ln POP_{it} + \varphi_2 \ln PGDP_{it} + \varphi_3 \ln RD_{it} + \varphi_4 \ln URB_{it} I(PGDP \leq \gamma') \\ + \varphi_5 \ln URB_{it} I(PGDP > \gamma') + \pi_{it} \qquad (8)$$

In Eqs. (7) and (8), $I(\cdot)$ is the indicator function that defines the regime in terms of threshold variables URB and PGDP. γ and γ' are two threshold values. If the conditions in parentheses are satisfied, $I(\cdot)$ is equal to 1 or 0 otherwise. Eqs. (7) and (8) measure the effects of urbanization on carbon emission performance across different levels of urbanization and economic development, respectively. In other words, Eqs. (7) and (8) describe the relationship between carbon emission performance and urbanization under the constraints of different urbanization and economic development levels due to the nonlinear conversion characteristics defined by the threshold values above.

Furthermore, Eqs. (7) and (8) assume that there is one urbanization threshold value and one economic development level threshold value. In other words, the relationship between carbon emission performance and urbanization has two mechanisms. However, triple urbanization thresholds and double economic development level thresholds may also appear according to Northam's (1979) S-curve. Assuming $\gamma_1 < \gamma_2$ and $\gamma_1' < \gamma_2'$, the models are modified into Eqs. (9) and (10), as follows:

$$\ln TCPI_{it} = a_0 + a_1 \ln POP_{it} + a_2 \ln PGDP_{it} + a_3 \ln RD_{it} + a_4 \ln URB_{it} I(URB \leq \gamma_1) \\ + a_5 \ln URB_{it} I(\gamma_1 < URB \leq \gamma_2) + a_6 \ln URB_{it} I(\gamma_2 < URB \leq \gamma_3) + a_7 \ln URB_{it} I(URB > \gamma_3) + u_{it} \qquad (9)$$

$$\ln TCPI_{it} = b_0 + b_1 \ln POP_{it} + b_2 \ln PGDP_{it} + b_3 \ln RD_{it} + b_4 \ln URB_{it} I\left(PGDP \leq \gamma_1'\right) \\ + b_5 \ln URB_{it} I\left(\gamma_1' < PGDP \leq \gamma_2'\right) + b_6 \ln URB_{it} I\left(PGDP > \gamma_2'\right) + m_{it} \qquad (10)$$

3.3 Data

This study, constrained by data accessibility, examines a panel dataset comprising 29 provinces in China covering 2000 to 2015. We exclude Tibet, Ningxia, Taiwan, Hong Kong, and

Macau due to lack of data. Inputs are capital (K), labor (L), and energy (E); desirable output is gross regional product (Y); and undesirable output is carbon emissions (C). The input and output variables are as follows:

(1) Capital (K): Based on Zhang et al. (2004), we recalculate capital stocks by employing a perpetual inventory (stock) system. The values are deflated by a GDP deflator to the constant price in the base year of 2000. The data come from the National Bureau of Statistics of China.

(2) Labor (L): We estimate labor input using the number of employees at the end of each year in each province. The data are extracted from the China Population and Employment Statistics Yearbooks (NBSC 2000–2015).

(3) Energy (E): Following Shan et al. (2016, 2018), total energy consumption is calculated using the following equation: total final consumption for each province + energy inputs − energy outputs − losses − non-energy use − Chinese airplanes and ships refueled abroad + foreign airplanes and ships refueling in China. The provincial energy inventories from 2000 to 2015 are obtained from China Emission Accounts and Datasets.

(4) GDP (Y): The annual GDP of each province is the real price GDP calculated at a constant price level in 2000. The data come from the National Bureau of Statistics of China.

(5) Carbon emissions (C): According to the IPCC Guidelines for National Greenhouse Gas Inventories, carbon emissions (CE) can be calculated as in Eq. (11):

$$
\begin{aligned}
CE &= \sum AD_i \times EF_i \\
&= \sum AD_i \times N_i \times C_i \times O_i
\end{aligned} \tag{11}
$$

where CE represents the total aggregated carbon emissions from different fossil fuels i. AD_i denotes combustion of fossil fuel i, and EF_i is the emission factors for fossil fuel i. Following Liu et al. (2015) and Shan et al. (2016, 2018), we calculate carbon emissions in various provinces in China. The emission factor (EF_i) is the product of the net calorific value (N_i), carbon content (C_i), and oxidation rate (O_i) for each energy source.

The selected variables and their statistics are presented in Table 1.

In the panel threshold model, we use the share of the urban population in the total population to express the urbanization rate (URB). The data on total and urban population are taken from the China Statistical Yearbook Statistical Bulletin and the National Census National Key Project Research Report 2000. As we lack urban population data for Shanghai and Guangdong for 2001 to 2004, for Hebei Province for 2002, and for Sichuan Province for 2001, we use the share of non-agricultural population as the proxy variable. We also employ the population per unit area to

Table 1 Descriptive statistics of inputs and outputs

	Variable	Unit	Obs	Mean	SD	Min.	Max.
Input	K	10^8 yuan	464	24,510	21,359	1570	128,086
	L	10^4 people	464	2555	1642	284	6636
	E	10^4 tons of standard coal	464	9937	7258	387	34,241
Output	Y	10^8 yuan	464	8170	7379	264	42,159
	C	10^6 t	464	251	222	1	1554

Table 2 Descriptive statistics for variables used in the panel threshold model

Variable	Obs	Mean	SD	Min.	Max.
lnURB	464	− 0.7742	0.3092	− 1.4610	− 0.1098
lnPOP	464	− 1.4362	1.2719	− 4.9364	1.4310
lnPGDP	464	8.9467	0.8634	4.3003	10.2979
lnRD	464	2.6249	0.6908	0.8241	4.2161

represent population density (*POP*) and the number of patent grants owned by every hundred people to represent R&D intensity (*RD*). Moreover, we use GDP at the 2000 constant price divided by population to reflect per capita GDP (*PGDP*). The data for population density and R&D intensity are taken from the China Statistical Yearbook and the China Science and Technology Statistical Yearbook.

The variables' descriptive statistics are presented in Table 2.

4 Results and discussion

4.1 Results of TCPI based on the non-radical direction distance function

This study calculates the *TCPI* based on a non-radical direction distance function. Figures 1 and 2 present the *TCPIs* for the 29 provinces from 2000 to 2015. Regarding individual provinces, Beijing, Shanghai, and Guangdong had the highest carbon emission performance levels. Beijing's *TCPI* reached the maximum of 1. The average values in Shanghai and Guangdong reached 0.9493 and 0.9402, respectively. On the whole, Beijing has always been
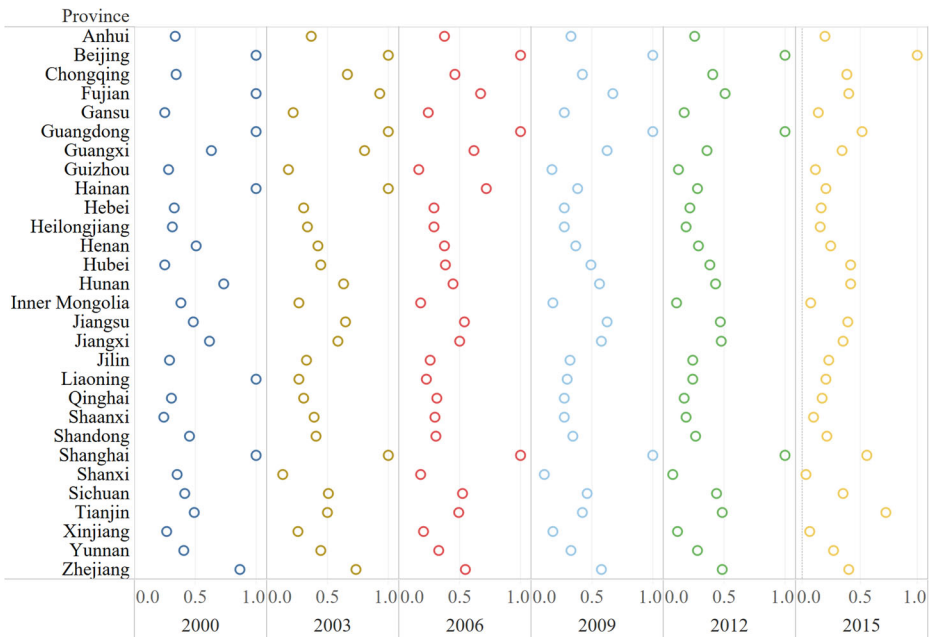

Fig. 1 The *TCPI* values based on a non-radial direction distance function
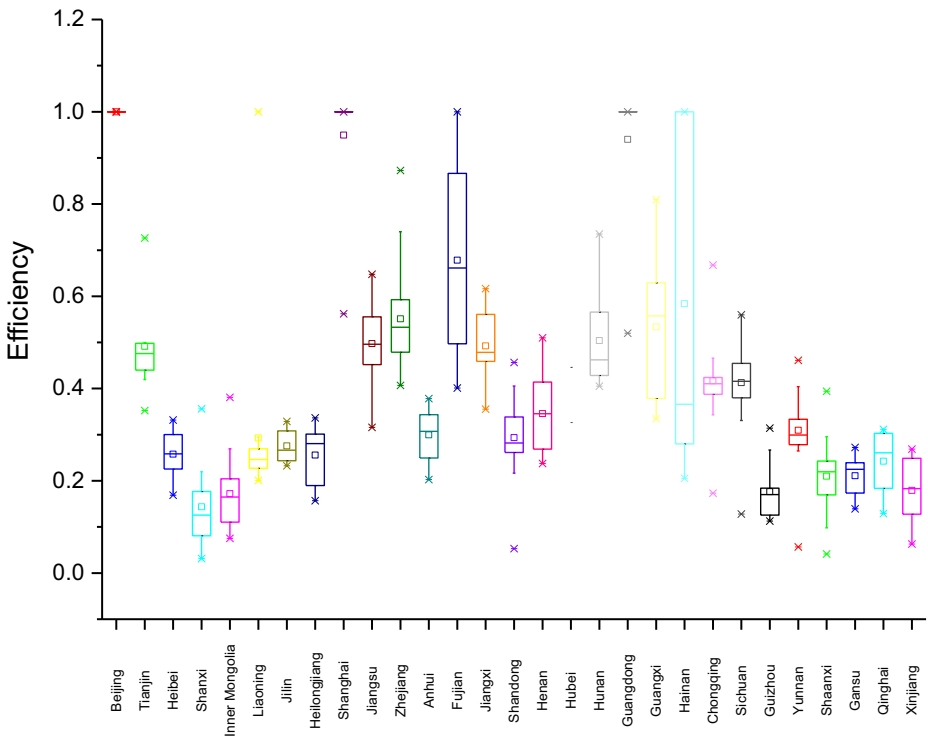
Fig. 2 The *TCPI* mean, maximum, minimum, and median in 29 provinces in China. This shows the *TCPI* mean, maximum, minimum, and median for all years in the 29 provinces in China. The upper and lower sides of the rectangle represent the upper and lower quartiles, respectively, and the asterisk represents the outlier

in the lead. Carbon emission performance in some provinces—such as Tianjin, Hubei, and Chongqing—shows a clear upward trend. However, the *TCPI* values in Shanxi, Inner Mongolia, and Hainan were among the lowest during these years.

The Chinese government has implemented key energy-saving and emission-reducing policies to improve energy efficiency and promote low-carbon technologies. Specifically, the Eleventh Five-year Plan (2006–2010) indicates that energy saving and emission reduction are important for adjusting China's economic structure and accelerating the transformation of its economic development methods (Cao and Karplus 2014). Subsequently, the Twelfth Five-year Plan (2011–2015) requires that China's local governments reduce pollutant emissions and increase energy efficiency. These measures can improve carbon emission performance. The 62% *TCPI* in provinces, such as Tianjin, around 2004, shows that the situation was particularly bad

Table 3 Threshold effect test of urbanization stages

Hypothesis	F value	p value
H_0: No threshold; H_a: Single threshold	14.1356	0.0000***
H_0: Single threshold; H_a: Double threshold	11.3137	0.0060***
H_0: Double threshold; H_a: Triple threshold	8.7085	0.0060***

***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

Table 4 Estimations and confidence intervals of threshold values of urbanization stages

Threshold value	Value	Confidence interval of 95%
$\widehat{\gamma}_1$	25.47%***	(24.86, 25.47)
$\widehat{\gamma}_2$	46.12%***	(46.12, 47.34)
$\widehat{\gamma}_3$	57.06%***	(50.98, 58.27)

***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

then. The severe acute respiratory syndrome that affected the national economy at that time reduced carbon emission performance in 2003 (Zhao et al. 2003); this negative effect lasted until 2004.

4.2 Heterogeneous relationship between urbanization and TCPI due to urbanization

Table 3 presents the threshold effect test for the urbanization stages. The results, shown in Table 4, indicate that the estimated threshold values for the urbanization stages are 25.47%, 46.12%, and 57.06%. Therefore, we divide the sample into four subpanels to estimate the parameters, which shows that the relationship between carbon emission performance and urbanization is nonlinear.

The regression results that consider heterogeneity across urbanization stages are shown in Table 5. When the proportion of the urban population to the total population is less than 25.47%, the coefficient is -0.4393, indicating that urbanization suppresses carbon emission performance when it is low. When the urbanization rate is between 25.47% and 46.12%, the coefficient is -0.2204 but is not significant, indicating that the inhibiting effect is not obvious. Furthermore, as urbanization increases, the positive effect of urbanization on carbon emission performance gradually emerges. It is worth noting that urbanization significantly affects carbon emission performance when the urbanization rate is greater than 57.06% and the coefficient is 0.5686. Thus, there is a U-shaped relationship between urbanization and carbon emission performance. This finding is consistent with recent results for various countries in the studies by Ehrhardt-Martinez et al. (2002), Martínez-Zarzoso and Maruotti (2011), Salim and Shafiei (2014), and Zhang et al. (2017).

Amid increasing urbanization, immigrant households purchase more appliances, which stimulate civil electricity energy consumption (Holtedahl and Joutz 2004). In addition, population increases cause housing and infrastructure expansion, which drives the development of high-energy-consuming industries such as the steel and cement sectors. Furthermore, growth

Table 5 Regression considering heterogeneity across urbanization stages

Explanatory variable	Coefficient
$\ln POP_{it}$	-0.8838*** (0.1851)
$\ln PGDP_{it}$	-0.4223*** (0.1023)
$\ln RD_{it}$	0.0873** (0.0439)
$\ln URB_{it}I(URB \leq 25.47\%)$	-0.4393*** (0.1625)
$\ln URB_{it}I(25.47\% < URB \leq 46.12\%)$	-0.2204 (0.2028)
$\ln URB_{it}I(46.12\% < URB \leq 57.06\%)$	0.1130 (0.2256)
$\ln URB_{it}I(URB > 57.06\%)$	0.5686** (0.2681)

Robust standard errors are shown in parentheses; ***, **, and * denote $p < 0.01$, $p < 0.05$, and * denote $p < 0.1$, respectively

Table 6 Threshold effect test of economic development level

Hypothesis	F value	p value
H_0: No threshold; H_a: Single threshold	12.1016	0.0000***
H_0: Single threshold; H_a: Double threshold	8.0290	0.0080***

***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

in the number of private cars increases the consumption of energy such as petroleum. Moreover, per capita *GDP* has increased along with urbanization, and the pattern of household consumption has changed from a survival model to a development model, or enjoyment model (Ji and Chen 2017). Increasing travel has also increased energy consumption in the urban transportation sector (Wright and Fulton 2005). In addition, the technological effect can have an energy-saving impact, and some scholars argue that technological advances can promote changes in the energy structure (Fan et al. 2017), leading to an increase in carbon emission performance. The acceleration of urbanization, the rapid concentration of labor, capital, and other factors, combined with increasing specialization in the labor force have accelerated the formation of economies of scale. By sharing infrastructure, affiliated enterprises can reduce transportation and storage costs. Therefore, affiliated enterprises can reduce energy consumption and energy intensity, which can enhance carbon emission performance.

China is at an accelerated stage of urbanization. China's urbanization rate tends to exceed 57.06% in eastern coastal provinces such as Tianjin and Shanghai. The rate elsewhere is less than 57.06%, but most provinces have experienced increased emission efficiency in recent years. Therefore, the current relationship between China's urbanization and carbon emission performance is near the right-hand side of the inflection point of the U-shaped curve. This suggests that, as of this point in time, urbanization is improving carbon emission performance in China.

4.3 Heterogeneous urbanization–TCPI relationship across economic development levels

Table 6 shows the threshold effect test for economic development level. We find that there are two thresholds, indicating that the relationship between carbon emission performance and urbanization is nonlinear across economic development levels. The two threshold values are 5088.8596 and 10,498.0826 and they are both significant at the 1% level, as shown in Table 7.

Table 8 shows the results of the panel threshold model for the economic development levels. When per capita *GDP* is less than 5088.8596, the coefficient is -0.6705, indicating that urbanization inhibits carbon emission performance. When per capita *GDP* is between 5088.8596 and 10,498.0826, the inhibiting effect begins to increase, and the coefficient is $-$

Table 7 Estimations and confidence intervals of threshold values of economic development level

Threshold value	Value	Confidence interval of 95%
$\widehat{\gamma}_1'$	5088.8596***	(4968.6547, 5329.2695)
$\widehat{\gamma}_2'$	10,498.0826***	(8454.5984, 11,100.0000)

***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

Table 8 Regression considering heterogeneity across economic development levels

Explanatory variable	Coefficient
$1nPOP_{it}$	− 0.1622 (0.2358)
$1nPGDP_{it}$	− 0.4844*** (0.1085)
$\ln RD_{it}$	0.0777* (0.2358)
$\ln URB_{it}I(PGDP \leq 5088.8596)$	− 0.6705*** (0.1473)
$\ln URB_{it}I(5088.8596 < PGDP \leq 10498.0826)$	− 0.8750*** (0.1635)
$\ln URB_{it}I(PGDP > 10498.0826)$	− 1.3651*** (0.3077)

Robust standard errors are shown in parentheses; ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

0.8750. Moreover, urbanization has a stronger inhibiting effect on carbon emission performance when per capita *GDP* is greater than 10,498.0826 and the coefficient is − 1.3651.

China is on a high carbon-intensive urbanization path. China's economic development has triggered energy and environmental issues involving significant energy consumption and carbon emissions. As mentioned, urbanization acceleration is greater in China's eastern coastal areas than in other regions, and economic development is more advanced there than it is in the inland areas. Energy consumption and carbon emissions have also increased due to the construction of urban infrastructure. Amid the increase in per capita *GDP*, China's household expenditure has shifted from food and clothing to high carbon-intensive housing, automobiles, air conditioners, refrigerators, and other products. Therefore, China must pursue low-carbon urbanization to meet its emission-mitigation targets.

4.4 Robustness test: An alternative to TCPI

As Tables 9 and 10 show, we use carbon intensity (carbon emissions per unit of *GDP*) to verify the previous relationship results. We find that greater carbon intensity leads to greater carbon emissions, at least to some extent. These results suggest that our analysis is robust. Specifically, the coefficients of the different urbanization stages are 0.3646, 0.0872, − 0.1544, and − 0.3271, respectively, indicating that the relationship between carbon intensity and urbanization is an inverted U-shaped curve (see Table 10). Table 11 shows the results of the analysis on the relationship between urbanization and carbon intensity that considers heterogeneity across economic development levels. We find that urbanization promotes carbon intensity across different per capita *GDP* stages. Furthermore, urbanization has a weaker

Table 9 Analysis of the relationship between urbanization and carbon intensity considering heterogeneity across urbanization stages

Explanatory variable	Coefficient
$1nPOP_{it}$	− 0.3735** (0.1751)
$1nPGDP_{it}$	0.2214** (0.0881)
$1nRD_{it}$	− 0.2617*** (0.0388)
$\ln URB_{it}I(\mathbf{URB} \leq 25.47\%)$	0.3646* (0.2112)
$\ln URB_{it}I(25.47\% < \mathbf{URB} \leq 45.51\%)$	0.0872 (0.1624)
$\ln URB_{it}I(45.51\% < \mathbf{URB} \leq 49.77\%)$	− 0.1544 (0.1614)
$\ln URB_{it}I(\mathbf{URB} > 49.77\%)$	− 0.3271* (0.1775)

Robust standard errors are shown in parentheses; ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

Table 10 Analysis of the relationship between urbanization and carbon intensity considering heterogeneity across economic development levels

Explanatory Variable	Coefficient
$\ln POP_{it}$	-0.6514^{***} (0.1859)
$\ln PGDP_{it}$	-0.1018 (0.1334)
$\ln RD_{it}$	-0.2800^{***} (0.0461)
$\ln URB_{it}I(PGDP \leq 375.5255)$	1.5411^{***} (0.3717)
$\ln URB_{it}I(375.5255 < PGDP \leq 7044.5270)$	0.7374^{***} (0.2480)
$\ln URB_{it}I(PGDP > 7044.5270)$	0.5001^{**} (0.2197)

Robust standard errors are shown in parentheses; ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively

enhancement effect on carbon intensity as per capita *GDP* increases. The coefficients are 1.5411, 0.7374, and 0.5001, all significant at the 1% level. Therefore, our previous results are robust.[1]

5 Conclusions and policy implications

Considering heterogeneity across different urbanization stages and economic development levels, we use panel threshold models based on an extended STIRPAT model to explore how urbanization impacts carbon emission performance in China's 29 provinces from 2000 to 2015. The *TCPI* is introduced as a proxy variable for environmental impact (I) in the STIRPAT model. The *TCPI* reflects the carbon emission performance of each province, calculated from the non-radial directional distance function. The key findings are as follows.

First, we find significant heterogeneity in the *TCPI* across the provinces. Beijing, Shanghai, and Guangdong have the highest levels of carbon emission performance during this timeframe. The performance in some provinces—such as Tianjin, Hubei, and Chongqing—shows a clear upward trend. However, the *TCPI* values in Shanxi, Inner Mongolia, and Hainan are among the lowest during the study period.

Second, analyzing heterogeneity in the urbanization stages shows that the effect of urbanization on carbon emission performance in China follows a U-shaped path. China is located near the right-hand side of the inflection point of the U-shaped curve, suggesting that urbanization improves carbon emission performance in China in the present stage.

Finally, regarding heterogeneity across economic development levels, urbanization shows an inhibiting effect on carbon emission performance. Urbanization has a stronger inhibiting effect on carbon emission performance as economic development advances, suggesting that China's urbanization will consume more energy as its economic development progresses.

From a global perspective, our findings imply the need for the following climate-mitigation strategies for a low-carbon urbanization path: (1) In the process of urbanization in developing countries like China, countries need to implement detailed regional policy planning tailored to local conditions. For regions with lower carbon emission performance, energy-consumption standards must be strictly enforced to control carbon emissions and achieve global carbon emission-mitigation goals when infrastructure construction for urbanization is introduced

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[1] If we exclude the four municipalities, we lose the highest threshold, but the results for the low thresholds remain unchanged.

(Song et al. 2018). (2) Currently, in China, urbanization tends to improve carbon emission performance amid its heterogeneity of urbanization stages. This result suggests that developing countries should promote investment in research and applications related to energy-saving and emission-reducing technologies to foster low-carbon urbanization conducted using limited resources (Liao and Shi 2018). (3) Along with economic development, urbanization has different effects on carbon emission performance. Therefore, developing countries should promote the use of public transportation as their economies continue to develop, that is, prioritize public transportation over private cars in urban design. Developing countries also need to encourage residents to take public transportation through measures such as low public transport tariffs, restrictions on the use of private cars, and public campaigns to change residents' behaviors.

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