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RESEARCH ARTICLE

The impact of public transportation on carbon emissions: a panel quantile analysis based on Chinese provincial data

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Abstract
Although the Chinese government emphasizes the significance of public transportation development and encourages green travel, no empirical study has examined whether the expansion of public transportation facilitates the mitigation of carbon emissions. To this end, we employ a panel quantile regression to test the endogenous relationship between public transportation scale and carbon emissions. The results suggest that the effect of public transportation scale on carbon emissions is heterogeneous across China's provinces based on the level of carbon emissions. Even so, the results still support a stable inverted U-shaped relationship between public transportation scale and carbon emissions for provinces with different levels of carbon emissions. That is, when public transportation scale exceeds a threshold value, the relationship between public transportation and carbon emissions will turn from positive to negative. Our findings provide evidence advocating for public transportation development and green travel. It is of great significance for China to respond to climate changes.

Keywords Public transportation · Carbon emissions · Quantile regression · Inverted U-shaped

Introduction

As the world's largest carbon emitter, the rapid growth of carbon emissions in China over the past 40 years has attracted global attention (Guo et al. 2018). According to the International Energy Agency (IEA 2011) and Chang et al. (2013), the transportation industry is the second biggest energy consumption industry (accounting for 22% of the world's carbon emissions) followed by the power industry (accounting for 41% of the world's carbon emissions) in 2008. It is widely believed that the Chinese transportation industry will continue to expand in the next few decades (Yin et al. 2015). The acceleration of urbanization has led to an expansion of vehicles, especially private cars, which causes environmental problems, such as smog and carbon emissions. The Chinese Ministry of Transportation issued the 13th Five-Year Plan for urban public transportation in 2016, which emphasized the significance of public transportation development and promoted the priority development strategy of public transportation (Chinese Ministry of Transportation 2016)[1]. Although the expansion of the scale of public transportation increases energy consumption and carbon emissions, it may also trigger an agglomeration effect, which facilitates carbon emission reduction. However, whether the expansion of public transportation scale, measured by the amount of urban public transportation and passenger volume of public transportation, can reduce pollution and improve environmental quality is still a controversial topic (Beaudoin et al. 2015). The purpose of this study is to assess the impact of public transportation scale on carbon emissions based on provincial-level data during the Chinese industrialization and urbanization process. The results may provide support for promoting green travel and policy recommendations for carbon emission mitigation.

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A growing literature focuses on the environmental impacts of the transportation scale. Clarke and Ko (1996) found that volatile organic compound emissions by vehicles accounted for almost half of all emissions. Thijsse et al. (1999) argued that traffic emissions accounted for 80–90% of air pollution in urban areas in Berlin, while accounting for 60% in the suburbs. Chen and Whalley (2012) found that Taipei's railway had a significant effect on air pollution mitigation and could effectively reduce CO emissions. Lalive et al. (2013) found that enhancing the frequency of German railway services could reduce NO, NO_2, and CO emissions. In their review of the existing literature on transportation, Beaudoin et al. (2015) showed that public transportation had a green reputation, and it was believed that it could solve congestion and improve air quality, although the benefit was uncertain in different regions. Beaudoin and Lin Lawell (2016) found that, although public transportation might cause common interests to lose, US public transportation significantly improved air quality from 1991–2011. Song et al. (2016) used the DEA model and found that the railway had a positive effect on environmental efficiency. Xie et al. (2017) found that highway length increased urban carbon emissions, but that it was only significant in large- and medium-sized cities. Xie et al. (2018) found that there existed an inverse U-shaped relationship between traffic density and smog pollution (PM 2.5) in large- and medium-sized cities, while it was not significant in small cities.

There is a wide gap between China's provinces in terms of economic development, energy resources, and industrial structure. Provinces with geographical relationships, as well as similar policy backgrounds and economic characteristics, are more likely to exchange goods, labor, and capital (Huang 2018). Therefore, some studies claim that spatial spillover effects may exist among Chinese provinces. Some researchers investigate the driving factors of regional energy intensity or carbon emissions with spatial approaches to test spatial spillover impacts (e.g., Jiang et al. 2014; Kang et al. 2016; Huang et al. 2017a; Huang et al. 2017c). Furthermore, several scholars have considered regional disparities and analyzed how impacts differ at different distribution levels by quantile regression (e.g., Marques et al. 2011; You et al. 2015; Hübler 2017).

In recent years, while numerous studies have focused on the impact of traffic on environmental pollution, few scholars examined the impact of public transportation scale on carbon emissions. As public transportation is essential for urbanization and economic development, it is necessary to study the green property of the public transportation scale. Therefore, based on the theoretical analysis of the influencing mechanisms of the direct emission effect and agglomeration effect, we use the data of China's 30 provinces over the period from 2002 to 2015 and construct an empirical model to explore the nonlinear relationship between public transportation scale and carbon emissions. Furthermore, considering regional disparities, we conduct a quantile regression with a panel quantile fixed-effect model to assess the influence of public transportation on different provincial carbon emissions throughout the conditional distribution. This discussion is of great significance for in its response to climate change issues and the promotion of public transportation development and green travel.

Our study contributes to the existing literature in the following ways. First, we analyze the influencing mechanisms of the direct emission effect and the agglomeration effect. Previous studies have neglected the relationship between public transportation scale and carbon emissions and lack rigorous theoretical analysis about the impact of the public transportation scale on the environment. Second, although the Chinese government advocates using public transportation in daily life and promote green travel, it lacks empirical evidence to support it. We construct an empirical model, including the public transportation scale variable. We find that there exists a stable inverted U-shaped relationship between public transportation and carbon emissions. That is, when the public transportation scale exceeds a threshold value, the relationship between public transportation and carbon emissions will turn from positive to negative. Third, we use a new panel quantile regression model with non-additive fixed effects and assess the impacts of public transportation on carbon emissions throughout the conditional distribution, with a particular focus on the provinces with the most and least emissions, which are arguably of the most interest. From a policy perspective, it is more interesting to understand what happens at the extremes of a distribution.

The remainder of the paper is organized as follows. The "Theoretical framework and hypothesis" section is the theoretical framework about the influencing mechanisms and hypothesis. The "Methodology and data" section introduces the methodology and data. The "Empirical analysis" section presents the empirical results and discussions. The "Conclusion" section concludes the paper with policy recommendations.

Theoretical framework and hypothesis

Public transportation affects carbon emissions through the direct emission effect and the agglomeration effect (including the scale effect and the technology effect), which may cause an inverted U-shaped relationship between public transportation scale and carbon emissions. The direct emission effect of public transportation holds that energy consumption increases as public transportation grows, which leads to an increase in carbon emissions (see Fig. 1). In the initial stage, although public transportation scale increases, the convenience of public transportation services is not attractive. It has not yet formed an agglomeration effect. That is, with the growth of the amount of public transportation and passenger volume, the corresponding public transportation expansion directly leads to carbon emission growth in the initial stage.

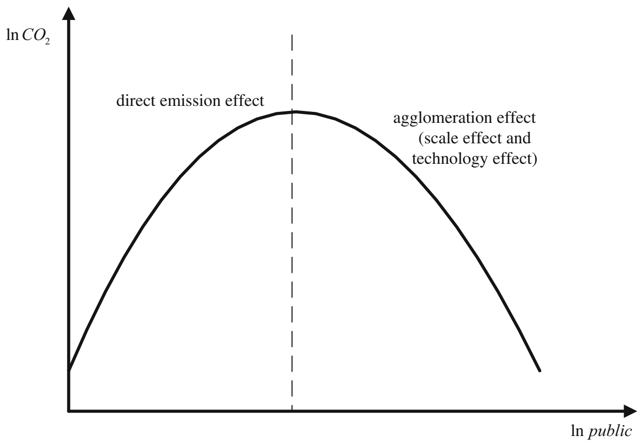

Fig. 1 Inverted U-shaped relationship between public transportation scale and carbon emissions. Notes: $\ln CO_2$ denotes CO_2 emissions and lnPublic denotes urban public transportation scale

With the continuous expansion of public transportation, the agglomeration effect, which includes the scale effect and the technology effect, increases. For example, with the emergence of rail transit, more residents have come to favor the convenience of public transportation. Residents who rely on private cars may turn to public transportation, which may reduce the usage and possession of private cars (Zheng et al. 2017). More residents choose public transportation as a means of travel and form the scale effect, which will surpass the negative externality of environmental pollution caused by the expansion of public transportation. Lu et al. (2007) found that the rapid growth of vehicles is a major factor in the increase of carbon emissions. Private cars are a major source of energy consumption for urban transportation and a major contributor to urban transportation carbon emissions. Kennedy (2002) pointed out that public transportation was less energy intensive and produced lower carbon emissions. Vincent and Jerram (2006) conducted a scenario simulation and found that public transportation had a greater potential to reduce greenhouse gas than private cars.

Mohring (1972) pointed out that the growth of urban bus transportation frequency and residents' use rate could produce a scale effect. Farsi et al. (2007) confirmed that the establishment and development of multi-modal urban public transportation could increase economies of scale and scope. Xie et al. (2018) proposed that the increase in traffic density could lead to population scale and economic agglomeration. Therefore, the expansion of the amount of public transportation and passenger volume can lead to an enhanced scale effect, which may negatively affect carbon emissions. More specifically, the expansion of public transportation can effectively reduce travel costs, improve regional accessibility, and contribute to the mobility of populations and production factors (Fan et al. 2012; Beaudoin et al. 2015). Fujita et al. (2001) indicated that the reduction in travel costs could bring about population concentration. At the same time, the expansion of public transportation can facilitate intra-regional trade and economic expansion as the cost of transportation declines (Lakshmanan 2011).

Meanwhile, the expansion of public transportation leads to the continuous gathering of the population, production factors, and economic activities, which produces a significant agglomeration economic effect and enhances total factor productivity (Brakman et al. 1996). All these changes lead to the technology effect. The improvement of total factor productivity enhances energy efficiency and reduces pollution emissions (Lin et al. 2011; Otsuka 2014). Moreover, the agglomeration effect promotes knowledge spillover and information exchange, which forms a good innovation environment and improves technological progress and energy efficiency (Xie et al. 2017). Glaeser and Kahn (2010) proposed that the scale economy brought about by the agglomeration effect of population and economic activities is an important mechanism for controlling and reducing energy consumption.

To summarize, we suppose that public transportation does not reach the optimal scale in the initial stage and the direct emission effect plays a major role. The expansion of public transportation will lead to the increase of carbon emissions. Furthermore, when the scale of public transportation expands to a certain extent, the agglomeration effect, including the scale effect and the technology effect, will result in carbon emission reduction. That is, the carbon emissions caused by public transportation expansion may be reduced when public transportation expands to a certain extent. Based on the analytic mechanisms commented on above, we propose the following hypothesis.

Hypothesis: There exists an inverted U-shaped relationship between public transportation scale and carbon emissions.

Methodology and data

Methodology

Because public transportation affects carbon emissions through the direct emission effect and the agglomeration effect, we establish an empirical model by adding the public transportation scale variable. Inspired by Xie et al. (2018), we also add its quadratic term to the model to investigate the possible nonlinear relationship between public transportation scale and carbon emissions.

Meanwhile, we consider five control variables in our empirical model. First, following Dietz and Rosa (1994), who indicated that population factors could affect pollution emissions, we consider population in our model. The absolute indicator of population size is not scientifically comparable due to the large discrepancy between the sizes of administrative divisions and the populations of cities (Xie et al. 2018). We use population density to reflect population in provinces. Second, to test whether there is an environmental Kuznets curve (EKC) in China, we add per capita GDP (PGDP) and its quadratic term to our empirical model. Third, we include energy consumption in our model. Scholars have found that energy consumption has a significant impact on pollutants (e.g., Nasir and Rehman 2011; Li et al. 2016). Fourth, we choose the ratio of total trade to GDP as the proxy variable of the openness level. Scholars indicate that trade openness can affect energy intensity through technology spillover, which has a great influence on carbon emissions (e.g., Yan 2015; Huang et al. 2017b; Huang et al. 2018). Fifth, we consider the impacts of foreign direct investment (FDI) on carbon emissions. Several studies have analyzed the impact of FDI on the environment, as developed regions may transfer pollution emissions to developing regions through FDI (Coughlin and Segev 2000; Zhang and Zhou 2016; Xie et al. 2018). The empirical model is as follows:

$$\begin{aligned}\ln CO_{2it} &= \alpha_0 + \beta_1 \ln Public_{it} + \beta_2 \ln Public_{it}{}^2 \\ &+\beta_3 \ln Urban_{it} + \beta_4 \ln PGDP_{it} + \beta_5 \ln PGDP^2{}_{it} \\ &+\beta_6 \ln EC_{it} + \beta_7 \ln Open_{it} + \beta_8 \ln FDI_{it} + \mu_i + \delta_t + \varepsilon_{it}\end{aligned} \tag{1}$$

where CO_2 is the CO_2 emissions; Public denotes the number of urban public transportation; Urban denotes the population density; PGDP is the per capita GDP; EC is the energy consumption; Open means the trade openness level, measured by the total trade volume divided by GDP; and FDI represents the foreign direct investment.

Furthermore, to investigate the heterogeneity of the effect of urban public transportation scale on different levels of CO_2 emissions, we employ a panel quantile regression model with the non-additive fixed effects proposed by Powell (2016). Quantile regression is appropriate when the variables of interest have varying effects at different points of the conditional distribution of the outcome variable. There has been a growing body of literature that combines quantile estimation with panel data. In the mean regression, panel data allows for the inclusion of fixed effects to capture within-group variation. Many quantile panel data estimators use an analogous method and include additive fixed effects. However, the additive fixed effects change the underlying model. We implement the quantile regression estimator for panel data (QRPD) with the non-additive fixed effects introduced by Powell (2016).

The main advantage of this method relative to the existing quantile estimators with additive fixed effects (α_i) is that it provides estimates of the distribution of $\ln CO_{2it}$ given D_{it}, instead of $\ln CO_{2it} - \alpha_i$ given D_{it}. Powell (2016) noted that the latter is undesirable. This is because observations at the top of the ($\ln CO_{2it} - \alpha_i$) distribution may be at the bottom of the $\ln CO_{2it}$distribution and, therefore, the additive fixed effect models cannot provide information about the effects of the policy variables on the outcome distribution. Thus, Powell's (2016) method provides point estimates that can be interpreted in the same way as the ones coming from a cross-sectional regression. It is also consistent with a small T. The underlying model is:

$$\ln CO_{2it} = \sum_{j=1}^{8} D'_{it}\beta_j\left(U^*_{it}\right), \tag{2}$$

where $\ln CO_{2it}$ is the CO_2 emissions for province i at year t; β_{it} is the parameter of interest; and D_{it} is the set of explanatory variables (here, we choose eight explanatory variables: public transportation scale and its quadratic term, GDP per capita and its quadratic term, urban population density, total energy consumption, FDI, and trade openness). U^*_{it} is the error term that may be a function of several disturbance terms, some fixed and some time-varying. The model is linear in terms of parameters and $D'_{it}\beta(\tau)$ is strictly increasing in τ. In general, for the τth quantile of $\ln CO_{2it}$, the quantile regression relies on the conditional restriction:

$$P\left(\ln CO_{2it} \le D'_{it}\beta(\tau)|D_{it}\right) = \tau \tag{3}$$

Equation (3) indicates that the probability of the outcome variable is smaller than the quantile function, which is the same for all D_{it} and equal to τ. Powell's (2016) QRPD estimator allows this probability to vary by individual and even within individuals as long as such variation is orthogonal to the instruments. Thus, QRPD relies on a conditional restriction and an unconditional restriction, letting $D_i = (D_{it}, \cdots, D_{iT})$:

$$\begin{aligned}&P\left(\ln CO_{2it} \le D'_{it}\beta(\tau)|D_{it}\right) = P\left(\ln CO_{2it} \le D'_{is}\beta(\tau)|D_{it}\right),\\ &P\left(\ln CO_{2it} \le D'_{it}\beta(\tau)\right) = \tau\end{aligned} \tag{4}$$

Powell (2016) develops the estimator in an instrumental variables context given instruments $Z_{it} = (Z_{i1}, \cdots, Z_{iT})$, but notes that, if the explanatory variables are exogenous (in which case $D_i = Z_i$), many of the identification conditions are met trivially. Estimation uses the generalized method of moments. Sample moments are defined as:

$$\begin{aligned}\hat{g}(b) &= \frac{1}{N}\sum_{i=1}^{N} g_i(b) \,\text{with}\, g_i(b) \\ &= \frac{1}{T}\left\{\sum_{i=1}^{T}\left(Z_{it} - \overline{Z}_i\right)\left[1\left(\ln CO_{2it} \le D'_{it}b\right)\right]\right\}\end{aligned} \tag{5}$$

where $\overline{Z}_i = \frac{1}{T}\sum_{i=1}^{T} Z_{it}$.

Using Eq. (5), the parameter set is defined as: $B \equiv \left\{b|\tau - \frac{1}{N} \le \frac{1}{N}\sum_{t=1}^{N} 1\left(LnCO_{2it} \le D'_{it}b\right) \le \tau\right\}$ for all t. Then, the parameter of interest is estimated as $\hat{\beta}(\tau) = \arg\min_{b \in \beta} \hat{g}'(b)$

$\hat{A}\hat{g}'(b)$ for some weighting matrix $\hat{A}$. The model is estimated using the Markov chain Monte Carlo (MCMC) optimization method[2].

Data

We use a balanced panel dataset of 30 provinces in China from 2002–2015. Tibet, Hong Kong, Macao, and Taiwan are excluded due to the unavailability of data. The key explanatory variable in our analysis is urban public transportation. We use the amount of urban public transportation and passenger volume of urban public transportation to represent the public transportation scale. The urban public transportation of each province includes busses, tramcars, and rail traffic. The data are taken from the Wind database.

We also incorporate five control variables into the model. The data on PGDP, FDI, trade openness, and urban population density are collected from the China Statistical Yearbook. All monetary value data are calculated at constant prices in 2002. The data of energy consumption are obtained from the China Energy Statistical Yearbook. The data of CO_2 emissions for 30 provinces are collected from the China Emission Accounts and Datasets (CEADS)[3] according to Shan et al. (2016). For variable definitions and units, please refer to Table 1.

The statistical descriptions of variables are shown in Table 2. All variables are expressed in natural logarithms. It can be seen by comparing the 0.5 quantiles (i.e., the median values) with the mean values of the variables that the distributions of these variables are distinct. For example, the 0.5 quantile of CO_2 emissions is 5.265 and its mean value is 5.243. In addition, the Jarque-Bera (JB) test statistic for normality confirms rejection of the null hypothesis for all series at a 1% level of significance. The skewness and kurtosis tests also indicate that the distribution of sample data is not normal. These statistic results together reveal that the linear regression model based on the conditional mean estimation may encounter challenges (Zhu et al. 2016). These results further inspire us to employ the quantile regression approach to detect whether the effect of public transportation on CO_2 emissions is heterogeneous across economies based on their level of CO_2 emissions in this paper.

Figure 2 reports two scatter plots. The first one shows a positive relationship between the amount of urban public transportation and carbon emissions, whereas with an increase in the number of urban public transportation, the positive relationship between them gradually decreases and tends towards negative. As shown in the second plot, a clear association between CO_2 emissions and the passenger volume of urban public transportation is plotted as an inverted U-shape.

Table 1 Variable definition

Variable	Explanation	Unit
CO_2	CO_2 emissions	Ten thousand tons
Public	Urban public transportation number	–
Trans	Passenger volume of urban public transportation	Ten thousand people
Urban	Urban population density	People/km^2
PGDP	GDP per capita	RMB
EC	Energy consumption	kg of oil equivalent
Open	Total amount of import and export trade (% GDP)	Percent (%)
FDI	Foreign direct investment	Ten thousand RMB

This result reflects that there is a positive relationship between the passenger volume of urban public transportation and CO_2 emissions when the passenger volume of urban public transportation is at a lower level, while it is negative at higher levels. This result provides a direct explanation for the construction of nonlinear models.

Empirical analysis

Panel unit root test and panel cointegration results

Before estimating the panel regression models, we test whether these variables are stationary. If this condition is not met, the results could show spurious relationships. We check the stationary properties for all variables in this paper, as well as the detailed results of the Fisher ADF unit root tests (Maddala and Wu 1999), Fisher PP tests (Choi 2001), and CIPS test (Pesaran 2007), and these are shown in Table 3. The ADF-Fisher and Fisher PP tests are designed to test the null hypothesis of the individual unit roots in the panel versus the stationary alternative. The CIPS test accounts for the presence of cross-section dependence. We find that all variables are $I(1)$ series at the 1% significance level for the sample data.

With a strong evidence that all variables are stationary at the first difference, the panel cointegration test is applied to estimate the existence of the long-run equilibrium relationship among CO_2 emissions and their determinants (including public transportation, energy use, per capita GDP, urban population density, trade openness and FDI). More specifically, the panel cointegration is checked by the Pedroni (2004) and Kao (1999) tests, the results of which are presented in Table 4. According to the Pedroni test for the full data sample, two out of the four panel-based statistics reveal evidence of panel cointegration among the variables at a 1% level of significance. Additionally, two of the three group test statistics reveal evidence of panel cointegration at a 1% level of significance.

[2] All estimations are done in STATA using David Powell's quantile estimator with non-additive fixed effects available at

[3] http://www.ceads.net/

Table 2 Descriptive statistics

	$lnCO_2$	lnPublic	lnTrans	lnUrban	lnPGDP	lnEC	lnOpen	lnFDI
Mean	5.243	9.137	11.921	7.546	11.335	9.084	2.936	14.946
q(25)	4.761	8.680	11.476	7.219	9.951	8.673	2.192	13.533
q(50)	5.265	9.171	11.960	7.648	11.053	9.120	2.584	15.285
q(75)	5.849	9.751	12.514	7.993	11.854	9.638	3.652	16.386
Maximum	7.348	10.981	13.911	8.749	28.618	10.569	5.171	18.187
Minimum	0.000	6.811	9.059	4.522	8.089	6.400	1.273	10.049
Std. dev.	0.924	0.799	0.870	0.739	3.052	0.760	1.001	1.848
Skewness	− 1.219	− 0.476	− 0.528	− 1.199	4.458	− 0.676	0.677	− 0.440
Kurtosis	7.732	3.043	3.511	5.146	24.689	3.767	2.366	2.353
Jarque-Bera	495.931***	15.884***	24.074	181.307***	9623.711	42.268***	39.111***	20.869***
Obs.	420	420	420	420	420	420	420	420

Notes: *, **, *** are statistical significance at 10%, 5%, and 1%, respectively

In sum, four of the seven tests suggest that there is panel cointegration among these variables. The Kao test also suggests that there is panel cointegration at a 1% level of significance. Overall, there is strong statistical evidence in favor of panel cointegration between carbon emissions and their driving factors.

Panel causality test

The existence of a panel long-run cointegration relationship among CO_2 emissions and their determinants suggests that there must be the Granger causality in at least one direction. This study employs two approaches of causality testing among panels to examine the causal relationship between the impact factors and CO_2 emission. The first is to treat the panel data as one large, stacked set of data, and then perform the Granger causality test in the standard way, with the exception of not letting data from one cross-section enter the lagged values of data from the next cross-section. This method assumes that all coefficients are the same across all cross-sections. A second approach adopted by Dumitrescu-Hurlin (2012) makes an extreme opposite assumption, allowing all coefficients to be different across cross-sections. Because this paper mainly investigates the relationship between public transportation and carbon emissions, we only list the test of causality between public transportation and carbon emissions. The panel Granger causality results are presented in Table 5.

By using the first approach, we find non-bidirectional causality from public transportation scale to carbon emissions. Under the framework of Dumitrescu-Hurlin (2012), we find that our results reject the null hypothesis that lnPublic does not homogeneously cause $lnCO_2$. Our results reveal that public transportation has a significant impact on carbon emissions. Overall, there is strong statistical evidence in favor of causality running from public transportation scale to carbon emissions.

Fig. 2 Scatter plot: relationship of CO_2 emission and urban public transportation number, and the passenger volume of urban public transportation, respectively. Notes: $lnCO_2$ denotes CO_2 emissions and lnPublic denotes urban public transportation number, and lnTrans denotes the passenger volume of urban public transportation

Table 3 Panel unit root test

	Level			First difference		
	CIPS	ADF	PP	CIPS	ADF	PP
$\ln CO_2$	− 1.358 (0.894)	4.844 (1.000)	2.529 (1.000)	− 3.056*** (0.000)	233.495*** (0.000)	263.316*** (0.000)
lnPublic	− 1.956 (0.120)	1.417 (1.000)	1.247 (1.000)	− 2.301*** (0.000)	209.123*** (0.000)	239.644*** (0.000)
lnTrans	− 1.786 (0.371)	5.687 (1.000)	1.229 (1.000)	− 2.738*** (0.000)	174.015*** (0.000)	253.425*** (0.000)
lnEC	− 1.65 (0.636)	7.959 (1.000)	0.222 (1.000)	− 2.261*** (0.000)	150.586*** (0.000)	166.048*** (0.000)
lnUrban	− 1.114 (0.999)	7.876 (1.000)	7.447 (1.000)	− 2.184*** (0.010)	354.906*** (0.000)	395.273*** (0.000)
lnPGDP	− 1.458 (0.904)	22.815 (1.000)	7.126 (1.000)	− 2.682*** (0.000)	97.800*** (0.000)	96.102*** (0.000)
lnOpen	− 0.471 (1.000)	38.608 (0.986)	49.162 (0.839)	− 2.468*** (0.000)	312.486*** (0.000)	333.505*** (0.000)
lnFDI	− 1.788 (0.368)	5.236 (1.000)	1.409 (1.000)	− 2.317*** (0.000)	115.496*** (0.000)	169.191*** (0.000)

Note: The significance probabilities for corresponding tests are reported in parentheses

*, **, *** are statistical significance at 10%, 5%, and 1%, respectively

Basic results of panel regression model

Before the model estimation, we test multi-collinearity between the public transportation scale variable and other explanatory variables, specifically the population scale variable. It proves that there is no multi-collinearity among explanatory variables. We conduct our regression using a fixed effect model, and the results are shown in Table 6. The first column only considers public transportation as an explanatory variable, the second column adds the quadratic term of public transportation into the model, and the third column adds control variables, such as population density, per capita GDP and its quadratic term, energy consumption, openness, and FDI.

As seen in column (1) of Table 6, public transportation is significantly positive at the 1% level, which indicates that the expansion of public transportation increases carbon emissions. This result is similar to that of Xie et al. (2017), who also focus on the effect of transportation on emissions, which indicates that construction of transportation infrastructure increases urban carbon emissions. However, Xie et al. (2017) did not investigate the nonlinear relationship between public transportation and carbon emissions.

Further, we consider the quadratic term of public transportation and the results in the second column show that the coefficient of public transportation is significantly positive, whereas the quadratic term coefficient is significantly negative. This result indicates that there is an inverted U-shaped relationship between public transportation and carbon emissions. When adding control variables gradually, the results remain stable. Public transportation has a direct emission effect and agglomeration effect on carbon emissions. When the scale of public transportation exceeds the threshold value, the agglomeration effect may exceed the direct emission effect, and the expansion of public transportation will help promote the reduction of carbon emissions. Chinese provinces should focus on constructing public transportation systems and rationally expanding public transportation in order to cross the threshold value early. The results in Xie et al. (2018) made similar conclusions, as they found an inverted U-shaped relationship

Table 4 Panel cointegration test

Panel 1, the Pedroni test		
Test statistics	Statistic	Prob.
Panel v-statistic (weighted)	− 4.581	1.000
Panel ρ-statistic (weighted)	5.252	1.000
Panel PP-statistic (weighted)	− 14.649***	0.000
Panel ADF-statistic (weighted)	− 2.433***	0.008
Group ρ-statistic	7.676	1.000
Group PP-statistic	− 23.638***	0.000
Group ADF-statistic	− 1.879***	0.030
Panel 2, the Kao test		
	t-statistic	Prob.
ADF	− 2.526***	0.006

Notes: *, **, *** are statistical significance at 10%, 5%, and 1%, respectively

Table 5 Panel causality test

Panel 1: Panel causality test: stacked test	
Null hypothesis:	F-statistic
lnPublic does not the Granger cause $\ln CO_2$	5.299***
$\ln CO_2$ does not the Granger cause lnPublic	1.648
Panel 2: Panel causality test: the pairwise Dumitrescu-Hurlin (2012) test	Zbar-stat.
Null hypothesis:	
lnPublic does not homogeneously cause $\ln CO_2$	5.459***
$\ln CO_2$ does not homogeneously cause lnPublic	4.245***

Notes: *, **, *** are statistical significance at 10%, 5% and 1%, respectively

Table 6 Panel fixed effect regression results (urban public transportation number)

	(1)	(2)	(3)
ln Public	1.514*** (22.33)	6.696*** (10.87)	4.539*** (8.73)
ln Public^2		−0.287*** (−8.46)	−0.238*** (−8.60)
lnUrban			−0.056** (−2.21)
lnPGDP			−0.014 (−0.15)
lnPGDP^2			0.001 (0.25)
lnEC			1.131*** (9.38)
lnOpen			−0.006 (−0.12)
lnFDI			0.027 (0.96)
Constant	−8.590*** (−13.86)	−31.820*** (−11.34)	−26.409*** (−11.40)
R^2	0.562	0.630	0.771
Obs.	420	420	420

Notes: *Z*-statistics are in parentheses; ***, **, and * denotes significance at 1%, 5%, and 10%, respectively

between urban transportation density and smog pollution. Nevertheless, they did not discuss the impact of public transportation on the environment.

From column (1), considering all control variables, the coefficient of population density is negative at the 5% significant level. This result indicates that the increase in urban population density can have an agglomeration effect, which helps to reduce carbon emissions. This result is consistent with the conclusions of Xie et al. (2018). The technological progress is significantly positive, indicating that energy consumption leads to an increase in provincial carbon emissions. Increased energy consumption is the main cause of carbon emissions (Wang et al. 2014). However, the per capita GDP and its quadratic term are not significant, which indicates that the EKC hypothesis is not obvious. The relationship between economic development and carbon emissions does not show an inverted U-shaped relationship. Additionally, there is no significant evidence to suggest that a relationship exists between openness, FDI, and carbon emissions. Such results may be because the basic regression is based on conditional mean ordinary least squares (OLS) estimation and does not take into account the heterogeneity of the distribution, which may result in overestimation or underestimation (Zhu et al. 2016; Hübler 2017). Therefore, we use a panel quantile model with fixed effects to further clarify the impact of public transportation on carbon emissions.

Panel quantile results

To investigate whether the effect of public transportation on CO_2 emissions varied across different provinces, we employ a panel quantile regression with the non-additive fixed effects proposed by Powell (2016). Quantile regression is able to describe the entire conditional distribution of the dependent

Table 7 Panel quantile regression results (urban public transportation number)

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
ln Public	1.696*** (20.490)	1.395*** (44.750)	0.710*** (2.920)	0.082 (0.452)	0.282*** (2.710)	1.123*** (22.210)	0.705*** (5.980)	0.495*** (3.070)	0.129 (1.220)
ln Public^2	−0.102** (−22.340)	−0.088*** (−53.850)	−0.050*** (−4.190)	−0.014** (−1.960)	−0.027*** (−4.080)	−0.068*** (−20.570)	−0.049*** (−6.340)	−0.044*** (−5.040)	−0.021*** (−3.310)
lnUrban	0.024*** (8.470)	0.036*** (6.400)	−0.016* (−1.790)	1.273 (−0.890)	−0.053*** (−8.510)	−0.046*** (−24.300)	−0.030*** (−5.560)	0.004* (1.720)	0.025*** (4.140)
lnPGDP	0.185*** (18.480)	0.137*** (10.240)	0.066*** (3.200)	0.177*** (6.210)	0.150*** (4.240)	0.270*** (21.560)	0.208*** (12.400)	0.216*** (14.190)	0.135*** (4.770)
lnPGDP^2	−0.005*** (−17.670)	−0.004*** (−10.700)	−0.002*** (−3.590)	−0.005*** (−6.460)	−0.004*** (−4.510)	−0.007*** (−23.670)	−0.006*** (−14.010)	−0.006*** (−13.840)	−0.004*** (−4.930)
lnEC	1.312*** (8.470)	1.297*** (390.390)	1.304*** (19.960)	1.273*** (81.880)	1.240*** (31.460)	1.177*** (80.190)	1.138*** (50.990)	1.129*** (89.030)	1.135*** (39.300)
lnOpen	0.035*** (10.150)	0.061*** (16.420)	0.003 (0.120)	−0.032** (−2.080)	−0.045*** (−2.050)	−0.072*** (−8.380)	−0.067*** (−8.640)	−0.092*** (−29.440)	−0.107*** (−12.750)
lnFDI	−0.095*** (−34.830)	−0.072*** (−26.800)	−0.053*** (−5.600)	−0.053*** (−10.210)	−0.028*** (−6.030)	−0.047*** (−34.540)	−0.009* (−1.810)	0.026*** (3.730)	0.011* (1.730)

Notes: *Z*-statistics are in parentheses; ***, **, and * denotes significance at 1%, 5%, and 10%, respectively variable (carbon emissions). Using this model, we are able to assess the determinants of carbon emissions throughout the conditional distribution, with a particular focus on the provinces with the most and least emissions—those that are

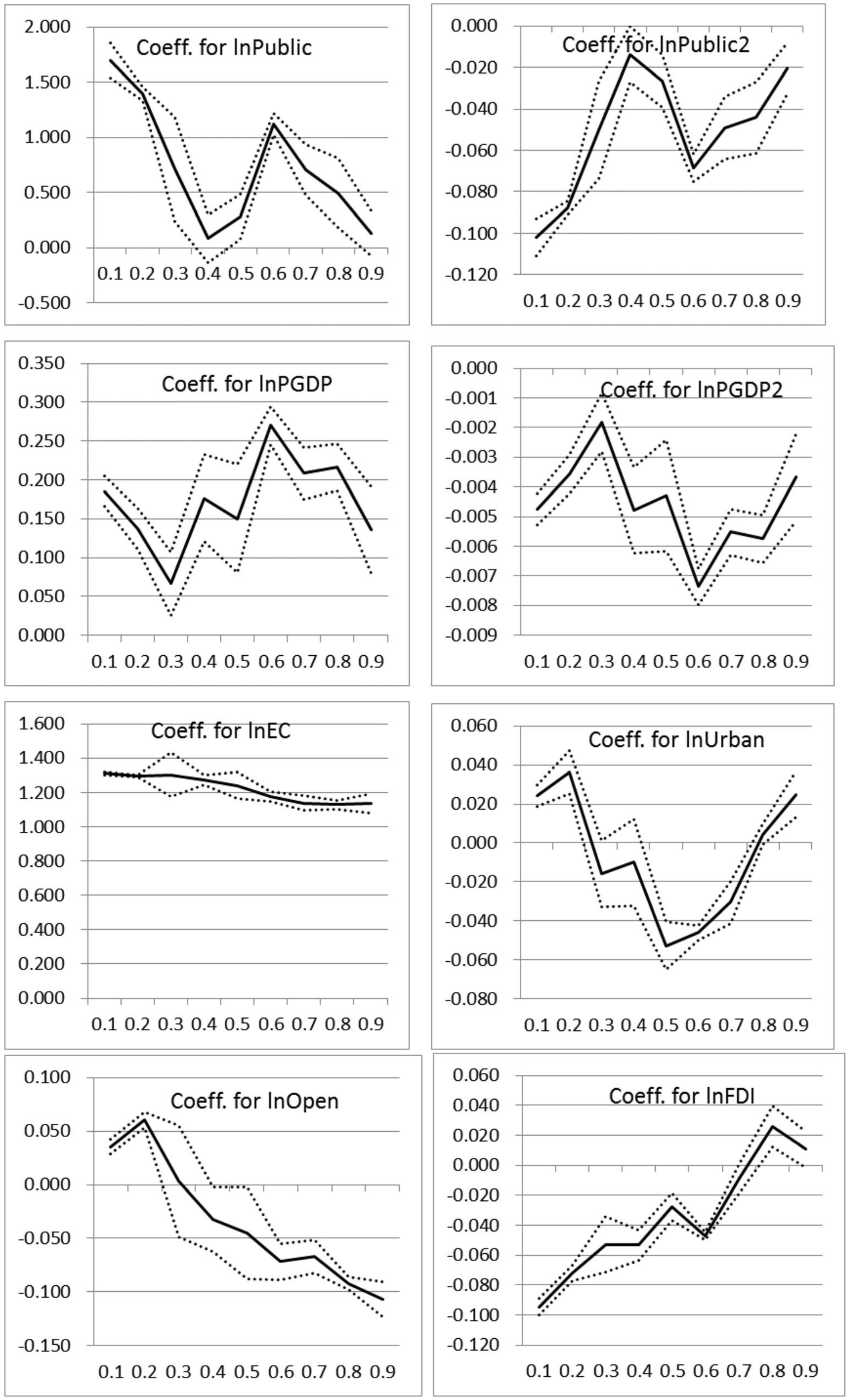

Fig. 3 Dynamic of panel quantile regressions coefficients. Notes: The dashed line represents the 95% confidence interval for the quantile regression estimator

arguably of the most interest. The results are reported for the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th percentiles of the conditional emission distribution in Table 7. To see the dynamics of estimated elasticity for the effects of key factors on carbon emissions across different quantiles, this paper lists the curve of the coefficient in Fig. 3. The empirical results show that the impacts of various factors, particularly public transportation, on carbon emissions are heterogeneous.

With regard to public transportation, the results show that the response of carbon emissions to public transportation is clearly heterogeneous across different quantiles, but they still support that the expansion of public transportation has a significant positive effect on carbon emissions for most quantiles when controlling for other factors. More specifically, at the lower quantiles, such as the 10th and 20th quantiles, which correspond to the provinces with lower carbon emissions, the estimated coefficients of lnPublic are 1.696 and 1.395 and it is significant at the 10% level. In contrast, at the higher quantiles, such as the 70th and 80th quantiles, which correspond to the provinces with higher CO_2 emissions, the coefficients of lnPublic are 0.705 and 0.495, which pass the significance test at the 10% level, as well. By comparing the coefficient of lnPublic in the lower quantiles and higher quantiles, it is revealed that the increase of public transportation has a much greater effect on increasing carbon emissions in these provinces with fewer carbon emissions than in those provinces with higher carbon emissions. As seen in Fig. 3, as the quantiles increase (i.e., as CO_2 emissions increase), the effect of the public transportation on CO_2 emission fluctuates between 0.5 and 1.75. Furthermore, the empirical results in Table 7 and Fig. 3 indicate that, at each quantile, the coefficients of $\ln\text{Public}^2$ are negative and significant but different at each quantile. Even so, overall, this indicates that the relationship between public transportation and CO_2 emissions is an inverted U-shape for China's provinces with different levels of carbon emissions. This result means that, when the public transportation scale exceeds a threshold value, the relationship between public transportation and carbon emissions will turn from positive to negative. This finding is in line with the results of the basic regression and validates the analysis of the previous mechanism.

For control variables, we find that energy consumption has a positive impact on carbon emissions, but there exist heterogeneous effects on carbon emissions across different quantiles. In particular, as seen in Fig. 3, as the quantiles increase, the size of the effect of urban public transportation on CO_2 emissions decreases. This result indicates that, for these provinces with lower carbon emissions, energy use has a greater effect on increasing carbon emissions than in those provinces with higher carbon emissions. Overall, the increase in energy consumption causes the increase in carbon emissions. This result is consistent with that of Zhu et al. (2016), which indicated that energy consumption would cause more carbon emissions unless more renewable energy was applied. Moreover, we find that the coefficient of per capita GDP is positive, and its quadratic term coefficient is negative at each quantile, which proves the (EKC) hypothesis for Chinese provinces at different levels of carbon emissions. This finding is in line with the results of You et al. (2015), who verified the inverted U-shaped relationship between income and pollutant emissions at different quantiles by using a panel quantiles model.

Concerning urban population density, we find that the effects of population density on carbon emissions are heterogeneous, as well. A large slope coefficient is observed when carbon emissions are sufficiently close to the tails of the distribution, and a small coefficient should be observed when CO_2 emissions are close to the median. That is, for the provinces with smaller carbon emissions and larger carbon emissions, increased population density would increase carbon emissions, but for provinces with moderate carbon emissions, increasing population density would help reduce carbon emissions. This result indicates that a higher population density can relieve carbon emissions in moderate emission provinces.

In addition, it is found that there is clear heterogeneity in the impact of openness on carbon emissions. In particular, at lower quantiles, such as the 10th and 20th, the coefficients of lnOpen are significant and positive at the 10% significance level. However, at the higher quantiles, such as the 60th, 70th, 80th, and 90th, we find that the coefficients of lnOpen are significantly negative. This result indicates that, for provinces with lower carbon emissions, openness has a positive effect on carbon emissions, while it plays a negative role for provinces with higher carbon emissions.

The impact of FDI on carbon emissions in Chinese provinces is not homogeneous. FDI has a negative effect on carbon emissions for provinces with lower carbon emissions (e.g., at

Table 8 Panel fixed effect regression results (passenger volume of public transportation)

	(1)	(2)	(3)
lnTrans	1.032*** (22.85)	5.155*** (9.69)	4.391*** (10.59)
$\ln\text{Trans}^2$		− 0.177*** (− 7.77)	− 0.178*** (− 10.08)
lnUrban			− 0.056** (− 2.32)
lnPGDP			0.019 (0.22)
$\ln\text{PGDP}^2$			− 0.001 (− 0.16)
lnEC			1.087*** (9.69)
lnOpen			0.019 (0.38)
lnFDI			0.012 (0.46)
Constant	− 7.063*** (− 13.11)	− 30.889*** (− 9.95)	− 31.371*** (− 13.12)
R^2	0.573	0.631	0.792
Obs.	420	420	420

Notes: *Z*-statistics are in parentheses; ***, **, and * denotes significance at 1%, 5%, and 10%, respectively

Table 9 Panel quantile regression (passenger volume of public transportation)

	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
lnTrans	2.468*** (47.140)	2.601*** (27.460)	1.238*** (4.660)	0.218*** (1.760)	0.919*** (12.100)	0.657*** (20.59)	0.663*** (16.320)	0.783*** (21.010)	0.870*** (8.910)
lnTrans^2	−0.110*** (−51.620)	−0.115*** (−32.460)	−0.058*** (−6.230)	−0.012 (−1.900)	−0.047*** (−14.420)	−0.035*** (−20.990)	−0.037*** (−21.540)	−0.041*** (−19.360)	−0.044*** (−10.510)
lnUrban	−0.017*** (−5.210)	−0.010*** (−5.230)	0.015*** (0.820)	13.230 (0.060)	−0.020*** (−12.430)	−0.027*** (−9.530)	−0.010*** (−6.630)	0.002 (0.180)	0.070*** (11.910)
lnPGDP	0.206*** (28.890)	0.230*** (47.180)	0.178*** (15.250)	0.195*** (4.090)	0.156*** (46.980)	0.233*** (14.830)	0.310*** (33.220)	0.272*** (6.270)	0.197*** (12.360)
lnPGDP^2	−0.005*** (−29.040)	−0.006*** (−38.860)	−0.005*** (−17.060)	−0.005*** (−4.170)	−0.004*** (−46.270)	−0.006*** (−14.890)	−0.008*** (−32.730)	−0.007*** (−7.300)	−0.005*** (−13.150)
lnEC	1.202*** (240.540)	1.223*** (61.940)	1.261*** (44.350)	1.155*** (13.230)	1.267*** (206.560)	1.152*** (39.140)	1.119*** (245.160)	1.072** * (108.510)	1.074*** (71.460)
lnOpen	0.033*** (8.300)	0.064*** (10.930)	0.067*** (5.090)	−0.027 (−1.150)	−0.008*** (−7.970)	−14.890*** (−7.990)	−0.072*** (−28.870)	−0.124*** (−9.640)	−0.121*** (−15.690)
lnFDI	−0.041*** (−31.780)	−0.078*** (−33.200)	−0.079*** (−15.430)	−0.062*** (−5.070)	−0.045*** (−32.230)	−0.038*** (−23.140)	−0.025*** (−12.340)	0.004 (0.380)	−0.004 (−0.004)

Notes: Z-statistics are in parentheses; ***, **, and * denotes significance at 1%, 5%, and 10%, respectively

the 10th, 20th, and 30th quantiles), whereas it has a positive effect on carbon emissions for provinces with higher CO_2 emissions (e.g., at the 80th and 90th quantiles). This result supports the halo effect hypothesis in most Chinese provinces, especially in low emission provinces. Our results are similar to those of Zhang and Zhou (2016) who found evidence in support of the halo effect hypothesis in China.

The different results of per capita GDP, trade openness, and FDI in the panel quantile regression show that our study is corrected for distributional heterogeneity, which could reduce the likelihood of under- or over-estimating the relevant coefficients. The results provide evidence that OLS regression only provides an incomplete explanation of the effect of public transportation and control variables on carbon emissions.

Robustness analysis

To evaluate the robustness of our results, we replace the measurement of public transportation with the passenger volume of urban public transportation (lnTrans). The results are shown in Table 8. The results show that, regardless of the quadratic term of public transportation, public transportation has a positive effect on carbon emissions at a 1% significance level. Considering the quadratic term of public transportation, there is a significant, inverted U-shaped relationship between public transportation and carbon emissions. Thus, the role of public transportation in reducing emissions by influencing residents' travel habits or choice of means of transportation is revealed. The increase in the passenger volume of urban public transportation means that more people choose public transportation rather than private cars. Other control variables are consistent with the previous regression results. Although the expansion of public transportation increases carbon emissions in the short term, it can facilitate carbon emission reduction once it exceeds the threshold value.

Using the passenger volume of public transportation to replace the measurement of public transportation, we re-estimate the panel quantile model. The results are shown in Table 9. We still find that, at different quantiles, there is an inverted U-shaped relationship between public transportation and carbon emissions. This result illustrates that certain scales of public transportation can facilitate carbon emissions both for high and low emission provinces. Our results are robust.

Conclusion

The traffic industry is the second biggest energy consuming industry, followed by the power industry, and contributes greatly to Chinese carbon emissions. Although the Chinese government emphasizes the significance of public transportation development and encourages green travel, there is no empirical evidence supporting whether public transportation facilitates carbon emission mitigation. Therefore, given this background, examining the impact of public transportation scale on carbon emissions is of great significance for promoting green travel and public transportation construction. In this study, we consider the environmental impact mechanisms of the public transportation scale from the perspective of the direct emission effect and the agglomeration effect. Empirically, we investigate the impact of public transportation on carbon emissions using panel data from 30 provinces in China from 2002–2015. The results are outlined as follows.

(1) We find that (i) the effect of public transportation scale on carbon emissions is heterogeneous across China's provinces based on the different distribution of carbon emissions. (ii) There is a stable, inverted U-shaped relationship between public transportation and carbon emissions. That is, when the public transportation scale exceeds a threshold value, the relationship between public transportation and carbon emissions will turn from positive to negative. (iii) Under the framework of a panel quantile model, we find that the inverted U-shaped relationship is robust, although it varied slightly across the different provincial carbon emission distribution. Therefore, local governments should develop different public transportation construction plans based on their actual carbon emission levels.

(2) There exist heterogeneous effects of control variables on carbon emissions across different quantiles, as well. More specifically, for provinces with lower carbon emissions, energy use has a greater effect on increasing carbon emissions than in those provinces with higher carbon emissions. Population density increases carbon emissions in provinces with smaller carbon emissions and larger carbon emissions, while it has a negative impact on carbon emissions in moderate carbon emission provinces.

(3) The EKC hypothesis is confirmed in Chinese provinces with different levels of carbon emissions. Openness can help to reduce carbon emissions in provinces with higher carbon emissions, while it increases carbon emissions in provinces with lower carbon emissions. However, FDI can reduce carbon emissions in provinces with lower carbon emissions. The results for FDI support the halo effect hypothesis in most Chinese provinces, especially in low emission provinces.

Based on these findings, we make some policy suggestions. First, the Chinese government should focus on constructing and improving the green transportation system and increasing public transportation investment. There is a stable, inverted U-shaped relationship between China's public transportation and carbon emissions. Although the initial public transportation scale increases carbon emissions, a larger public transportation system can certainly help to reduce emissions. Provinces with different emission levels should expand their public transportation according to their threshold values.

Second, in the process of urbanization, the Chinese government should relax the household registration policy that restricts population movement. Doing so can enhance economic scale and facilitate carbon emission reduction through the agglomeration effect. Meanwhile, the scale of public transportation should be adapted to the regional population density and economic development level. Doing so can promote provinces to cross the threshold point earlier and achieve carbon emission reduction.

Finally, the Chinese government and manufacturers should focus on improving energy efficiency and reducing the direct carbon emissions of public transportation vehicles. Since the direct emission effect still plays a major role, it is important to reduce the direct emissions of public transportation. The government should reasonably formulate emission standards for public transportation vehicles. These standards should provide support policies and encourage manufacturers to carry out technological innovation and promote the application of clean technology in order to reduce the carbon emissions of public transportation.

As for relevant research in the future, some topics, such the impacts of different forms of transportation on the environment, deserve further study. It will be interesting to explore the differences in the effects of different kinds of transportation as China advocates for green development modes.

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References

Beaudoin J, Lin Lawel CYC (2016) Is public transit's "green" reputation deserved?: evaluating the effects of transit supply on air quality. In University of California at Davis Working Paper

Beaudoin J, Farzin YH, Lawell CYCL (2015) Public transit investment and sustainable transportation: a review of studies of transit's impact on traffic congestion and air quality. Res Transp Econ 52:15–22

Brakman S, Garretsen H, Gigengack R, Marrewijk CV, Wagenvoort R (1996) Negative feedbacks in the economy and industrial location. J Reg Sci 36(4):631–651

Chang YT, Zhang N, Danao D, Zhang N (2013) Environmental efficiency analysis of transportation system in China: a non-radial DEA approach. Energy Policy 58:277–283

Chen Y, Whalley A (2012) Green infrastructure: the effects of urban rail transit on air quality. Am Econ J Econ Pol 4(1):58–97

Chinese Ministry of Transportation (2016) The 13th Five-Year Plan for urban public transportation

Choi I (2001) Unit root tests for panel data. J Int Money Financ 20(2): 249–272

Clarke AG, Ko YH (1996) The relative significance of vehicular emissions and other emissions of volatile organic compounds in the urban area of Leeds, UK. Sci Total Environ 189:401–407

Coughlin CC, Segev E (2000) Foreign direct investment in China: a spatial econometric study. World Econ 23(1):1–23

Dietz T, Rosa EA (1994) Rethinking the environmental impacts of population, affluence and technology. Hum Ecol Rev 1(2):277–300

Dumitrescu EI, Hurlin C (2012) Testing for Granger non-causality in heterogeneous panels. Econ Model 29(4):1450–1460

Fan Y, Guthrie A, Levinson D (2012) Impact of light-rail implementation on labor market accessibility: a transportation equity perspective. J Transp Land Use 5(3):28–39
Farsi M, Fetz A, Filippini M (2007) Economies of scale and scope in local public transportation. J Trans Econ Pol 41(3):345–361
Fujita M, Krugman PR, Venables AJ (2001) The spatial economy: cities, regions, and international trade. MIT press
Glaeser EL, Kahn ME (2010) The greenness of cities: carbon dioxide emissions and urban development. J Urban Econ 67(3):404–418
Guo D, Chen H, Long R (2018) Can China fulfill its commitment to reducing carbon dioxide emissions in the Paris Agreement? Analysis based on a back-propagation neural network. Environ Sci Pollut Res 25(27):27451–27462
Huang J (2018) Investigating the driving forces of China's carbon intensity based on a dynamic spatial model. Environ Sci Pollut Res 25(22):21833–21843
Huang J, Chen X, Huang B, Yang XG (2017a) Economic and environmental impacts of foreign direct investment in China: a spatial spillover analysis. China Econ Rev 45:289–309
Huang J, Du D, Tao Q (2017b) An analysis of technological factors and energy intensity in China. Energy Policy 109:1–9
Huang J, Du D, Hao Y (2017c) The driving forces of the change in China's energy intensity: an empirical research using DEA-Malmquist and spatial panel estimations. Econ Model 65:41–50
Huang J, Liu Q, Cai XC, Hao Y, Lei HY (2018) The effect of technological factors on China's carbon intensity: new evidence from a panel threshold model. Energy Policy 115:32–42
Hübler M (2017) The inequality-emissions nexus in the context of trade and development: a quantile regression approach. Ecol Econ 134: 174–185
International Energy Agency (2011) CO2 Emissions from fuel combustion highlights. In: Cancún Mexico
Jiang L, Folmer H, Ji M (2014) The drivers of energy intensity in China: a spatial panel data approach. China Econ Rev 31:351–360
Kang YQ, Zhao T, Yang YY (2016) Environmental Kuznets curve for CO_2 emissions in China: a spatial panel data approach. Ecol Indic 63:231–239
Kao C (1999) Spurious regression and residual-based tests for cointegration in panel data. J Econ 90(1):1–44
Kennedy CA (2002) A comparison of the sustainability of public and private transportation systems: study of the Greater Toronto Area. Transportation 29(4):459–493
Lakshmanan TR (2011) The broader economic consequences of transportation infrastructure investments. J Transp Geogr 19(1):1–12
Lalive R, Luechinger S, Schmutzler A (2013) Does supporting passenger railways reduce road traffic externalities?. CEPR discussion paper
Li T, Wang Y, Zhao D (2016) Environmental Kuznets curve in China: new evidence from dynamic panel analysis. Energy Policy 91:138–147
Lin HL, Li HY, Yang CH (2011) Agglomeration and productivity: firm-level evidence from China's textile industry. China Econ Rev 22(3): 313–329
Lu IJ, Lin SJ, Lewis C (2007) Decomposition and decoupling effects of carbon dioxide emission from highway transportation in Taiwan, Germany, Japan and South Korea. Energy Policy 35(6):3226–3235
Maddala GS, Wu S (1999) A comparative study of unit root tests with panel data and a new simple test. Oxf Bull Econ Stat 61(S1):631–652
Marques AC, Fuinhas JA, Manso JP (2011) A quantile approach to identify factors promoting renewable energy in European countries. Environ Resour Econ 49(3):351–366
Mohring H (1972) Optimization and scale economies in urban bus transportation. Am Econ Rev 62(4):591–604
Nasir M, Rehman FU (2011) Environmental Kuznets curve for carbon emissions in Pakistan: an empirical investigation. Energy Policy 39(3):1857–1864
Otsuka A, Goto M, Sueyoshi T (2014) Energy efficiency and agglomeration economies: the case of Japanese manufacturing industries. Reg Sci Policy & Prac 6(2):195–212
Pedroni P (2004) Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. Econ Theory 20(03):597–625
Pesaran MH (2007) A simple panel unit root test in the presence of cross-section dependence. J Appl Econ 22(2):265–312
Powell D (2016) Quantile regression with nonadditive fixed effects. Quantile Treatment Effects.
Shan Y, Liu J, Liu Z, Xu X, Shao S, Wang P, Guan D (2016) New provincial CO_2 emission inventories in China based on apparent energy consumption data and updated emission factors. Appl Energy 184:742–750
Song M, Zhang G, Zeng W, Liu J, Fang K (2016) Railway transportation and environmental efficiency in China. Transportation Research Part D: Transportation and Environment 48:488–498
Thijsse TR, Van Oss RF, Lenschow P (1999) Determination of source contributions to ambient volatile organic compound concentrations in Berlin. J Air Waste Manage Assoc 49(12):1394–1404
Vincent W, Jerram LC (2006) The potential for bus rapid transit to reduce transportation-related CO_2 emissions. J Public Trans 9(3):219–237
Wang S, Fang C, Guan X, Pang B, Ma H (2014) Urbanization, energy consumption, and carbon dioxide emissions in China: a panel data analysis of China's provinces. Appl Energy 136:738–749
Xie R, Fang J, Liu C (2017) The effects of transportation infrastructure on urban carbon emissions. Appl Energy 196:199–207
Xie R., Wei D, Han F, Lu Y, Fang J Y, Liu Y, Wang J F (2018) The effect of traffic density on smog pollution: evidence from Chinese cities. Technological Forecasting and Social Change, in press
Yan H (2015) Provincial energy intensity in China: the role of urbanization. Energy Policy 86:635–650
Yin X, Chen W, Eom J, Clarke LE, Kim SH, Patel PL, Kyle GP (2015) China's transportation energy consumption and CO_2 emissions from a global perspective. Energy Policy 82:233–248
You WH, Zhu HM, Yu K, Peng C (2015) Democracy, financial openness, and global carbon dioxide emissions: heterogeneity across existing emission levels. World Dev 66:189–207
Zhang C, Zhou X (2016) Does foreign direct investment lead to lower CO_2 emissions? Evidence from a regional analysis in China. Renew Sust Energ Rev 58:943–951
Zheng S, Zhang X, Sun W, Wang J (2017) The effect of a new subway line on local air quality: a case study in Changsha. Transportation Research Part D: Transportation and Environment, in press
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. Econ Model 58:237–248