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Rational planning strategies of urban structure, metro, and car use for reducing transport carbon dioxide emissions in developing cities

Liu Yang[1] · Yuanqing Wang[2] · Yujun Lian[3] · Xin Dong[1] · Jianhong Liu[4] · Yuanyuan Liu[5] · Zhouhao Wu[6]

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Abstract
Understanding transport carbon dioxide (CO_2) emission impact factors' effects is important for the rational planning strategy making in reducing the emissions. This study determines transport emission impact factors' heterogeneous effects and proposes urban and transport planning strategies in typical developing cities. Quantile regression is applied to overcome the insufficiency of factors' mean effects and to avoid the biased estimations when the outcome variable is non-normally distributed and heteroscedastic. It is found that, from the low emitters at the 10th quantile to the high emitters at the 90th quantile, transport emissions' increasing rates are 8.8 times and 79.6 times that of car availability and home-to-center/subcenter distance (HCD/HSD), respectively. When commute distance reaches 5.8 km or farther, and car availability percentage is 41.2% or greater, the effects that metro services have on reducing emissions decrease by 37.8%. Polycentric and satellite city forms can greatly reduce emission increases, which are caused by HCD growth when HCD is more than 10–15 km. According to these findings, the following planning strategies are recommended, including limiting oil-fueled car use to about 40% among the urban residents, forming employment and life circles within a 5–6 km radius, allocating better public transit services around metro stations, providing high service levels of bicycle lanes, pedestrian streets, and greenways to attract more transfers to metros, controlling urban radius within 10–15 km under the monocentric pattern, and fostering polycentric structures and satellite cities when city continuously sprawls. This study can provide empirical evidence and reference value globally.

Keywords Transport CO_2 emission · Metro and rail transit · Polycentric and satellite city · Urban radius · Employment and life circle · Quantile regression model

Liu Yang and Yuanqing Wang are Co-First Authors, and they contribute equally to the research.

✉ Liu Yang
philoyl@163.com

Extended author information available on the last page of the article

1 Introduction

Transport CO_2 emissions contribute substantially to global greenhouse gas (GHG) emission increases, which will cause climate change and increase the vulnerability of ecosystems and human societies (Ostad-Ali-Askar et al., 2018). It is projected by the International Energy Agency's World Energy Outlook 2013 that transport fuel demand will increase nearly 40% globally by 2035 (ADB, 2016), and there will be large increases of transport CO_2 emissions from developing Asian countries (Timilsina & Shrestha, 2009).

Understanding transport CO_2 emission factors' effects comprehensively is important for making rational planning strategies. Previous studies have examined and modeled the relationships between transport CO_2 emissions and their significant factors, including socio-economic characteristics, urban form factors, and metro accessibility. It is found that car availability, high income, and location in the outer and sprawling areas will notably cause larger transport CO_2 emissions (Brand & Boardman, 2008; Brand & Preston, 2010; Brand et al., 2013; Büchs & Schnepf, 2013; Ko et al., 2011; Shuai et al., 2018; Wang et al., 2017; Yang et al., 2018, 2019, 2020). Fostering polycentric and satellite cities can decrease transport CO_2 emissions significantly (Cirilli & Veneri, 2014; Grunfelder et al., 2015; Knaap et al., 2016; Modarres, 2011; Sun, Zacharias, et al., 2016; Sun, Zhou, et al., 2016; Veneri, 2010; Yang et al., 2018, 2020). Metro or light rail constructions can reduce driving distance and transport CO_2 emissions (Cao, 2019; Huang et al., 2019; Spears et al., 2017; Boarnet et al., 2017). These previous studies have only examined the average effects of the significant transport CO_2 emission impact factors. However, if the variation effects of these factors among different locations of transport emission distribution are further measured, a detailed view of the relationship between transport CO_2 emissions and their impact factors can be obtained. Then, the results will guide for more effective urban and transport planning strategy making. Presently, research with such focus is lacking, though. Thus, this paper will identify the heterogeneous effects of transport CO_2 emission impact factors by using the quantile regression model. This method can estimate the factors' effects at any quantile of the outcome variable's distribution, and thus capture a more comprehensive evaluation of the characteristics among transport emitters. Also, this method can overcome the shortcomings of the models based on the conditional mean method, which means that when the outcome variable is not normally distributed and heteroscedastic, the estimation results would probably be biased (Koenker & Hallock, 2001; Wang et al., 2019; Xu & Lin, 2016). Then, according to the quantile regression model results, this study will propose urban and transport planning strategies for emission reduction and climate change mitigation in developing cities.

China and India, with most of their cities in the inland areas, are two economic giants experiencing rapid economic growth, urban expansion, and motorization. Transport CO_2 emission increases have been evident in recent decades. It is necessary to focus on Chinese and Indian developing cities for mitigating transport CO_2 emission increases. Thus, four typical inland Chinese and Indian cities are selected as case cities, namely Beijing, Xian, and Wuhan in China, and Bangalore in India. Beijing, located in the eastern part, with a strong center, is the capital city of China. Xi'an and Wuhan are two provincial cities located in the western and middle inland, respectively; their noticeable differences lie in the urban forms (Xi'an has a strong center, while Wuhan has a polycentric urban form, separated by two big rivers). In India, Bangalore is located in the southern part of the inland, with a strong center, and is known as 'Asia's Silicon Valley', with famous information technology industries. These four inland cities have experienced urban expansions, as well as population, motorization, and economic increases in recent decades, representing the general situations of urban and transport developments among Chinese and Indian cities. Due to the large number of commute trips in urban transportation, as well as the inflexibility of these trips, this study intends to focus on the CO_2 emissions that result from commuting.

In recent decades, Chinese and Indian cities are experiencing important stages of development, in terms of urban growths, motorization and economic increases, metro and rail network constructions, urban agglomeration developments, energy technology improvements, and new energy vehicle promotions. These developments are crucial issues for transport emission increases and climate change, not only in China and India, but also in other global cities. Therefore, this paper's findings will provide empirical evidence and reference value globally.

The remainder of the paper is organized into the following sections. In Sect. 2, previous studies on transport CO_2 emission impact factors and the research gap will be discussed. In Sect. 3, the process of data collection in the four case cities will be briefly introduced, and the quantile regression model will be illustrated for measuring the heterogeneous effects of transport CO_2 emission factors. Section 4 analyzes the model results. The last section provides discussions and conclusions of this study.

2 Literature review

Exploring and measuring significant impact factors of transport CO_2 emissions, as well as travel behaviors, have been interests of scholarly research for many years. They are the key steps for rational planning strategies to develop sustainable travel patterns and mitigate transport CO_2 emission increases. Numerous researchers have found that household and commuter socio-economic characteristics can significantly affect transport CO_2 emissions. Car availability is found to be the most notable predictor of transport CO_2 emissions (Brand & Boardman, 2008; Brand & Preston, 2010; Brand et al., 2013; Ko et al., 2011). By using the linear regression method, with log-transformed transport CO_2 emissions as the explained variable, it has been found that, in the UK, owning at least one car tends to increase the weekly transport CO_2 emissions by 44%-59% (Brand et al., 2013), and owning two cars or more can increase the individual transport CO_2 emissions by 13.3% (Brand & Preston, 2010). Higher income can also increase transport CO_2 emissions (Ko et al., 2011; Büchs & Schnepf, 2013; Brand et al., 2013; Brand & Preston, 2010; Brand & Boardman, 2008; Susilo & Stead, 2009; Carlsson-Kanyama & Lindén, 1999). A 1% increase of household annual income can increase the total annual transport CO_2 emissions by 59.8% (Büchs & Schnepf, 2013). Individuals with incomes higher than £40,000 have 49.9% larger transport CO_2 emissions (Brand & Preston, 2010). Additionally, better education backgrounds could have effects on the emission increases. Individuals with education backgrounds of more than 16 years produce 15.4% larger transport CO_2 emissions (Büchs & Schnepf, 2013). Similarly, full-time employment, commuters with professional occupations, and those working in the government and in foreign companies produce more transport CO_2 emissions than those with part-time jobs and other work unit types (Brand & Preston, 2010; Brand et al., 2013; Ko et al., 2011; Wang et al., 2017; Yang et al., 2017).

Urban form factor effects on travel patterns and transport CO_2 emissions have also attracted considerable interest from scholars in recent decades. Many studies found that cities with polycentric patterns can promote more sustainable travel patterns and less transport CO_2 emissions. Higher degrees of polycentricity and higher job-to-population ratios can result in shorter commute times in some Chinese cities, Italian metropolitan areas, and Southern California (Modarres, 2011; Sun, Zacharias, et al., 2016; Sun, Zhou, et al., 2016; Veneri, 2010), and can also decrease commuting distances in Danish city regions (Grunfelder et al., 2015). Employment share increases in the central cities have shown to cause larger commuter CO_2 emissions in Italy (Cirilli & Veneri, 2014). Compared to a metropolis with one strong center in China, the polycentric city of Wuhan has shorter commuting distances, smaller car mode share, more public bus usage, and more local commute trips (Yang et al., 2018). Under the scenario of a polycentric pattern, the average commuter's CO_2 emissions are 15% smaller than cities with one strong center and similar economic levels, and 51%-75% of the resident transport CO_2 emissions will be reduced in future (Yang et al., 2020). Also, developing satellite cities can make individuals commute shorter distances, make more local trips, and use more non-motorized modes of transportation, thus producing significantly less transport CO_2 emissions (Yang et al., 2019). Fostering satellite cities will reduce transport CO_2 emissions by 75–82% in the long-run in developing cities (Yang et al., 2020). Numerous studies also find that household locations can influence transport CO_2 emissions significantly. It is found that in the Greater Toronto Area, a 1 km increase of the straight-line distance from the city center will cause a 0.25 km increase of vehicle miles travelled (Miller & Ibrahim, 1998). In the Minneapolis-St. Paul Twin Cities Area, a 1 mile increase of the distance to the downtown area is connected to approximately 0.08–0.1 kg increase of transport CO_2 emissions per day (Wu et al., 2019). Households located near the radial road and outer ring road areas produce much more transport CO_2 emissions than those located in the city center in Chinese cities (Wang et al., 2017; Yang et al., 2017, 2019). In developing Chinese and Indian cities, when commuters are located in the outer areas, more than 10 km from the city center, their commuting CO_2 emissions per trip tend to be about 0.3 kg larger than emissions of those located in the inner areas, within 5 km from the center (Yang et al., 2020).

Presently, numerous cities have begun metro or light rail constructions to provide mass public transportation services, with fast speeds, for the urban residents. Plenty of scholars have started to focus on the impacts of rail transit on travel behaviors and transport CO_2 emissions. Moving into metro neighborhoods is found to be positively related to decreased driving distances by autos and more transit uses (Cao & Ermagun, 2016; Huang et al., 2019), and living in new housing near rail stations can reduce auto ownership (Chatman, 2013). Evidence from a study based in Minneapolis shows that in light rail corridors, residents' vehicle miles driven will be reduced by approximately 20% more than those in the urban control corridors, after controlled for neighborhood characteristics (Cao, 2019). Driving distances can be reduced by 10 miles per day among the households living within 1 km walking distance to the light rail transits, compared to controlled households located farther away (Spears et al., 2017). Households located within a half mile of light rail transits produce smaller transport CO_2 emissions (Boarnet et al., 2017). Developing cities with metro services will generally produce less resident transport CO_2 emissions by 43–62% by 2050 (Yang et al., 2020). In recent years, some new forms of transfer modes greatly promote the first-and-last mile access trips to metros, such as shared bicycles/cars, feeder buses/customized shuttle buses, electric bicycles/motors, and electric scooters (Baek et al., 2021; Chen et al., 2021; Zuo et al., 2020). These convenient transfers have attracted more residents to use transit and metro modes, and have reduced transport CO_2 emissions to some extent.

Also, recent study results show that nature-based solutions can improve and protect ecosystem services, and can bring about changes in land use and land cover in urban areas (Zwierzchowska et al., 2021; Pan et al., 2021). Greenways can reduce pedestrian exposure to air pollution (Ahn, et al., 2021), and residents living near the greenway drive less, and thus, reduce their transport emissions (Ngo et al., 2018). Pedestrian and environmentally-friendly designed streets can promote walkability and access to metro trips (Sun, Zacharias, et al., 2016; Sun, Zhou, et al., 2016). All these nature-based solutions will be beneficial for reducing transport emissions and mitigating climate change.

The above predictors of transport CO_2 emissions have been discussed extensively, but limitations still exist. At present, few studies describe the varied effects of the impact factors at different locations of transport CO_2 emission distribution. It is vital to obtain heterogeneous emission factor characteristics comprehensively to effectively make planning strategies and implement specific emission reduction policies to address the current developing situations of Chinese and Indian cities. These development situations include urban growths, motorization and economic increases, metro and rail network constructions, urban agglomeration developments, energy technology improvements, and new energy vehicle promotions. In order to identify factors' heterogenous effects, models based on the conditional mean method, which are frequently used in the previous studies (Huang et al., 2019; Spears et al., 2017; Boarnet et al., 2017; Sun, Zhou, et al., 2016; Sun, Zacharias, et al., 2016; Brand et al., 2013; Brand & Preston, 2010; Büchs & Schnepf, 2013; Cirilli & Veneri, 2014), are not appropriate. The conditional mean method can only provide average effects of the impact factors from transport emissions, neglecting the various characteristics of factors' effects among the high and low emitters. In addition, the conditional mean method generally assumes that the outcome variable is normally distributed and homoscedastic. However, in most cases, these two assumptions cannot be satisfied. In terms of transport CO_2 emissions, they are always larger than zero and are non-normally distributed in most cases. If the conditional mean method is applied for the transport emission model estimation, the results would probably be biased, which may lead to ineffective or insufficient planning strategies or policy suggestions. However, the quantile regression method can overcome the above shortcomings. This method is robust to outlying observations and does not make distributional assumptions (Koenker & Hallock, 2001; Xu & Lin, 2016). It can provide specific estimations on each quantile of the emission distribution and, therefore, describe the relations between the outcome variable and the independent variables more completely (Cameron & Trivedi, 2009).

To address the above limitations in the existing research, this study will explore the heterogeneous relationships among the impact factors and transport CO_2 emissions in typical developing Chinese and Indian cities. The quantile regression model will be used, and then, varied characteristics of factors' effects can be analyzed at high and low levels of transport emissions. The significant impact factors' heterogenous effects to be identified include car availability, distance to the center/subcenters, polycentric and satellite city forms, and whether the city has metro services or not. According to the model results, rational planning strategies will be proposed for reducing transport CO_2 emissions and mitigating climate change in developing cities.

3 Data and methodology

3.1 Data collection and description

Simple random samplings were carried out in the urban areas of Beijing, Xi'an, Wuhan, and Bangalore in the years of 2010, 2012, 2010, and 2011–2012, respectively. Face-to-face inquiries were implemented in the household neighborhoods. Altogether, 1,400 households and 1,915 commuters were interviewed in Beijing, 1,501 households and 2,449 commuters in Xi'an, 1,194 households and 2,050 commuters in Wuhan, and 1,967 households and 3,934 commuters in Bangalore. The questionnaires included inquiries related to commuting trip information (distance, travel mode, workplace, and household location) and household and commuter socio-economic characteristics (car availability, household income, housing tenure, age, work unit type, and educational background). Home-to-center distances (HCD) in Beijing, Xi'an, and Bangalore, and home-to-subcenter distances (HSD) in Wuhan, were calculated by using ArcGIS software. The same calculations were done for home-to-work distances, as well.

Beijing is the political, economic, and cultural center of China. Beijing has 1,268 km^2 of urban built-up area, and there is a population of 12.8 million people in the main urban area. The per capita GDP amounts to about US$ 11,218, and the motor vehicles amount to 4.8 million. Xi'an has 522 km^2 of urban built-up area, and there is a population of 4.5 million people in the main urban area. The per capita GDP is approximately US$ 8,140, and the motor vehicles are about 1.47 million. Wuhan has 520 km^2 of urban built-up area, and there is a population of 5.46 million people in the main urban area. The per capita GDP is about US$ 10,563, and the motor vehicles are about 1.19 million. Bangalore has 741 km^2 of urban built-up area, and there is a population of 5.83 million people in the main urban area. The per capita GDP is about US$ 8,664, and the two-wheelers amount to 3.72 million, taking up 69.1% of the total motor vehicles. In regards to the aspect of urban form, monocentric patterns have been fostered in Beijing, Xi'an, and Bangalore, while Wuhan developed polycentric forms, with three towns (HanKou, WuChang, and HanYang) separated by the Yangtze and Han Rivers, since the city's initial formation. Satellite cities in the outer areas of Beijing have evolved in recent decades, including Changping, Huairou, Shunyi, Miyun, Pinggu, Fangshan, and Daxing. More detailed information of the four case cities can be obtained in the literature of Yang et al. (2020). The three Chinese cities' metro lines have been in operation, but Bangalore's metro line was under construction during the survey year.

Commuting CO_2 emissions are equal to the CO_2 emission factor (by mode, fuel type, and occupancy) multiplied by the commuting trip distance (IPCC 1997). Well-To-Wheel (WTW) CO_2 emission intensities for different fuel types were calculated to obtain CO_2 emission factors. The calculation method is described in greater detail in Wang et al. (2017) and Yang et al., (2017, 2019, and 2020). Table 1 reports the statistics and percentiles of individual commuting CO_2 emissions in the four city samples. Bangalore in India has larger transport CO_2 emissions than the Chinese city of Xi'an, despite their similar economic levels and urban forms. Beijing's top 25% emitters produce the most transport

Table 1 Summary statistics of individual commuting CO_2 emissions

CO_2 (kg)	Obs	10th	25th	50th	75th	90th	Std. Dev	Min[a]	Max
Beijing	1,863	0.000	0.000	0.185	0.771	2.309	1.083	0.000	5.640
Xi'an	1,952	0.000	0.015	0.080	0.306	0.994	0.450	0.000	2.327
Wuhan	1,863	0.000	0.000	0.042	0.225	0.754	0.472	0.000	2.815
Bangalore	2,433	0.000	0.067	0.268	0.641	1.005	0.454	0.000	2.400
Pooled Samples	8,111	0.000	0.000	0.132	0.500	1.151	0.677	0.000	5.640

[(a)]. The minimum transport CO_2 emissions are zeros, indicating that commuters are using bicycles or in walking mode

CO_2 emissions. Wuhan has the smallest transport CO_2 emissions, and Xi'an's emissions are in the middle level.

3.2 The quantile regression model

The quantile regression model was first introduced by Koenker and Bassett (1978). This method can depict a more complete picture about the relationship between the outcome y and the regressors x at different points in the conditional distribution of y (Cameron & Trivedi, 2009). Compared to the conditional mean regression method used in the previous studies, such as the frequently used ordinary least square (OLS) method, or other methods based on the OLS method, quantile regression has several advantages. First, OLS regression is sensitive to outliers; however, quantile regression estimates are more robust to address this problem. Second, quantile regression could estimate the covariate effects on any percentile of the distribution, not only obtaining the conditional mean estimation on the entire distribution. Third, the quantile regression method avoids assumptions about the regression error distribution. This means that if the regression error is not normally distributed and is heteroscedastic, using OLS method would produce biased estimation results. The quantile regression method does not need to be applied under the above assumptions. (Cameron & Trivedi, 2009; Wang et al., 2019; Xu & Lin, 2016).

The standard quantile approach is used to specify the conditional quantile function to be linear, and parameters of the intercept and slope may vary with each quantile. The q th conditional quantile function of y given x is denoted as $Q_q(y|x)$. The standard linear conditional quantile function is

$$y_i = \boldsymbol{x}_i' \boldsymbol{\beta}_q + \varepsilon_{qi}, \quad 0 < q < 1 \tag{1}$$

$$Q_q\left(y_i|\boldsymbol{x}_i\right) = \boldsymbol{x}_i' \boldsymbol{\beta}_q \tag{2}$$

where $Q_q\left(y_i|x_i\right)$ means the q th quantile of the dependent variable y_i; $\boldsymbol{x}_i'$ indicates the vector of independent variables; $\boldsymbol{\beta}_q$ is the vector of estimated coefficients; ε_{qi} indicates a random error term.

The q th quantile regression estimator $\widehat{\boldsymbol{\beta}}_q$ is the solution of minimizing the following function

$$Q\left(\boldsymbol{\beta}_q\right) = \sum_{i:y_i \geq \boldsymbol{x}_i'\boldsymbol{\beta}_q}^{N} q\left|y_i - \boldsymbol{x}_i'\boldsymbol{\beta}_q\right| + \sum_{i:y_i < \boldsymbol{x}_i'\boldsymbol{\beta}_q}^{N} (1-q)\left|y_i - \boldsymbol{x}_i'\boldsymbol{\beta}_q\right| \tag{3}$$

From Eq. (3) it can be seen that quantile regression could be considered as a weighted regression. As Cameron and Trivedi (2009, pp. 207) point out, "If $q = 0.9$, for example, then much more weight is placed on prediction for observations with $y_i \geq \boldsymbol{x}_i'\boldsymbol{\beta}_q$ than for observations with $y_i < \boldsymbol{x}_i'\boldsymbol{\beta}_q$".

Since the objective function (3) is not differentiable, it is not applicable to use gradient optimization methods. However, the linear programming method can be used and can provide relatively fast computation of $\widehat{\boldsymbol{\beta}}_q$ (Cameron & Trivedi, 2005). The following concisely introduces this method, quoted from StataCorp (2017, pp. 2158):

"Define τ as the quantile to be estimated; the median is $\tau = 0.5$. For each observation i, let ε_i be the residual

$$\varepsilon_i = y_i - \mathbf{x}_i'\hat{\boldsymbol{\beta}}_\tau$$

The objective function to be minimized is

$$\begin{aligned} c_\tau(\varepsilon_i) &= \left(\tau\mathbf{1}\{\varepsilon_i \geq 0\} + (1-\tau)\mathbf{1}\{\varepsilon_i < 0\}\right)\left|\varepsilon_i\right| \\ &= \left(\tau\mathbf{1}\{\varepsilon_i \geq 0\} - (1-\tau)\mathbf{1}\{\varepsilon_i < 0\}\right)\varepsilon_i \\ &= \left(\tau - \mathbf{1}\{\varepsilon_i < 0\}\right)\varepsilon_i \end{aligned} \tag{4}$$

where $\mathbf{1}\{\cdot\}$ is the indicator function. This function is referred to as the check function; the slope of $c_\tau(\varepsilon_i)$ is τ when $\varepsilon_\mathrm{i} > 0$ $\varepsilon_i > 0$ and is $\tau - 1$ when $\varepsilon_\mathrm{i} < 0$ $\varepsilon_i < 0$, but is undefined for $\varepsilon_\mathrm{i} = 0$ $\varepsilon_i = 0$. Choosing the $\hat{\beta}_\tau$ $\hat{\boldsymbol{\beta}}_\tau$ that minimize $c_\tau(\varepsilon_i)$ is equivalent to finding the $\hat{\boldsymbol{\beta}}_\tau$ that make $\boldsymbol{x\beta}_\tau$ best fit the quantiles of the distribution of y conditional on $\boldsymbol{x}$.

This minimization problem is set up as a linear programming problem and is solved with linear programming techniques. Here $2n$ slack variable, $u_{n\times1}$ and $v_{n\times1}$, are introduced, where $u_i \geq 0, v_i \geq 0$ and $u_i \times v_i = 0$, reformulating the problem as

$$\min_{\beta_\tau,u,v}\{\tau\mathbf{1}_n'u + (1-\tau)\mathbf{1}_n'v|y - \boldsymbol{X\beta}_\tau = u - v\} \tag{5}$$

where 1_n $\mathbf{1}_n$ is a vector of 1*s*. This is a linear objective function on a polyhedral constraint set with $\binom{\mathrm{n}}{\mathrm{k}}\binom{n}{k}$ vertices, and the goal is to find the vertex that minimizes (4). Each step in the search is described by a set of k observations through which the regression plane passes, called the basis. A step is taken by replacing a point in the basis if the linear objective function can be improved. If this occurs, a line is printed in the iteration log. The definition of convergence is exact in the sense that no amount of added iterations could improve the objective function. A series of weighted least-squares (WLS) regression is used to identify a set of observations as a starting basis. The WLS algorithm for $\tau = 0.5$ is taken from Schlossmacher (1973) with a generalization for $0 < \mathrm{\tau} < 1$ $0 < \tau < 1$ implied from Hunter and Lange (2000)."

The bootstrap method is applied to acquire the standard errors and confidence intervals of the estimated coefficients in the quantile regression model. In order to obtain a sound estimation, the bootstrap replications should be more than 500 or 1,000 times (Efron & Tibshirani, 1993). In our estimations, the bootstrap replications are 1,000 times.

The independent variables in the quantile regression model consist of the following impact factors: household car availability, household annual income, dummy variable of whether the city form is polycentric or has a strong center, dummy variable of whether a commuter is located in the satellite cities, dummy variable of whether a city has metro services, and distance from home to the city center/subcenter (HCD/HSD). The dependent variable is individual commuting CO_2 emissions in the form of a natural logarithm. Table 2 presents the definitions and the summary statistics of the variables in the quantile regression models.

Table 2 Definitions and summary statistics of the variables in the quantile regression models

	Beijing			Xi'an			Wuhan			Bangalore			Pooled Samples		
	Obs	Mean	Std.Dev	Obs	Mean	Std.Dev	Obs	Mean	Std.Dev	Obs	Mean	Std.Dev	Obs	Mean	Std.Dev
Car Availability[a]	1,863	0.438	0.496	1,952	0.403	0.491	1,863	0.243	0.429	2433	0.670[a]	0.470	8,111	0.454	0.498
HInc US$ 6,000–10,000[b]	1,863	0.181	0.385	1,952	0.184	0.388	1,863	0.392	0.488	2433	0.187	0.390	8,111	0.232	0.422
HInc US$ 10,000–20,000[b]	1,863	0.397	0.489	1,952	0.651	0.477	1,863	0.288	0.453	2433	0.104	0.306	8,111	0.345	0.475
HInc US$ 20,000–40,000[b]	1,863	0.256	0.437	1,952	0.090	0.286	1,863	0.077	0.267	2433	0.031	0.174	8,111	0.108	0.310
HInc > US$ 40,000[b]	1,863	0.039	0.194	1,952	0.025	0.156	1,863	0.022	0.147	2433			8,111	0.020	0.140
Polycentric City[c]	1,863			1,952			1,863	1.000	0.000	2433			8,111	0.230	0.421
Satellite City[d]	1,863	0.193	0.395	1,952			1,863			2433			8,111	0.044	0.206
Metro[e]	1,863	1.000	0.000	1,952	1.000	0.000	1,863	1.000	0.000	2433			8,111	0.700	0.458
HCD/HSD (km)[f]	1,791	16.540[g]	15.870[g]	1,445	6.552	2.638	1,828	5.467	3.729	2433	8.269	3.808	7,497	9.230[h]	9.354[h]

[(a)]. Dummy variable; 1 indicates the household owns a car, and 0 refers to no car in the household. In Bangalore's survey, car mode and two-wheeler mode are combined in one choice in the questionnaire. [(b)]. Dummy variable; HInc refers to household annual income in US$. [(c)]. Dummy variable; 1 refers to commuter's city has polycentric urban form, and 0 refers to the monocentric urban form; [(d)]. Dummy variable; 1 refers to commuters are located in the satellite cities, and 0 refers to not; [(e)]. Dummy variable; 1 refers to commuter's city has metro services, and 0 refers to not; [(f)]. HCD/HSD refers to home-center distance or home-subcenter distance in the unit of kilometers. [(g)]. These two numbers refer to all the samples in Beijing, including commuters in the main urban area inside the 6th Ring Rd. (1,431 observations) and in the outer suburbs of the satellite cities (360 observations). The average HCD of the samples in the main urban area inside the 6th Ring Rd. is 9.798 km, with the standard deviation of 5.486 km. The average HCD of samples in the satellite cities outside the 6th Ring Rd. is 43.325 km, with the standard deviation of 15.355 km. [(h)]. These two numbers refer to all the samples in the four case cities, including commuters located in the satellite cities in Beijing's outer suburbs with much longer distances to the city center

4 Quantile regression model results

4.1 Pooled samples of four case cities

Columns 1 to 5 in Table 3 shows the quantile regression model results of the pooled samples at the 10th, 25th, 50th, 75th, and 90th quantiles of commuting CO_2 emissions. Column 6 in Table 3 shows the estimation results using the OLS regression method. Figure 1 illustrates the varied coefficients at different quantiles of the emissions, the coefficients' mean levels using the OLS method, and the distribution of commuting CO_2 emissions. It is found that the signs of the estimated coefficients are consistent between the quantile regression and OLS methods. The OLS coefficients are approximately at the middle level of the upper and lower limits of the quantile regression method Fig. 2.

Results in Table 3 show that the changing tendency of the coefficient of car availability turns out to be an inverted U-shape. As commuting CO_2 emissions increase from the lower level to the middle level, the positive coefficient of car availability displays a tendency to increase rapidly. At the 10th quantile, car availability could increase 69.5% of the emissions, while this percentage will amount to 118% at the 50th quantile. When the commuting CO_2 emissions are larger than the middle level, the positive coefficient of car availability has a slight decrease, increasing 93.2–115.8% of the emissions. Car availability's effect

Table 3 Quantile regression model results of four case city pooled samples

Variables	q10	q25	q50	q75	q90	OLS
Car Availability	0.695*** (0.0857)	0.925*** (0.0646)	1.180*** (0.0527)	1.158*** (0.0427)	0.932*** (0.0445)	1.042*** (0.0348)
HInc US$ 6,000–10,000	0.321*** (0.111)	0.174** (0.0773)	0.144** (0.0572)	0.0689 (0.0585)	0.0962* (0.0555)	0.127*** (0.0454)
HInc US$ 10,000–20,000	0.245* (0.126)	0.134 (0.0826)	0.200*** (0.0559)	0.146** (0.0572)	0.174*** (0.0652)	0.140*** (0.0479)
HInc US$ 20,000–40,000	0.815*** (0.148)	0.778*** (0.104)	0.828*** (0.0877)	0.855*** (0.0779)	0.848*** (0.0847)	0.758*** (0.0669)
HInc > US$ 40,000	1.016*** (0.285)	0.769*** (0.211)	0.891*** (0.217)	0.889*** (0.124)	0.969*** (0.132)	0.866*** (0.125)
Polycentric City	− 0.399*** (0.0881)	− 0.148** (0.0714)	− 0.00844 (0.0571)	− 0.0601 (0.0545)	− 0.117[a] (0.0727)	− 0.125*** (0.0469)
Satellite City	0.0535 (0.414)	− 0.247 (0.259)	− 0.827*** (0.188)	− 0.924*** (0.192)	− 0.564** (0.244)	− 0.599*** (0.158)
HCD/HSD	0.00783 (0.00914)	0.0216*** (0.00608)	0.0341*** (0.00470)	0.0377*** (0.00366)	0.0246*** (0.00495)	0.0278*** (0.00340)
City has metro	− 0.343** (0.142)	− 0.391*** (0.0934)	− 0.231*** (0.0696)	− 0.135** (0.0630)	− 0.094[b] (0.0623)	− 0.228*** (0.0483)
Constant	− 3.428*** (0.112)	− 2.751*** (0.0774)	− 2.253*** (0.0708)	− 1.553*** (0.0584)	− 0.763*** (0.0630)	− 2.178*** (0.0471)
Observations	5599	5599	5599	5599	5599	5599

[(a)]. The t-statistic is − 10.117/0.0727 = − 1.609, and the p-value is 0.106. This indicates that the dummy variable of polycentric city is almost statistically significant at 10% level. [(b)]. The t-statistic is − 0.094/0.0623 = − 1.508, and the *p*-value is 0.131. This indicates that the dummy variable of city has metro service is almost statistically significant at the 10% level. [(c)]. Standard errors are in parentheses, calculated by the bootstrap method of 1,000 times random samplings with replacements; [(d)]. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

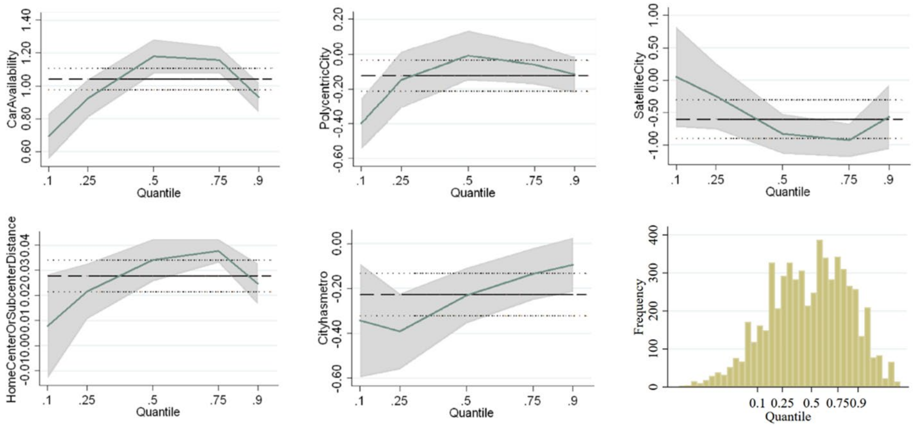


Fig. 1 Quantile regression coefficients and commuting CO_2 emission distribution. Note: (**a**). The lines in bold black refer to the coefficients of OLS regression; (**b**). The lines in dark green refer to the varied coefficients in the quantile regression; (**c**). The gray bands refer to the confidential intervals of the coefficients in the quantile regression; (**d**). The bar graph shows the distribution of commuting CO_2 emissions

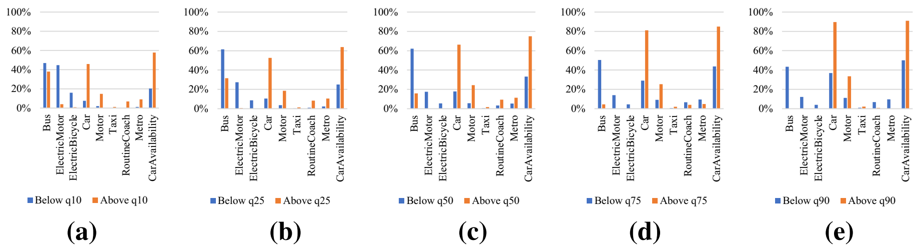


Fig. 2 Percentages of mode choice and car availability below and above the 10th, 25th, 50th, 75th, and 90th quantiles in the pooled samples

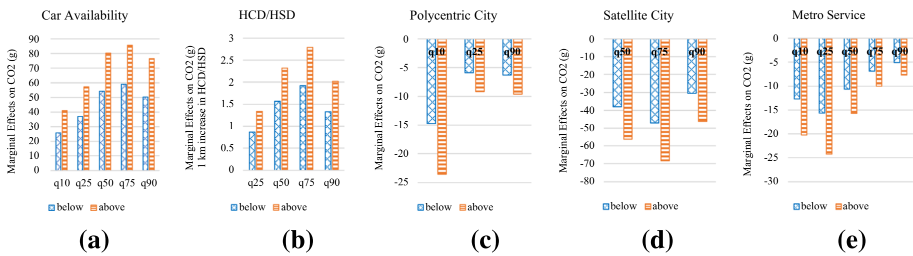


Fig. 3 Average marginal effects on commuting CO_2 emissions below and above the 10th, 25th, 50th, 75th, and 90th quantiles in the pooled samples

on increasing the emissions rises by approximately 30% as emissions rise from the 10th quantile to the 50th quantile. As shown in Fig. 3, the marginal effects of car availability are between 33.36 g and 72.38 g of CO_2 per trip. At the 75th quantile, the marginal effect turns out to be the largest, registering at 2.2 times that of the minimum. These results are mainly due to the fact that, shown in Fig. 2 and Fig. 4, longer commute distances (averaging

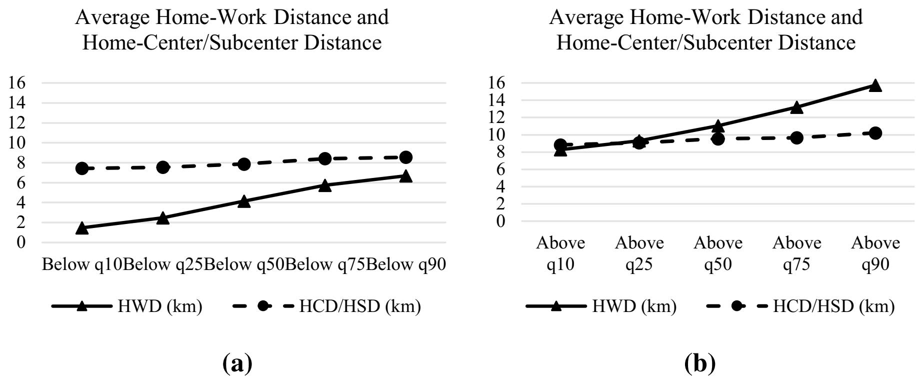


Fig. 4 Average distance below and above the 10th, 25th, 50th, 75th, and 90th percentiles in the pooled samples

11 km), as well as higher car mode share (66.3%), exist among the commuters with emissions larger than the middle level. Among the low emitters, with emissions smaller than the middle level, the average commute distance is only 4.2 km, and the car mode share is only 17.9%. Conversely, the bus mode share for these individuals is as high as 62.1%.

The changing tendency of the coefficient of HCD/HSD also turns out to be an inverted U-shape. The positive coefficient of HCD/HSD has a slight increasing trend as commuting CO_2 emissions increase to the 75th quantile. At the 25th quantile, a 1 km increase of HCD/HSD causes the emissions to increase by 2.16%; at the 75th quantile, this quantity increases to 3.77%. HCD/HSD's effect on increasing the emissions rises by 32% as emissions rise from the 25th quantile to the 75th quantile. At the 90th quantile, the positive coefficient of HCD/HSD has a slight decrease, increasing 2.46% of the emissions. The marginal effects of HCD/HSD also increase as emissions increase to the 75th quantile. Figure 3b shows that a 1 km increase of HCD/HSD could cause 1.1 g to 1.67 g increases of emissions per trip. At the 75th quantile, the marginal effect becomes the biggest, at 2.1 times that of the minimum. These results are caused by the increased commute distances as quantiles increase, from the smallest average level of 1.47 km, increasing to the largest average level of 15.75 km, shown in Fig. 4.

Model results also indicate that, among the high emitters with emissions larger than the middle level, satellite city forms could reduce 56.4–92.4% of the commuting CO_2 emissions. These effects are not statistically significant among the low emitters at the 10th or 25th quantiles. Figure 3(d) shows that the marginal effects of satellite cities are between − 38.35 g and − 57.75 g of CO_2 per trip. At the 75th percentile, the marginal effect turns out to be the largest, at 1.5 times that of the minimum. Additionally, polycentric urban forms could generally reduce commuting CO_2 emissions. At the 10th, 25th, and 90th quantiles, polycentricity could reduce 39.9%, 14.8%, and 11.7% of the emissions, respectively. Figure 3c reports that the marginal effects of polycentric forms are between − 7.55 g to − 19.15 g of CO_2 per trip. At the 10th percentile, the marginal effect becomes the largest, calculated as being 2.5 times that of the minimum level.

The significant effects polycentric or satellite city forms have on reducing emissions can be illustrated from the following characteristics. High emitters are characterized by much longer commute distances and more frequent car usage, especially for the high emitters in the top 10th percentile. These commuters have an average travel distance of 15.75 km, with a car mode share of 89.6%, shown in Fig. 2e and Fig. 4b. However, polycentric and satellite city urban forms can promote job-to-housing balances, shorten commute distances, and, thus, reduce driving frequency, which will substantially lower transport CO_2 emissions. Among the samples taken from the polycentric city of Wuhan, fewer driving trips, more non-motorized trips, and more intra-trips inside the three subcenters existed, resulting in lower levels of transport CO_2 emissions. Among the samples taken from the satellite cities in Beijing, more local trips inside the satellite cities were observed, and, thus, the transport CO_2 emissions were lower, compared with the sprawling areas.

Based on the above results, it can be concluded that controlling the percentage of oil-fueled cars, shortening the HCD/HSD, and developing satellite cities have the largest effects for reducing transport CO_2 emissions from the emitters of the middle and higher levels. Moreover, these middle and higher levels of emitters account for about 50% of the total emitters. Therefore, the above policies will have enormous effects on transport CO_2 emission reductions.

Another notable finding reveals that the effects metro services have on reducing the emissions decrease as the emissions increase from the 25th quantile to the 90th quantile. At the 10th quantile, cities with metro services could reduce 34.3% of the emissions, and at the 25th quantile, cities with metro services could reduce 39.1% of the emissions; while at the 75th quantile, this effect drops to 13.5%, and at the 90th quantile, this effect becomes the lowest, at only 9.41%. Calculated from the model results, it can be obtained that the effects of metro services reducing the emissions will suffer a 19% decrease when commuting CO_2 emissions increase by 1 kg. Figure 3e and Fig. 5 indicate that the marginal effects of this impact factor are between − 19.94 g to − 6.4 g of CO_2 per trip. At the 25th quantile, the marginal effect is the greatest, at 3.1 times that of the minimum. On the one hand, these results are due to the increasing tendencies of car availability, household income, driving frequencies, and commute distances, and the decreasing tendency of metro mode usage as transport CO_2 emissions increase, as reflected in Fig. 2 and Fig. 4. Despite the advanced metro services and metro networks in the sprawling areas in Beijing, commuters will still heavily rely on driving when car availability and long-distance commutes are present. Another possible reason lies in the long travel times that exist while transferring to other modes when using buses and metros. For instance, among the bus or metro users of Beijing, half of the commuters take more than a 1/3 of their total travel time just in transferring; among the bus users in Bangalore, half of the commuters spend more than 1/2 of their total travel time before and after riding the bus.

Figure 5 shows that, between the 25th quantile and the 50th quantile of the emissions, metro's effects on reducing the emissions have a great extent of decrease. We analyze the samples' characteristics between the 25th to 50th quantile, between the 50th to 75th quantile, and between the 75th to 90th quantile. It is found that, when commuting distance reaches and exceeds 5.8 km, and the percentage of car availability reaches 41.2% or more, metro's effects in reducing the emissions drop continuously at a rate of 37.8%. Thus, for low-carbon transportation development, it is suggested to form employment and life circles within a 5–6 km radius. Meanwhile, in order to attract more high emitters to use metros, better transit resources, such as feeder buses or customized shuttle buses, need to be allocated around the metro stations. For the first-and-last mile access to metros, shared bicycles and electric scooters are now popularly used (Baek, 2021; Zuo et al., 2020; Chen et al., 2021), which can expand the access distance to metros, compared with walking, making transfer to metros more convenient for those residents located farther away from the station. These non-motorized travel modes need to be encouraged. Also, urban roads with better walkability and greenways can encourage

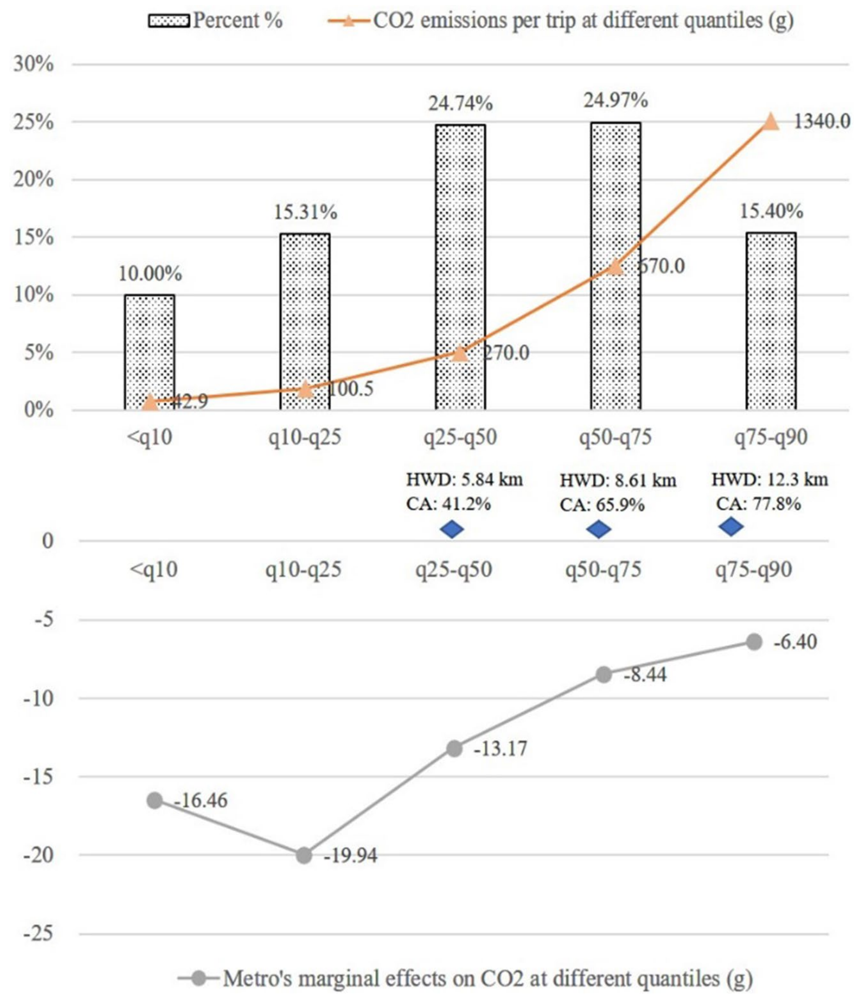
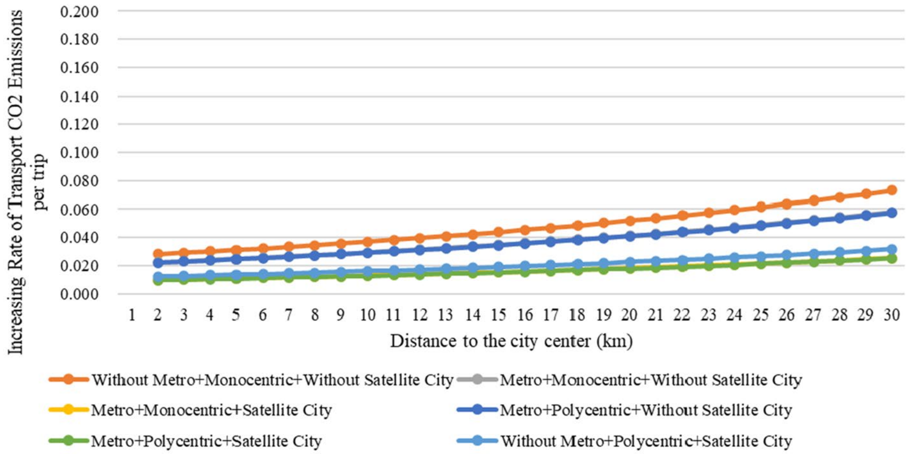


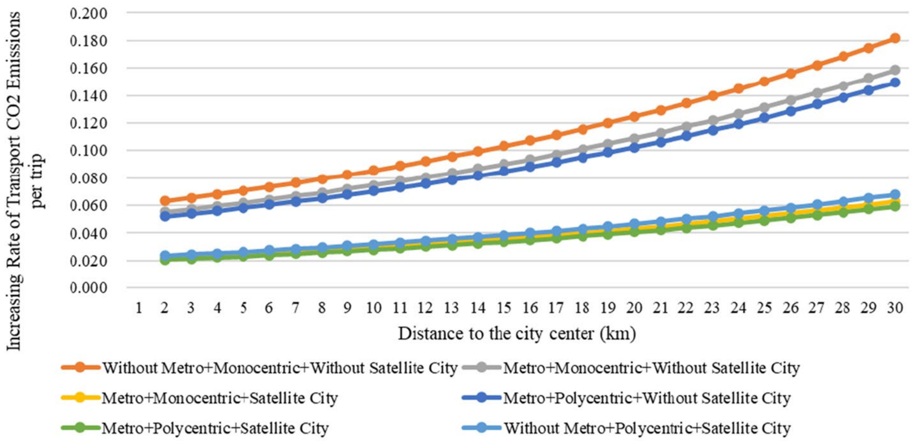
Fig. 5 Commuters' percentages, transport CO_2 emissions per trip, and metro's marginal effects at different quantiles. Note: HWD refers to home-work distance in kilometers; CA refers to car availability

more travelers to walk or use non-motorized traffic modes in their transfers to metros (Ahn, et al., 2021; Pan et al., 2021; Ngo et al., 2018; Sun, Zhou, et al., 2016; Sun, Zacharias, et al., 2016). Therefore, bicycle lanes, pedestrian streets, and greenways need to be constructed with high service levels. These above suggested measures will be beneficial for the first-and-last mile access to metros and will make metros more attractive to those commuters with cars and high income. In addition, it is necessary to combine proper traffic demand management policies and metro network construction together to control the driving frequencies. The percentage of oil-fueled cars in ownership needs to be controlled, and newer energy-operated vehicles need to be encouraged through the use of transport policies. Car ownership restriction or congestion pricing policymaking need to consider the travel behaviors and sensitivity of travel consumptions among the high-income commuters.

By using the model equations at the 50th, 75th, and 90th quantiles, the increasing rates of transport CO_2 emissions produced by the high emitters were calculated when the impact factors' values varied. These impact factors include distance to the city center, metro provision, mono/polycentric form, and whether satellite cities exist. The high emitters refer to those with car availability and higher household annual incomes between US$ 20,000–40,000. The results are shown in Fig. 6. As the distances to the city center increase, the increasing rates of transport CO_2 emissions increase continuously. At the 50th quantile, the increasing rates change between 0.01 and 0.07, at the 75th quantile, the increasing rates change between 0.02 and 0.18, and at the 90th quantile, the increasing rates change between 0.03 and 0.14. Generally, the increasing rates of transport CO_2 emissions become

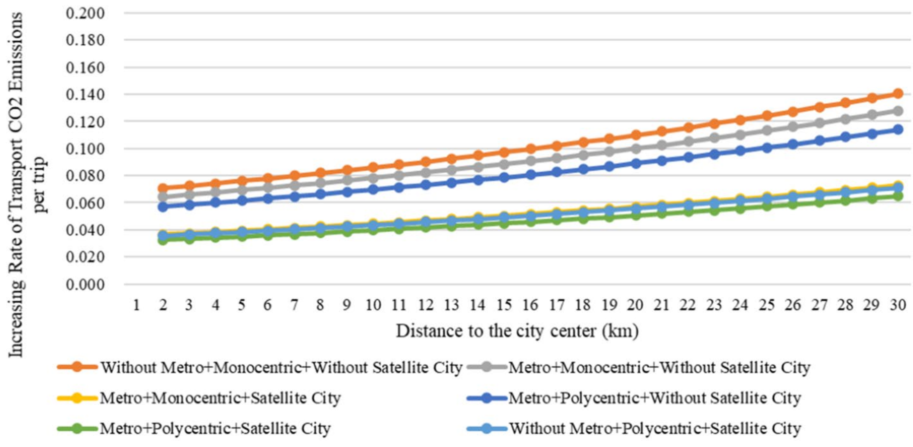


(a) Increasing rates at the 50th quantile



(b) Increasing rates at the 75th quantile

Fig. 6 Increasing rates of transport CO_2 emissions and distances to the city center under different scenarios



(c) Increasing rates at the 90th quantile

Fig. 6 (continued)

larger as the emissions increase. When there are metro provisions, polycentric forms, or satellite cities, the increasing rates of transport CO_2 emissions will decrease, especially for the scenarios with satellite city developments. It is noteworthy that, under the scenarios with polycentric and satellite city developments, as the distances to the city center increase, though, the increasing rates of transport CO_2 emissions will have more declines. At the 75th quantile, there exist larger extents of the decreased emissions when the distance to the city center is more than about 8–10 km, and at the 50th and 90th quantiles, the emissions will have more decreases when the distance to the city center is more than about 15–18 km. These results indicate that when the urban radius is more than approximately 10–15 km, transport CO_2 emissions in the outer areas will increase significantly, while developing polycentric and satellite cities can greatly decrease the increasing extents in the outer areas. These results suggest that, for transport emission reductions, it is necessary to control the urban development radius within 10–15 km under the monocentric pattern, and when the city continues to sprawl, polycentric structures and satellite cities need to be formed.

4.2 Samples of four single cities, car availability, high income, and polycentric/satellite cities

In order to test the robustness of the heterogeneous effects of the impact factors, different quantile regression models were established by using different subsamples. These subsamples include samples of the four single cities, a sample of the commuters with car availability, a sample of the commuters with high household annual income (> US$ 40,000), and a sample of the commuters located in the polycentric city or satellite city.

Table 4 shows the model results in the samples of the four single cities. In the cities of Beijing, Xi'an, and Bangalore, all of which have one strong center, the positive coefficients of car availability and HCD/HSD increase stably along with the increase of emissions, while in the polycentric city of Wuhan, such an increasing tendency does not exist. The positive coefficients of car availability become smaller when the emissions are larger than the middle level. Additionally, at the 10^{th}, 25th, 50th, and 90th quantiles, HCD/HSD

Table 4 Quantile regression model results of four case city samples

Variables	q10	q25	q50	q75	q90
Xi'an					
Car Availability	0.884*** (0.161)	1.408*** (0.126)	1.865*** (0.0689)	1.941*** (0.0589)	1.953*** (0.0531)
HCD/HSD	0.00123 (0.0256)	0.0250 (0.0153)	0.0263** (0.0119)	0.0286** (0.0112)	0.0219* (0.0113)
Constant	− 3.967*** (0.488)	− 3.071*** (0.260)	− 2.517*** (0.240)	− 2.168*** (0.126)	− 1.881*** (0.152)
Household Income	Yes	Yes	Yes	Yes	Yes
Observations	1271	1271	1271	1271	1271
Beijing					
Car Availability	0.603*** (0.142)	0.926*** (0.148)	1.320*** (0.0807)	1.502*** (0.0751)	1.468*** (0.0878)
HCD/HSD	0.00838 (0.0110)	0.0186** (0.00786)	0.0200*** (0.00500)	0.0286*** (0.00731)	0.0179*** (0.00508)
Satellite City	− 0.447 (0.410)	− 0.803** (0.332)	− 1.063*** (0.169)	− 0.984*** (0.291)	− 0.515** (0.237)
Constant	− 3.114*** (0.232)	− 2.490*** (0.157)	− 1.840*** (0.230)	− 1.238*** (0.115)	− 0.722*** (0.222)
Household Income	Yes	Yes	Yes	Yes	Yes
Observations	1222	1222	1222	1222	1222
Wuhan					
Car Availability	1.538*** (0.209)	1.905*** (0.198)	1.834*** (0.111)	1.618*** (0.0892)	1.247*** (0.129)
HCD_HSD	− 0.0185 (0.0243)	− 0.00671 (0.0144)	− 0.0118 (0.0131)	0.0195 (0.0136)	− 0.00400 (0.0146)
Constant	− 3.877*** (0.170)	− 3.161*** (0.158)	− 2.272*** (0.102)	− 1.642*** (0.105)	− 0.782*** (0.197)
Household Income	Yes	Yes	Yes	Yes	Yes
Observations	1113	1113	1113	1113	1113
Bangalore					
Car Availability	− 0.0148 (0.0196)	0.229* (0.117)	0.259*** (0.0675)	0.238*** (0.0544)	0.357*** (0.0619)
HCD_HSD	− 0 (0.000998)	− 0.00161 (0.0121)	0.0216** (0.00927)	0.0233*** (0.00810)	0.0193** (0.00940)
Constant	− 2.688*** (0.0235)	− 2.210*** (0.156)	− 1.481*** (0.117)	− 0.862*** (0.115)	− 0.410*** (0.120)
Household Income	Yes	Yes	Yes	Yes	Yes
Observations	1993	1993	1993	1993	1993

[a]. Household incomes are included in the quantile regression models; [b]. Standard errors are in parentheses, calculated by the bootstrap method of 1,000 times random samplings with replacements; [c]. ***$p<0.01$, **$p<0.05$, *$p<0.1$

does not have statistically significant effects on the emission increases, which illustrates that HCD/HSD is not the significant factor behind emission increases, under the polycentric form.

Results in Tables 5 and 6 report that, in the sample of the commuters with car availability, satellite city form's effects in reducing the emissions are statistically significant among

Table 5 Quantile regression results from the subsamples of car availability, high-income, and polycentric/satellite city

Variables	q10	q25	q50	q75	q90
Sample of car availability					
Satellite city	0.0148 (0.401)	− 0.308 (0.399)	− 0.786*** (0.272)	− 1.178*** (0.331)	− 0.583* (0.345)
HCD_HSD	− 0 (0.00538)	0.0101 (0.00760)	0.0204*** (0.00639)	0.0309*** (0.00593)	0.0297*** (0.00604)
Constant	− 2.703*** (0.0429)	− 2.072*** (0.138)	− 1.217*** (0.0726)	− 0.716*** (0.0846)	− 0.152 (0.119)
Household income	Yes	Yes	Yes	Yes	Yes
Observations	3036	3036	3036	3036	3036
Sample of high income					
Car availability	1.485*** (0.295)	1.799*** (0.444)	1.823*** (0.397)	1.986*** (0.495)	1.848** (0.706)
Polycentric city	0.0263 (0.415)	0.737 (0.586)	0.144 (0.360)	− 0.465** (0.233)	− 0.851*** (0.275)
Satellite city	− 3.902 (2.506)	− 6.372** (2.674)	− 6.639*** (1.840)	− 7.016*** (2.012)	− 4.241*** (1.497)
HCD_HSD	0.0726* (0.0421)	0.108** (0.0456)	0.0906*** (0.0317)	0.0826** (0.0364)	0.0255 (0.0278)
Constant	− 3.747*** (0.360)	− 3.876*** (0.488)	− 2.528*** (0.513)	− 1.789** (0.683)	− 0.687 (0.730)
Observations	107	107	107	107	107
Sample of polycentric or satellite cities					
Car availability	1.389*** (0.191)	1.646*** (0.205)	1.562*** (0.0969)	1.530*** (0.0936)	1.257*** (0.119)
HCD_HSD	0.00666 (0.00458)	0.0107** (0.00475)	0.0102*** (0.00366)	0.0140*** (0.00380)	0.0128*** (0.00279)
Constant	− 3.939*** (0.108)	− 3.233*** (0.130)	− 2.399*** (0.0811)	− 1.596*** (0.100)	− 0.909*** (0.153)
Household income	Yes	Yes	Yes	Yes	Yes
Observations	1276	1276	1276	1276	1276

(a). Household incomes are included in the quantile regression models; (b). High-income sample refers to household annual income larger than US$ 40,000; (c). Standard errors are in parentheses, calculated by the bootstrap method of 1,000 times random samplings with replacements; (d). $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

high emitters at the 50th, 75th, and 90th quantiles. At the 75th quantile, satellite city form could reduce as much as 117.8% of the emissions, which is about 2 times that of the minimum. The marginal effects are between − 48.8 g and − 98.5 g of CO_2 per trip. HCD/HSD effects are statistically significant and have a slight increasing tendency. At the 50th, 75th, and 90th quantiles, a 1 km increase in HCD/HSD could increase emissions by 2.04%, 3.09%, and 2.97%, respectively, with the marginal effects between 1.7 and 2.6 g of CO_2 per trip, showing larger effects compared with those in the pooled samples. At the 75th quantile, the marginal effect is the greatest, at about 1.53 times that of the minimum.

In the sample of the commuters with higher household annual incomes (> US$ 40,000), the positive coefficient of car availability increases with the emission increases, with the marginal effects between 254.5 g and 340.4 g of CO_2 per trip. At the 75th quantile, the marginal effect

Table 6 Marginal effects on commuting CO_2 emissions

Marginal Effects on CO_2 (g) per trip	Min	Avg	Max
Satellite city			
Sample of car availability	− 98.537	− 73.652	− 48.767
Sample of high income	− 1202.49	− 964.681	− 726.874
Pooled samples of four case cities	− 57.75	− 48.051	− 38.35
Polycentric city			
Sample of high income	− 145.855	− 112.776	− 79.697
Pooled Samples Of Four Case Cities	− 19.15	− 13.35	− 7.55
Metro service			
Pooled samples of four case cities	− 19.94	− 13.170	− 6.40
1 km increase of HCD/HSD			
Sample of car availability	1.706	2.146	2.585
Sample of high income	12.443	15.477	18.510
Sample of polycentric or satellite cities	0.429	0.508	0.588
Pooled samples of four case cities	1.10	1.729	2.36
Car availability			
Sample of high income	254.517	297.451	340.385
Sample of polycentric or satellite cities	52.8093	60.981	69.152
Pooled samples of four case cities	33.36	52.868	72.38

is the largest, at about 1.3 times that of the minimum. The effect of polycentric forms reducing emissions is significant among high emitters, with the marginal effects between − 79.7 g to − 145.9 g of CO_2 per trip. At the 90th quantile, the average marginal effect becomes the largest, at about 1.8 times that of the minimum. Meanwhile, the effect of satellite city forms reducing emissions is also significant among high emitters, with much larger marginal effects between − 726.9 g and − 1202.5 g of CO_2 per trip. At the 75th quantile, the marginal effect becomes the maximum, at about 1.7 times that of the minimum. Notably, the positive coefficients of HCD/HSD in the high-income sample are much larger than those in other samples. At the 25th, 50th, and 75th quantiles, a 1 km increase in HCD/HSD could increase the emissions by 10.8%, 9.06%, and 8.26%, respectively, with the marginal effects between 12.4 g and 18.5 g of CO_2 per trip. At the 25th quantile, the marginal effect turns out to be the largest, at about 1.5 times that of the minimum.

Looking at the results in the sample of the commuters located in the polycentric or satellite cities in Table 5, no increasing tendency exists in the positive coefficients of car availability, which is similar to the model results for the Wuhan sample in Table 4. In addition, the results show that the effect of car availability increasing the emissions becomes smaller compared with those in the high-income sample, and the effects of HCD/HSD increasing emissions also become smaller. A 1 km increase of HCD/HSD will increase emissions by 1% to 1.4%, with marginal effects between 0.4 to 0.6 g of CO_2 per trip.

5 Conclusion

In this study, to make rational planning strategies for reducing transport CO_2 emissions and climate change, heterogeneous effects of the significant impact factors from transport emissions were measured in four typical developing Chinese and Indian cities.

The quantile regression method was applied, because it can overcome the shortcomings of the conditional mean method, frequently used in the previous literature. The conditional mean method can only provide the mean level of the impact factors' effects, and the regression error has normal distribution and homoscedastic assumptions, while the quantile regression method can estimate the covariate effects on any percentile of transport emission's distribution and is not limited to the conditional mean model's assumptions. The quantile regression model is estimated by linear programming techniques, and the standard errors and confidence intervals of the estimated coefficients are calculated by the bootstrap method.

The significant impact factors of transport CO_2 emissions include household car availability, mono/polycentric urban form, satellite city development, metro service, and distance from home to the city center/subcenter. The statistical test and robust test results indicate the reliability of the model results. According to the study results, specific urban and transport planning strategies are proposed to reduce transport CO_2 emissions under Chinese and Indian cities' development situations. These development situations include urban growths, metro and rail network constructions, urban agglomeration formations, motorization and economic increases, energy technology improvements, and new energy vehicle promotions. The above development situations are equally important issues for other global cities. Therefore, this study's findings will be beneficial to transport CO_2 emission reductions globally.

Model results indicate that the marginal effects of a city having metro services vary from − 19.94 to − 6.4 g of CO_2 per trip. From the lowest emitters to the highest emitters, the effects of metros reducing the emissions drop at a rate of 27%, averagely. That means metro service provisions could not bring about substantial emission reductions among the high emitters, while the marginal effects of car availability change from 33.4 to 340.4 g of CO_2 per trip. From the low emitters to the high emitters, the effects of car availability increasing the emissions have a general rising tendency. The largest marginal effect of car availability increasing the emissions is seen within the high-income sample (254.5 g to 340.4 g of CO_2 per trip). It is also found that, after the commute distance reaches 5.8 km or more and the car availability's percentage amounts to 41.2% or greater, metro's effects on reducing the emissions decrease continuously at a rate of 37.8%.

Therefore, for low-carbon transportation development, it is recommended to form employment and life circles within a 5–6 km radius. Dependence only on metro construction cannot bring about desired emission reductions in future. It is necessary to combine traffic demand management policies together to reduce driving, including controlling the percentage of oil-fueled cars owned, car use restriction, and congestion pricing. In the policymaking of car restriction or congestion pricing, it is necessary to consider the travel behaviors and sensitivity of travel consumptions among the high-income commuters. In addition, to attract high emitters toward using public transit and metro services more often, better public transit resources (feeder buses or customized shuttle buses) need to be allocated around the metro stations. Additionally, high service levels of bike lane facilities, pedestrian streets, and greenways need to be constructed. These could attract more travelers to use low-carbon traffic modes when transferring to metros, and attract more residents located farther from metro stations to access metros.

Model results also indicate that the marginal effects of HCD/HSD are between 0.5 to 18.5 g of CO_2 per trip. The effects of HCD/HSD contributing to the increase of emissions grow at a rate of approximately 32.1%. In the sample of the commuters with car availability, marginal effects of HCD/HSD are a little larger (1.7–2.6 g of CO_2 per trip) than those in the pooled samples (1.1–2.3 g of CO_2 per trip), and in the high-income sample, the marginal effects turn out to be the largest, at 12.4–18.5 g of CO_2 per trip. Under future urban expansion and urban agglomeration development, HCD/HSD will continue to become longer. This reality, paired with the higher marginal effects of HCD/HSD among the high-income and car availability commuters, will inevitably create surges in transport CO_2 emissions. In order to mitigate these rapid increases in future, it is of great importance to foster polycentric forms inside the main city and develop satellite cities in the outer areas, since the model results report that polycentric and satellite city forms could reduce transport CO_2 emissions significantly, with marginal effects of − 145.9 g to − 7.6 g of CO_2 per trip and − 1202.5 g to − 38.4 g of CO_2 per trip, respectively. Additionally, these two factors' effects become larger in the high-income and car availability samples. Furthermore, car availability's and HCD/HSD's effects on increasing the emissions decline under the scenarios of developing polycentric and satellite city forms. Under the scenarios with polycentric and satellite city developments, as HCD increases farther, the increasing rates of transport CO_2 emissions have significant declines. When the distance to the city center is more than 8–10 km and 15–18 km, developing polycentric and satellite cities can greatly decrease the increasing extents of the emissions caused by the increase of HCD. These above results manifest that, under the situation of the urban form with one strong center, there will be smaller transport CO_2 emissions if the urban radius is within approximately 10–15 km. When the city sprawls beyond this range, transport CO_2 emissions will substantially increase. Therefore, it is necessary to control the urban radius within 10–15 km under the monocentric urban pattern and to foster polycentric structures and satellite cities in the outer areas.

In summary, for transport CO_2 emission reductions, it is necessary to combine the following planning strategies together, including controlling the percentages of oil-fueled cars, metro and rail network construction, and providing better public transit services around metro stations. Meanwhile, bicycle lanes, pedestrian streets, and greenways need to be constructed with high service levels for the first-and-last mile transfer to public transit or metros. Also, employment and life circles are suggested to be within a 5–6 km radius, and urban radius is recommended to be 10–15 km under the urban form with one strong center. When the city continuously sprawls, polycentric structures and satellite cities need to be formed.

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References

ADB (Asian Development Bank) (2016). Guidelines for estimating greenhouse gas emissions of asian development bank projects: additional guidance for transportation projects. https://www.adb.org/documents/guidelines-estimating-ghg-emissions-adb-transport-projects

Ahn, H., Lee, J., & Hong, A. (2021). Does urban greenway design affect air pollution exposure? A case study of Seoul. *South Korea. Sustainable Cities and Society, 72*(1), 103038.

Baek, K., Lee, H., Chung, J. H., & Kim, J. (2021). Electric scooter sharing: how do people value it as a last-mile transportation mode? *Transportation Research Part D: Transport and Environment, 90*, 102642.

Boarnet, M. G., Wang, X., & Houston, D. (2017). Can new light rail reduce personal vehicle carbon emissions? *A before-after, Experimental-Control Evaluation in Los Angeles, Journal of Regional Sciences, 57*(3), 523–539.

Brand, C., & Boardman, B. (2008). Taming of the few—the unequal distribution of greenhouse gas emissions from personal travel in the UK. *Energy Policy, 36*, 224–238.

Brand, C., Goodman, A., Rutter, H., Song, Y., & Ogilvie, D. (2013). Associations of individual, household and environmental characteristics with carbon dioxide emissions from motorized passenger travel. *Applied Energy, 104*(100), 158–169.

Brand, C., & Preston, J. (2010). '60-20 emission'-The unequal distribution of greenhouse gas emissions from personal, non-business travel in the UK. *Transport Policy, 17*(1), 9–19.

Büchs, M., & Schnepf, S. (2013). Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO_2 emissions. *Ecological Economics, 90*, 114–123.

Cameron, A. C., & Trivedi, P. K. (2009). *Microeconometrics using stata*. Stata Press.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and applications*. Cambridge University Press.

Cao, X. (2019). Examining the effect of the Hiawatha LRT on auto use in the Twin Cities. *Transport Policy, 81*, 284–292.

Cao, X., & Ermagun, A. (2016). Influences of LRT on travel behaviour: A retrospective study on movers in Minneapolis. *Urban Studies, 54*(11), 1–16.

Carlsson-Kanyama, A., & Lindén, A. L. (1999). Travel patterns and environmental effects now and in the future: Implications of differences in energy consumption among socio-economic groups. *Journal of Ecological Economics*, *30*, 405–417.

Chatman, D. G. (2013). Does TOD need the T? *Journal of the American Planning Association, 79*(1), 17–31.

Chen, S., Yan, X., Pan, H., & Deal, B. (2021). Using big data for last mile performance evaluation: An accessibility-based approach. *Travel Behaviour and Society, 25*, 153–163.

Cirilli, A., & Veneri, P. (2014). Spatial structure and carbon dioxide (CO_2) emissions due to commuting: An analysis of Italian urban areas. *Regional Studies, 48*(12), 1993–2005.

Efron, B., & Tibshirani, R. J. (1993). *An introduction to the bootstrap*. CRC Press.

Miller, E. J., & Ibrahim, A. (1998). Urban form and vehicular travel: Some empirical findings. *Journal of the Transportation Research Board, 1617*, 18–27.

Grunfelder, J., Nielsen, T. A. S., & Groth, N. B. (2015). Changes to urban form and commuting patterns: Trends in two Danish city regions. *Danish Journal of Geography, 115*(2), 73–87.

Huang, X., Cao, X. J., Yin, J., & Cao, X. (2019). Can metro transit reduce driving? Evidence from Xi'an, China. *Transport Policy*, *81*, 350–359.

Hunter, D. R., & Lange, K. (2000). Quantile regression via an MM algorithm. *Journal of Computational and Graphical Statistics, 9*, 60–77.

IPCC (Intergovernmental Panel on Climate Change) (1997). Revised 1996 IPCC guidelines for national greenhouse gas inventories.

Knaap, E., Ding, C., Niu, Y., & Mishra, S. (2016). Polycentrism as a sustainable development strategy: Empirical analysis from the state of Maryland. *Journal of Urbanism: International Research on Placemaking and Urban Sustainability, 9*(1), 73–92.

Koenker, R., & Basset, G. (1978). Regression quantiles. *Econometrica, 46*(1), 33–50.
Koenker, R., & Hallock, K. F. (2001). Quantile regression. *Journal of Economic Perspectives, 15*(4), 143–156.
Ko, J., Park, D., Lim, H., & Hwang, I. (2011). Who produces the most CO_2 emissions for trips in the Seoul Metropolis Area? *Transportation Research Part d: Transport and Environment, 16*, 358–364.
Modarres, A. (2011). Polycentricity, commuting pattern, urban form: The case of Southern California. *International Journal of Urban & Regional Research, 35*(6), 1193–1211.
Ngo, V. D., Frank, L. D., & Bigazzi, A. Y. (2018). Effects of new urban greenways on transportation energy use and greenhouse gas emissions: A longitudinal study from Vancouver, Canada. *Transportation Research Part d: Transport and Environment, 62*, 715–725.
Ostad-Ali-Askar, K., Su, R., & Liu, L. (2018). Water resources and climate change. Editorial. *Journal of Water and Climate Change., 9*(2), 239. https://doi.org/10.2166/wcc.2018.999
Pan, H., Page, J., Cong, C., Barthel, S., & Kalantari, Z. (2021). How ecosystems services drive urban growth: Integrating nature-based solutions. *Anthropocene*, *35*(19), 100297.
Schlossmacher, E. J. (1973). An iterative technique for absolute deviations curve fitting. *Journal of the American Statistical Association, 68*, 857–859.
Shuai, C., Chen, X., Wu, Y., Tan, Y., Zhang, Y., & Shen, L. (2018). Identifying the key impact factors of carbon emission in China: Results from a largely-expanded pool of potential impact factors. *Journal of Cleaner Production, 175*, 612–623.
Spears, S., Boarnet, M., & Houston, D. (2017). Driving reduction after the introduction of light rail transit: Evidence from an experimental-control group evaluation of the Los Angeles Expo Line. *Urban Studies, 54*(12), 2780–2799.
StataCorp. (2017). Stata base reference manual release 15, StataCorp LLC, Stata Press, College Station, Texas.
Sun, B., Zhou, H., Zhang, T., & Rui, W. (2016a). Urban spatial structure and commute duration: An empirical study of China. *International Journal of Sustainable Transportation, 10*(7), 638–644.
Sun, G., Zacharias, J., Ma, B., & Oreskovic, N. M. (2016). How do metro stations integrate with walking environments? Results from walking access within three types of built environment in Beijing. *Cities, 56*, 91–98.
Susilo, Y. O., & Stead, D. (2009). Individual carbon dioxide emissions and potential for reduction in the Netherlands and the United Kingdom. *Transportation Research Record*, *2139*, 142–152.
Timilsina, G. R., & Shrestha, A. (2009). Transport sector CO_2 emissions growth in Asia: Underlying factors and policy options. *Energy Policy, 37*(11), 4523–4539.
Veneri, P. (2010). Urban polycentricity and the costs of commuting: Evidence from Italian metropolitan areas. *Growth and Change, 41*(3), 403–429.
Wang, Y. Q., Yang, L., Han, S. S., Li, C., & Ramachandra, T. V. (2017). Urban CO_2 emissions in Xi'an and Bangalore by commuters: Implications for controlling urban transportation carbon dioxide emissions in developing countries. *Mitigation and Adaptation Strategies for Global Change, 22*(7), 993–1019.
Wang, S., Zeng, J., & Liu, X. (2019). Examining the multiple impacts of technological progress on CO_2 emissions in China: A panel quantile regression approach. *Renewable & Sustainable Energy Reviews, 103*, 140–150.
Wu, X., Tao, T., Cao, J., Fan, Y., & Ramaswami, A. (2019). Examining threshold effects of built environment elements on travel-related carbon-dioxide emissions. *Transportation Research Part D: Transport and Environment, 75*, 1–12.
Xu, B., & Lin, B. (2016). A quantile regression analysis of China's provincial CO_2 emissions: Where does the difference lie? *Energy Policy, 98*, 328–342.
Yang, L., Wang, Y. Q., Han, S. S., Li, C., Liu, Y. Y., & Ren, Q. (2017). Carbon dioxide emissions from commuter traffic in Xi'an, China. *Proceedings of the Institution of Civil Engineers-Transport, 170*(1), 8–18.
Yang, L., Wang, Y. Q., Bai, Q., & Han, S. S. (2018). Urban form and travel patterns by commuters: A comparative case study of Wuhan and Xi'an, China. *Journal of Urban Planning and Development, 144*(1), 05017014.
Yang, L., Wang, Y. Q., Han, S. S., & Liu, Y. Y. (2019). Urban transport carbon dioxide (CO_2) emissions by commuters in rapidly-developing cities: The comparative study of Beijing and Xi'an in China. *Transportation Research Part d: Transport & Environment, 68*, 65–83.
Yang, L., Wang, Y. Q., Lian, Y. J., & Han, S. S. (2020). Factors and scenario analysis of transport carbon dioxide emissions in rapidly-developing cities. *Transportation Research Part D: Transport and Environment, 80*, 102252.
Zuo, T., Wei, H., Chen, N., & Zhang, C. (2020). First-and-last mile solution via bicycling to improving transit accessibility and advancing transportation equity. *Cities, 99*, 102614.

Zwierzchowska, I., Haase, D., & Dushkova, D. (2021). Discovering the environmental potential of multi-family residential areas for nature-based solutions. A Central European cities perspective. *Landscape and Urban Planning*, *206*, 103975.

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Authors and Affiliations

Liu Yang[1] · Yuanqing Wang[2] · Yujun Lian[3] · Xin Dong[1] · Jianhong Liu[4] · Yuanyuan Liu[5] · Zhouhao Wu[6]

Yuanqing Wang
wyqing@chd.edu.cn

Yujun Lian
lianyj@mail.sysu.edu.cn

Xin Dong
dongxin@nwu.edu.cn

Jianhong Liu
jhliu@nwu.edu.cn

Yuanyuan Liu
liuyy@gdut.edu.cn

Zhouhao Wu
hero1989wzh@sina.com

[1] Department of Urban Planning, Shaanxi Key Laboratory of Earth Surface System and Environmental Carrying Capacity, College of Urban and Environmental Sciences, Northwest University, Xi'an, China

[2] College of Transportation Engineering, Chang'an University, Xi'an, China

[3] Lingnan College, Sun Yat-Sen University, Guangzhou, China

[4] Institute of Remote Sensing and Geographic Information Science, Shaanxi Key Laboratory of Earth Surface System and Environmental Carrying Capacity, College of Urban and Environmental Sciences, Northwest University, Xi'an, China

[5] School of Civil and Transportation Engineering, Guangdong University of Technology, Guangzhou, China

[6] Institute of Transportation Engineering, Tsinghua University, Beijing, China