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Factors and scenario analysis of transport carbon dioxide emissions in rapidly-developing cities

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ABSTRACT

To identify key factors of transport CO_2 emissions and determine effective policies for emission reductions in fast-growing cities, this study establishes transport CO_2 emission models, quantifying the influences of polycentricity and satellite cities and re-examining the effects of per capita GDP and metro service. Based on the model results, we forecast future residents' urban transport CO_2 emissions under several scenarios of different urban and transport policies and new energy technologies. We find nonlinear quadratic growth relationship between commuting CO_2 emissions and per capita GDP, and the elasticities of household and individual commuting CO_2 emission to per capita GDP are 1.90% and 1.45%, respectively. Developing job-housing balanced satellite cities and self-contained polycentric city can greatly decrease emissions from high emitters and can contribute to about 51–82% of the emission reductions by 2050 compared with the scenario of business as usual (BAU). Promotion of electric vehicles, electric public buses, metros, and improvement of traditional energy efficiency contributes to about 48–57% of the emission reductions by 2050 compared with the BAU. When these policies and technologies are combined, about 90% of the emissions could be reduced by 2050 compared with the BAU, and the emissions will be about 1.2–4.9 times of the present. The findings suggest that fostering polycentric urban form and job-housing balanced satellite cities is the key step for future transport CO_2 emission reductions. Metro network promotion, energy efficiency improvement, and new energy type applications can also be effective in emission reductions.

1. Introduction

In developing economies, motorized transport CO_2 emissions have become a significant contributor to the global problem of increasing greenhouse gas (GHG) emissions (ADB, 2019; Timilsina and Shrestha, 2009). By 2050, the transportation sector is expected to become the single largest GHG emitter, accounting for 80% of global GHG emissions, with most projected increases originating from developing Asian countries (ADB, 2019). To reduce transport CO_2 emissions, it is essential to understand their key impact factors and characteristics in fast-growing Asian cities, thus, more effective and adaptive measures and policies can be suggested and promoted. Previous studies have made contributions in identifying and modelling the correlations between travelers'

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socio-economic and household location characteristics and transport CO_2 emissions. Researchers have found that individuals and households with car availability, high income, higher level of education, located in the outer and sprawling areas and along the radial and ring roads produce larger amounts of transport CO_2 emissions (Yang et al., 2019; Shuai et al., 2018; Wang et al., 2017a; Wang et al., 2017b; Yang et al., 2017; Brand et al., 2013; Büchs and Schnepf, 2013; Ko et al., 2011; Brand and Preston, 2010; Susilo and Stead, 2009; Brand and Boardman, 2008; Carlsson-Kanyama and Lindén, 1999). Also, many studies have focused on the relationship between polycentric urban form and travel behavior and transport CO_2 emissions. These studies mainly target in developed and western countries and cities, and the findings tend to be mixed and sometimes controversial. And few studies quantify the effects of developing polycentricity and satellite cities on transport CO_2 emissions' changes. This will lead to incomparable effects among transport CO_2 emissions' impact factors, and will not benefit appropriate policy makings. To fill this gap, we intend to quantify the effects of developing polycentricity and satellite cities on transport CO_2 emissions in rapidly-growing cities chosen from Asia, by establishing transport CO_2 emission models using disaggregate individual travel data of multiple cities and Tobit modeling method on a micro level. We will also re-examine the impact factors of cities' metro services and cities' economic levels in the models.

In recent years, new types of energy vehicles such as electric vehicles (EVs), electric public buses (EPBs), metros, and other energy efficient improvement technologies have been promoted in rapidly-developing Asian cities. Meanwhile, these cities are undergoing continuously fast economic, population, and motorization growth, and urban expansion. What will be the future situations of transport CO_2 emissions under a series of emission-reduction policies/technologies and continuous urban growth, and what are the key and effective policies for mitigating the emission increases? To help address these questions and concerns, we intend to conduct future scenario analysis and transport CO_2 emission predictions under different mitigation policies/technologies in fast-growing cities selected from Asia using the established models.

Both China and India contain more than one third of the world's population. In developing Asian countries, they are the two most significant economies that are undergoing fast economic growth, urbanization, and motorization, and they produce large amounts of transport CO_2 emissions, which are expected to remain high in the future. Therefore, it is essential to take Chinese and Indian cities as case study examples in the effort to reduce transport CO_2 emissions in rapidly-growing Asian cities, and for overall global climate change mitigations. In this study, we choose four representative fast-growing cities, namely Beijing, Xian, and Wuhan in China and Bangalore in India for the case study. Since commuting traffic plays a major part in urban transportation (Meyer and Miller, 2001, p. 150), we will take commuting CO_2 emissions as the object in the models.

The established model for commuting CO_2 emissions in the four selected cities can be applied in the majority of rapidly-developing cities, with large and dense populations, fast economic growth, motorization, and urban developments. Also, the model can help understanding the characteristics and the key factors of transport CO_2 emissions in fast-growing cities. Based on the model results, scenario analysis and transport CO_2 emission predictions, with different mitigation policies/technologies, can help measuring these policies' effects and identifying the key actions needed for reducing the emissions.

The remainder of this paper is organized as follows. In the second section, we will discuss previous research on transport CO_2 emission impact factors and transport CO_2 emission forecasting models. Then, we will state our study objectives and approaches. In the third section, we will briefly introduce present urban developments and future planning in the four selected fast-growing cities from Asia and the process of data collections. In the fourth section, we will illustrate the method for establishing transport CO_2 emission models and analyze the model results. In the fifth section, we will conduct future scenario analyses, establish prediction models, and analyze the tendencies of transport CO_2 emissions under different urban and transport policies, and energy improvement technologies. In the sixth section, we will illustrate the study's limitations and future work. The last section provides the conclusions of this study.

2. Literature review

Relationships among mono/polycentricity, travel behaviors and transport CO_2 emissions have attracted researchers' considerable interests. Many studies found that a city's polycentrism have impacts on travel behaviors and transport CO_2 emissions. In North America and Europe, related studies are mainly focused on the metropolitan or regional scales and these areas are dominated by decentralized developments (Ding et al., 2018; Yang et al., 2012; Schwanen et al., 2001; 2003). On the one hand, some researchers found positive effects of polycentric pattern on promoting eco-friendly travel patterns and reducing transport CO_2 emissions (Knaap et al., 2016; Cirilli and Veneri, 2014; Grunfelder et al., 2015; Veneri, 2010). On the other hand, some studies show polycentrism's moderate and negative effects on the sustainable transport development (Burgalassi and Luzzati, 2015; Lee and Lee, 2014; Marie-Hélène et al., 2003; Schwanen et al., 2001; 2003; Cervero and Wu, 1998; Giuliano and Small, 1993). Car dependence, lack of public bus and non-motorized modes are the major issues in suburban travel patterns in U.S. metropolitan areas (Atash, 1994; Prevedouros and Schofer, 1991). Also, travel patterns in Toronto, Cologne, and Adelaide have similar characteristics, with the highest GHG emissions existing in suburbs, due to more private car usage (Scheiner and Holz-Rau, 2013; Vandeweghe and Kennedy, 2007; Soltani and Allan, 2006).

Despite the above mixed results, some studies in rapidly-developing Chinese cities in the urban area tend to produce consistent and optimistic findings of polycentricity's effects on the sustainable travel behaviors. Compared with developed and decentralized western countries, these cities have much different urban forms and travel patterns in terms of compactness, high densities, heavy traffic and increased motorization (Huang et al., 2018; Yang et al., 2018; Wang and Lin, 2014). In the case study of the polycentric city of Wuhan and the monocentric city of Xi'an, Wuhan has three centers in three towns, which are separated by two big rivers since city's original formation. Wuhan has shorter commute distances in the outer areas, less car mode use, more non-motorized mode use, more intra-commutes inside the subcenters, and more transit use in the inter-commutes among the subcenters (Yang et al., 2018). In

Beijing, the outer suburbs or satellite cities are characterized by independent and self-contained developments, and there exist more intra-commutes and fewer transport CO_2 emissions (Yang et al., 2019). By using aggregate data from 164 Chinese cities, Sun et al. (2016) found that higher degree of polycentricism brings about smaller average commute time.

However, these studies are limited and lack quantitative analysis of transport CO_2 emission changes due to developing polycentricity and satellite cities. Meanwhile, rapid growths in economic development, vehicle ownership, urban population, and urban sprawl exist in rapidly-developing Asian cities. Will these factors still increase transport CO_2 emissions a great extent in the context of developing polycentricity and satellite city? This question needs to be further examined.

Presently, faced with technologies of new energy types, energy efficiency improvements and metro promotions, and continuously fast economic, motorization and urban growths, many scholars forecast and make scenario analysis of transport CO_2 emissions under different policies and technologies in rapidly-developing Asian countries and cities, to find ways for reducing transport CO_2 emissions. A majority of these studies use vehicle population, vehicle kilometers travelled (VKT), and GDP or per capita income to estimate the future trends of CO_2 emissions from on-road transport (Li et al., 2016; Gambhir et al., 2015; Huo et al., 2007; Wang et al., 2007; He et al., 2005). In addition, some researchers also consider the population factor (Wang et al., 2017a; Yin et al., 2015) and the impacts of industry production in their estimations (Wang et al., 2014; Ramanathan and Parikh, 1999).

But these studies are mainly focused in the on-road transport CO_2 emissions, not in the scope of residents' urban transport CO_2 emissions. Factually, residents' urban transport CO_2 emissions are the significant part in transport sector so they deserve more attention when trying to achieve lower carbon transport development in urban areas (He et al., 2013). Also, the registered vehicle population in the city could not reflect their real numbers on road (He et al., 2013). Thus, it is necessary and important to establish residents' urban transport CO_2 emission models and make scenario analyses under different policies and technologies for future trends in fast-growing Asian cities.

Up until now, there is limited research focused on the residents' urban transport CO_2 emission estimations. Among these current research, they use average trip frequency, average trip distance, and population factors for the estimations, and their scenario design considers the factors of technologies of new energy types, energy efficiency improvement, and transport policies of traffic demand management (TDM) or transit promotion (Ma et al., 2015; Dhar and Shukla, 2015; He et al., 2013). Also, some studies have designed a combined scenario of TDM, transit promotion and polycentricity, and the results show that polycentricity has less significant influences on future emissions (Li et al., 2018). However, according to the empirical studies in Chinese cities, developing polycentricity and satellite cities will produce statistically significant influences on low-carbon travel behaviors and patterns (Yang et al., 2018; 2019; Sun et al., 2016). This indicates that we still need to further model and quantify the effects of urban form factors (polycentricity and satellite city) on future resident urban transport CO_2 emission changes. What's more, single and combined effects of urban form, new energy technologies and transport policies, and their comparisons are also important for decision makings to reduce transport CO_2 emissions.

In summary, this study will establish transport CO_2 emission model in the four selected rapidly-developing Asian cities to quantify polycentricity and satellite city's effects. Also, considering new energy technologies, transport and urban form policies, future scenarios of CO_2 emissions will be forecasted in the scope of residents' urban transport based on the model. Since residents' socio-economic characteristics, household location, city's economic factors and metro services will all have influences on transport CO_2 emissions (Yang et al., 2019; Wang et al., 2017b; Yang et al., 2017; Shen et al., 2016; Kaika and Zervas, 2013), all these factors will be examined in our modeling process.

3. Overview of the four case cities and data collection

3.1. The four typical case cities

The four typical case cities are chosen from China and India. China and India are home to more than one third of the world's population and are experiencing rapid economic and transport developments. These two countries are the focus in transport CO_2 emission mitigations. In China, the capital city of Beijing and two provincial cities of Wuhan and Xi'an, located in the eastern, middle, and western part of the inland, respectively, are chosen for this study. They are typical fast-growing Chinese cities in terms of location feature, economic level, city grading, and historical protection. In India, the rapidly-developing city of Bangalore is chosen for this study. Bangalore is located in the southern part of the inland and is famous for information technology (IT) industries, and is known as 'Asia's Silicon Valley'. Bangalore is an example of a quickly growing inland mega city in India in the aspects of economics and urban development. The size of the urban areas, the population, per capita GDP, and city GDP in the four cities are shown in Table 1. Brief introductions of the four case cities are shown in Table 2, including city's location and grade, economic and motorization developments, mono/polycentric pattern, urban form and sprawl, and future planning. The main industry areas, activity centers, road networks, and sampled households in the four case cities are shown in Fig. 1.

Among developing Asian cities, each one has its own unique factors such as socio-economic characteristics, culture, climate or population behavior, so only studying these four case cities in China and India may be not enough. However, these four typical Chinese and Indian cities can represent the general situations of urban developments in developing Asia to some degree.

3.2. Data collections

Household surveys were implemented in the urban areas of Beijing, Xi'an, Wuhan, and Bangalore in the years of 2010, 2012, 2010, and 2011–2012, respectively. We use a statistical method for determining the sample size (Meyer and Miller, 2001, p. 633).

Table 1
Areas by ring roads, urban built-up areas, population, per capita GDP, and city GDP for the four case cities.

	Areas by ring roads (RR) (km^2)						Urban built-up areas (km^2)
	1st RR	2nd RR	3rd RR	4th RR	5th RR	6th RR	
Beijing		62.5	159.1	300.2	664.8	2325.8	1268
Xi'an	12.3	74.5	347.3				522
Wuhan	44.62	137.93	522.69				520
Bangalore	15.65	203.35	493.97				741
	Total population (million)		Population in the main urban area (million)		Per capita GDP (1,000 US$)		City GDP (10 Billion US$)
Beijing	21.7		12.8		11.218		23.52
Xi'an	8.6		4.5		8.14		7.28
Wuhan	10.12		5.46		10.563		9.28
Bangalore	9.58		5.83		8.664		8.30

Note: The data in Beijing, Xi'an, Wuhan, and Bangalore refers to the years of 2010, 2012, 2010, 2011–2012, respectively, when the household surveys were conducted.

The equation is detailed stated in Wang et al. (2017b) and Yang et al. (2017, 2018, and 2019). Simple random samplings were implemented in the districts and counties, or traffic zones, in Beijing, Xi'an, Wuhan, and Bangalore by Renmin University of China, Chang'an University of China, Wuhan University of China, and the Indian Institute of Science, respectively. In total, we surveyed 1400 households and 1915 commuters in Beijing, 1501 households and 2449 commuters in Xi'an, 1194 households and 2050 commuters in Wuhan, and 1967 households and 3934 commuters in Bangalore. All four cities' sample sizes exceed the required minimum observations suggested by the statistical method in Meyer and Miller (2001, p. 633). The surveyors were well trained before the survey and conducted face-to-face inquiries within households. The contents of the household survey questionnaires consist of the commuting distance, commuting mode, commuter's workplace, household location, and housing tenure. Additionally, household and commuter socio-economic characteristics were investigated, including car availability, household income, commuter age, work unit type, and educational background.

The distributions of the sampled households in the four case cities are shown in Fig. 1, and the statistical results of the sampled households and commuters are shown in Table 3. The ring roads in the four case cities have differences, and this will cause different statistics of household locations separated by ring roads. In Bangalore, India, there are two ring roads outside the CBD, namely Outer Ring Rd. and Peripheral Ring Rd. Household locations are defined as the separations by the above two ring roads and the CBD area, with three categories. In Beijing, China, there are five ring roads, ranging from the 2nd Ring Rd. to the 6th Ring Rd., and household locations are divided into six categories, according to the order of the five ring roads. In Xi'an and Wuhan, China, there are three ring roads, ranging from the 1st Ring Rd. to the 3rd Ring Rd., and household locations are divided into four categories, according to the order of the three ring roads.

4. Commuting CO_2 emission model and results

4.1. Commuting CO_2 emission calculation and statistical results

The method proposed by IPCC for transport CO_2 emission calculations is used in this study. It is suggested that the commuting CO_2 emissions are equal to the CO_2 emission factor (by mode, fuel type, and occupancy) multiplied by commuting trip distance (IPCC 1997). The equation is detailed and stated in Wang et al. (2017b) and Yang et al. (2017 and 2019). Based on the research by Huo et al. (2012), we obtain the Well-To-Wheel (WTW) CO_2 emission intensities for different fuel types. For electricity-driven traffic modes (metro/electric-bicycle/electric-motorcycle), the data of CO_2 intensity consider different types of electricity generation (thermal power/ hydropower/ wind power) among the four case cities (NDRCC, 2011). We collect local data of fuel consumptions and vehicle occupancies, and their ranges in the four case cities through surveys. We calculate the range of the CO_2 emission factors by mode, vehicle type, and fuel type. The calculation results of the commuting CO_2 emission factors in the four case cities are shown in Table 4. In this study, we use the average values of the commuting CO_2 emission factors to calculate the four case cities' household and individual commuting CO_2 emissions.

Table 5 and Fig. 2 show the descriptive statistics, percentiles, and cumulative percentages of the commuting CO_2 emissions in the four case cities. The results manifest that the more-developed city of Beijing has the largest commuting CO_2 emission levels, especially for the top 20% of the high emitters. The average commuting CO_2 emissions turn out to be the smallest in the polycentric city of Wuhan, with generally lowest levels of emissions for all percentiles, seen in Fig. 2 (a).

As shown in Fig. 2 (b), for the three Chinese cities, the top 20% of the high emitters contribute more than 70% of the totals, and for the Indian city of Bangalore, the top 20% of the high emitters contribute more than 50% of the totals, and the top 30% of the high emitters contribute about 70% of the totals. These characteristics indicate that in the four case cities, high emitters make up smaller percentages of urban residents, but their transport CO_2 emission productions are greater, and much more attention should be paid to decrease their emissions.

Table 2
Brief descriptions of the four case cities.

City	Location and Grade	Economic and Motorization	Mono/Polycentric Pattern	Descriptions of Urban Form and Sprawl	Future Planning
Beijing	Eastern inland, mega and capital city of China; Political, economic, and cultural center of China	Beijing's population, economics, motor cars, and urban areas have increased greatly in recent decades. In recent years, Beijing implemented the lottery policy of buying private car to slow its increasing. It shows the desired effect when compared to other Chinese mega cities' rapidly increased motorizations.	Monocentric pattern	The city sprawled from the 2nd Ring Rd. to the 6th Ring Rd., with Tian'anmen Square as the city center. Inside the 2nd Ring Rd., or downtown area, numerous historic sites, and several business centers exist. Outside the downtown area, several high-tech industry development zones can be found. Outside the 6th Ring Rd., some satellite cities exist in the outer suburbs.	Beijing plans to dispel non-capital functions, to control the population size and its fast-increasing tendency, to build city sub-centers in Tongzhou district, and new towns and satellite cities in the outskirts, to develop more metro networks, and to develop more electric vehicles and buses. As Beijing-Tianjin-Hebei urban agglomeration and Xiong'an town develop, there will be faster economic growth, larger activity scales of urban residents, and more transportation and interactions in these districts.
Xi'an	Western inland central city of China; One of world's oldest cities	Xi'an has seen rapid increases in economic growth, urbanization, and motorization in recent decades.	Monocentric pattern	The city sprawled from the 1st Ring Rd. to the 3rd Ring Rd., with Bell Tower as the city center. Plenty of historic sites, and business centers are located inside the 1st Ring Rd., or downtown area, and three high-tech industry development zones are located outside the 2nd Ring Rd. There are controls on land developments inside the 1st Ring Rd., due to the large quantity of the historic landmarks. These characteristics in Xi'an are similar to the majority of cities with important history and fast developments.	Xi'an plans on developing polycentric urban forms, building new towns and satellite cities outside the main urban area, providing more metro coverage, developing more electric vehicles and buses, and developing into the nation's central city with historical and cultural characteristics. Xi'an is the central city of the national Guanzhong plain urban agglomeration, causing Xi'an to have faster urban growths including economics, motorization, urban residents' activity scales, and transportation, now and in the future.
Wuhan	Middle inland central city of China; Central city in the Yangtze River economic zone	Wuhan has seen rapid increases in economic growth, urbanization, and motorization in recent decades.	Polycentric pattern with three centers in Hankou, Hanyang, and Wuchang, which are separated by the Yangtze River and the Han River.	Wuhan has three outspread ring roads, and industry development zones are in the outer areas, which are similar to other Chinese cities. However, Wuhan is unique because it implemented polycentric forms from the beginning of its development. The Yangtze and Han Rivers separate this city into three towns naturally: Wuchang, Hankou, and Hanyang. Due to the city separated by two rivers, industry and self-contained developments exist inside each of the three towns from the beginning of the urban developments. The geographical separation and the limited capacity of the bridges formulated wedge-shaped urban growths in each of the three towns.	Wuhan will continue its polycentric pattern, developing new towns and satellite cities in the outskirts, developing more electric vehicles and buses, and expanding the metro network. Wuhan is the central city of the urban agglomeration in the middle reaches of Yangtze River, and is now planning to build a new town to develop a Yangtze River spindle. Implementations of these plans in the future will result in greater economic growths, larger activity scales of urban residents, and more transportation in Wuhan.
Bangalore	Southern inland central city of India;Asia's Silicon Valley	Bangalore has seen rapid increases in economic growth, urbanization, and motorization, especially huge two-wheelers, in recent decades. The IT industries contribute a great deal to its economic prosperity.	Monocentric pattern	Bangalore also builds outspread ring roads. Commercial centers and governmental offices are located inside the central business district (CBD) area. Outside this area, there are high-tech industry development zones along the Outer Ring Road or in the outside areas.	In the future, Bangalore plans to develop a polycentric urban pattern, promoting IT industry and its associated industries locally, expanding the metro network, and developing more electric vehicles and buses. Consequently, there will be more private cars, especially a great deal of two-wheelers, larger activity scales of urban residents, and more transportation in Bangalore.

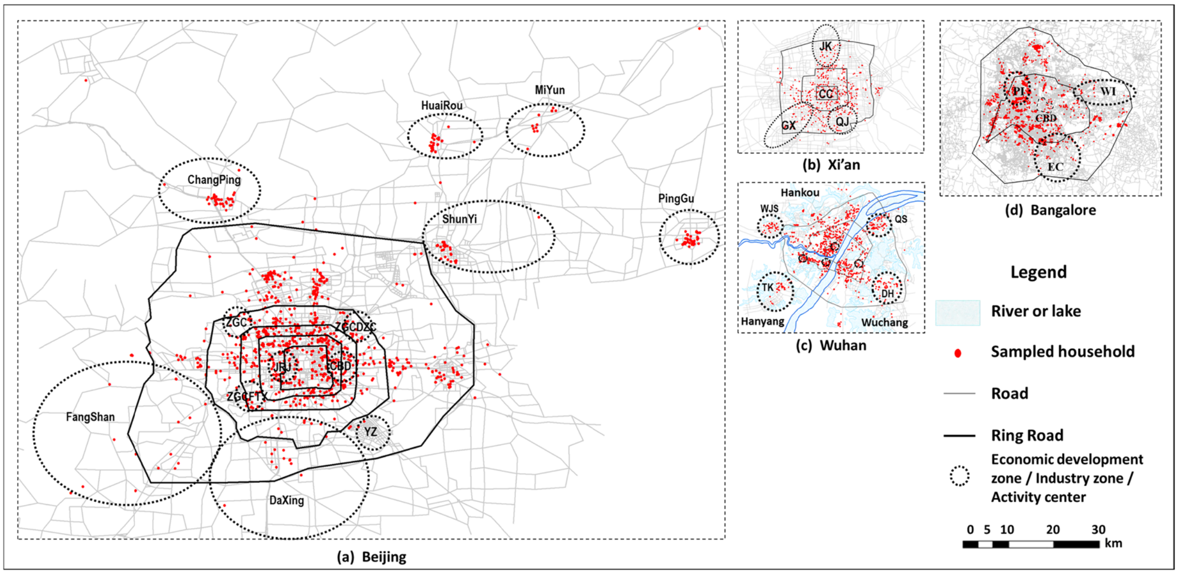


Fig. 1. Main industry areas, activity centers, road networks, and sampled households in the four case cities.

Table 3
Statistical results of the characteristics of the sampled households and commuters in four case cities.

	Levels	Total N	Beijing N	(%)	Xi'an N	(%)	Wuhan N	(%)	Bangalore N	(%)
Age	< 35 years old	2529	676	36.29%	971	49.74%	335	17.2%	547	13.9%
	35–55 years old	6659	1062	57.00%	907	46.47%	1571	80.8%	3119	79.3%
	greater than55 years old	468	98	5.26%	64	3.28%	38	2.0%	268	6.8%
Work unit type	Government	947	175	9.39%	78	4.00%	101	5.3%	593	19.9%
	Public institution	1683	538	28.88%	407	20.85%	504	26.7%	234	7.8%
	Foreign company	336	104	5.58%	26	1.33%	54	2.9%	152	5.1%
	Private company	2657	587	31.51%	869	44.52%	443	23.5%	758	25.4%
	State-owned company	1153	341	18.30%	314	16.09%	415	22.0%	83	2.8%
	Others	1820	69	3.70%	213	10.91%	372	19.7%	1166	39.0%
Education level	Middle school graduate	883	123	6.60%	149	7.63%	289	14.9%	322	8.5%
	Graduated from the high school or technical secondary school	2465	367	19.70%	377	19.31%	615	31.7%	1106	29.3%
	Graduated from college	1672	381	20.45%	478	24.49%	400	20.6%	413	10.9%
	Bachelor's degree	3483	774	41.55%	789	40.42%	529	27.2%	1391	36.8%
	Master's degree	828	186	9.98%	125	6.40%	91	4.7%	426	11.3%
	Ph.D. degree	185	27	1.45%	20	1.02%	19	1.0%	119	3.2%
Household traffic vehicles	Household car availability	2844	461	42.10%	507	40.89%	461	38.6%	1415[a]	71.9%[a]
Household annual income	< US$2,000	223	13	1.19%	3	0.24%	10	0.9%	197	10.0%
	US$2,000–6,000	1266	143	13.06%	51	4.11%	233	21.7%	839	42.7%
	US$6,000–10,000	1253	212	19.36%	246	19.84%	414	38.6%	381	19.4%
	US$10,000–20,000	1874	421	38.45%	778	62.74%	305	28.4%	370	18.9%
	US$20,000–40,000	587	262	23.93%	114	9.19%	86	8.0%	125	6.4%
	> US$40,000	150	41	3.74%	29	2.34%	25	2.3%	55	2.8%
Housing tenure	House owner occupied	3025	897	79.59%	992	80.00%	–	–	1136	58.2%
	House is rented	1234	230	20.41%	187	15.08%	–	–	817	41.8%
Household location by ring roads	Inside the 1st Ring Rd. / CBD	233			76	6.13%	145	12.1%	12	0.6%
	1st / CBD – 2nd / Outer Ring Rd.	1770			376	30.32%	432	36.2%	962	48.9%
	2nd / Outer – 3rd / Peripheral Ring Rd.	2136			734	59.19%	409	34.3%	993	50.5%
	Outside the 3rd / Peripheral Ring Rd.	262			54	4.35%	208	17.4%		
	Inside the 2nd Ring Rd.	84	84	7.67%						
	2nd – 3rd Ring Rd.	198	198	18.08%						
	3rd – 4th Ring Rd.	181	181	16.53%						
	4th – 5th Ring Rd.	136	136	12.42%						
	5th – 6th Ring Rd.	247	247	22.56%						
	Outside the 6th Ring Rd.	203	203	18.54%						

Note: (a) The car availability of the households in Bangalore's questionnaires includes both cars and two-wheelers; two-wheelers account for 77.1% of these two types of vehicles in Bangalore (BT, 2015).

Table 4
Well-To-Wheel CO_2 emission factors by fuel type, traffic mode, and vehicle type in the four case cities.

Mode	City	Fuel Type	WTW CO_2 Intensity (tons CO_2 eq./unit of fuel)[a]	Fuel Consumptions Per 100 km[b]	Vehicle Occupancy (passengers/ vehicle)[c]	WTW CO_2 Emission Factor (kg/passenger/km)	Average WTW CO_2 Emission Factor (kg/passenger/km)
Car	Beijing	Gasoline	3.87/ton	8.58 ~ 10.45 (L)	1 ~ 3	0.081 ~ 0.295	0.188
	Xi'an/Wuhan	Gasoline	3.87/ton	7.80 ~ 10.45 (L)	1 ~ 3	0.073 ~ 0.295	0.184
	Bangalore[d]	Gasoline	3.87/ton	1.23 ~ 10.45 (L)	1 ~ 3	0.032 ~ 0.184	0.067
Routine coach	Beijing/Xi'an/Wuhan	Diesel	3.94/ton	39.12 ~ 42.38 (L)	20 ~ 50	0.027 ~ 0.072	0.050
Taxi	Beijing/Xi'an/Wuhan	CNG	2.76/1000 m^3	8 ~ 10 (m^3)	2 ~ 5	0.044 ~ 0.138	0.091
	Bangalore	Gasoline	3.87/ton	7.80 ~ 10.45 (L)	2 ~ 5	0.044 ~ 0.148	0.096
Bus[e]	Beijing	Diesel	3.94/ton	39 ~ 42 (L)	80 ~ 100	0.013 ~ 0.020	0.017
		CNG	2.76/1000 m^3	52 ~ 58 (m^3)	80 ~ 100	0.013 ~ 0.020	0.017
	Xi'an	CNG	2.76/1000 m^3	52 ~ 58 (m^3)	60 ~ 100	0.014 ~ 0.027	0.021
	Wuhan	Diesel	3.94/ton	39 ~ 42 (L)/	60 ~ 100	0.013 ~ 0.027	0.020
		CNG	2.76/1000 m^3	52 ~ 58 (m^3)	60 ~ 100	0.013 ~ 0.027	0.020
	Bangalore	Diesel	3.94/ton	36 ~ 39 (L)	30 ~ 50	0.024 ~ 0.044	0.034
Metro	Beijing	Electricity	1.246/1000 kWh[f]	3400 ~ 3430 (kWh)[g]	1100 ~ 1600	0.026 ~ 0.039	0.033
	Xi'an	Electricity	0.83/1000 kWh[f]	3340 ~ 3350 (kWh)[g]	1100 ~ 1600	0.017 ~ 0.025	0.021
	Wuhan	Electricity	0.801/1000 kWh[f]	3340 ~ 3350 (kWh)[g]	1100 ~ 1600	0.017 ~ 0.024	0.021
Electric-bicycle[h]	Beijing	Electricity	1.246/1000 kWh	1.1 ~ 1.25 (kWh)[i]	1 ~ 2	0.007 ~ 0.016	0.012
	Xi'an	Electricity	0.83/1000 kWh	1.1 ~ 1.25 (kWh)	1 ~ 2	0.005 ~ 0.010	0.008
	Wuhan	Electricity	0.801/1000 kWh	1.1 ~ 1.25 (kWh)	1 ~ 2	0.004 ~ 0.010	0.007
Electric-motorcycle[j]	Beijing	Electricity	1.246/1000 kWh	1.6 ~ 1.7 (kWh)[i]	1 ~ 2	0.010 ~ 0.021	0.016
	Xi'an	Electricity	0.83/1000 kWh	1.6 ~ 1.7 (kWh)	1 ~ 2	0.007 ~ 0.014	0.011
	Wuhan	Electricity	0.801/1000 kWh	1.6 ~ 1.7 (kWh)	1 ~ 2	0.006 ~ 0.014	0.010

Note: (a) Data is from Huo et al. (2012). (b) Data are from Liu and Hou (2009), Huo et al. (2011), Zhang et al. (2014); and the fuel consumptions consider the factor of vehicle speed in peak hours. (c) Data come from Beijing Transport Development Annual Reports in 2010 (BTRC, 2010), Xi'an Transport Development Annual Reports in 2012 (XCTMCCU, 2012), Wuhan Transportation Annual Reports in 2012 (WLRPB & WTDSI, 2012), and the field surveys of four cities. (d) In Bangalore's questionnaires of the travel mode, car and two-wheeler are combined in one choice option, thus the CO_2 emission factor of car or two-wheeler is weighted by proportions of car and two-wheeler, which are 22.9% for cars and 77.1% for two-wheelers (BT, 2015); the average value of CO_2 emission factor for car and two-wheeler is 0.067 kg/passenger/km. (e) Buses in Beijing and Wuhan are partly driven by diesel, and the CO_2 emission factor of buses in Wuhan is weighted by the percentages of the diesel buses and CNG buses. (f) Data is from the 'Guidelines for the Provincial Greenhouse Gas Inventory [2011]1041' (NDRCC, 2011). These data consider different types of electricity generation (thermal power/hydropower/wind power) among the cities; (g) Data is collected from the survey data of the electricity consumption during the metro operations in Beijing, Xi'an, and Wuhan. (h) The maximum speed of the electric-bicycle is 20 km/h. (i) Data are from National Standard of the People's Republic of China, GB17761-1999: Electric bicycles - General technical requirements, issued by China State Bureau of Quality and Technical Supervision, and the surveys of electric-motorcycle users. (j) The maximum speed of the electric-motorcycle is more than 20 km/h.

Table 5
Descriptive statistics of individual and household commuting CO_2 emissions in the four case cities.

City	Individual Commuting CO_2 Emissions (kg/per trip)				Household Commuting CO_2 Emissions (kg/household trips)			
	mean	min	max	s.d.	mean	min	max	s.d.
Xi'an	0.284	0.000	2.327	0.450	0.447	0.000	3.957	0.648
Wuhan	0.241	0.000	2.815	0.471	0.419	0.000	5.630	0.755
Beijing	0.681	0.000	5.640	1.082	1.158	0.000	9.024	1.699
Bangalore	0.414	0.000	2.400	0.454	0.549	0.000	3.595	0.564

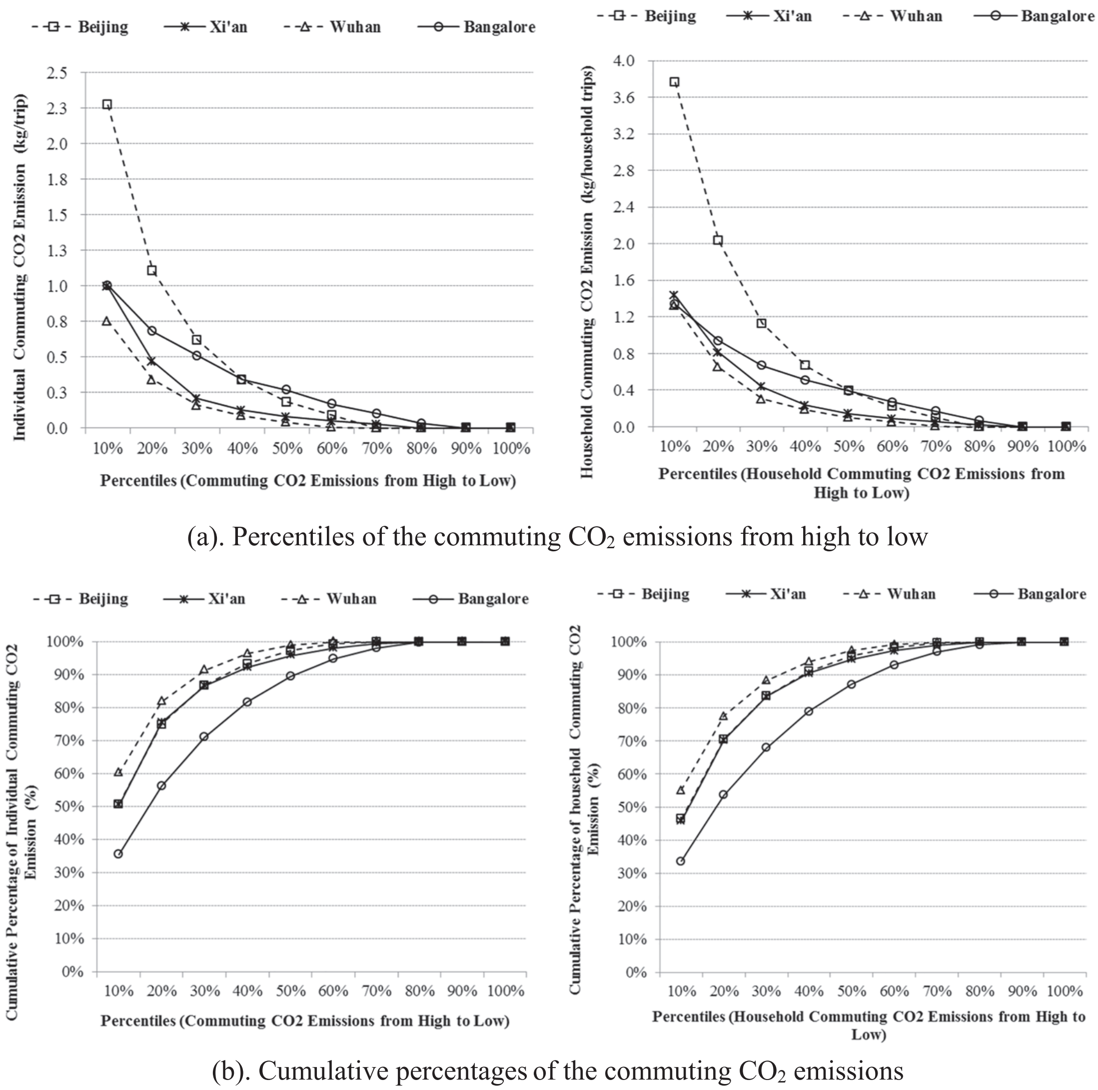


Fig. 2. Percentiles and cumulative percentages of the commuting CO_2 emissions in the four case cities.

4.2. *Tobit modeling method for commuting CO_2 emissions*

We analyze the distributions of the household and individual commuting CO_2 emissions in the four typical fast-growing cities, and it is found that they do not conform to the normal distributions. Since the household and individual commuting CO_2 emissions are left censored at zero, Tobit models with Tobit maximum likelihood estimation methods (Wooldridge, 2012, p. 597) are applied to establish commuting CO_2 emission model and to identify the key factors for the commuting CO_2 emissions in the four case cities. The Tobit model is shown in Equation (1):

$$y_i = \begin{cases} x'_i\beta + \varepsilon_i & if \quad y_i^* = x'_i\beta + \varepsilon_i > 0, \\ 0 & if \quad y_i^* = x'_i\beta + \varepsilon_i \leqslant 0. \end{cases} i = 1, 2, \cdots, N \tag{1}$$

where y_i is the dependent variable, referring to the observed household/individual commuting CO_2 emissions; y_i^* is the latent variable, which cannot be observed; x_i' is a vector of independent variables, including the impact factors of the commuting CO_2 emissions; β is a vector of estimable parameters; N is the number of observations; and ε_i is the random error.

4.3. Research hypotheses and variables in the models

Hypothesis 1:. *We assume that polycentrism will have statistically significant effects on reducing the commuting CO_2 emissions. The dummy variable of whether a city is polycentric or not will be added in the models. In our models, polycentric city refers to Wuhan. This city has one city center and two subcenters, namely the three towns of Hankou, Hanyang, and Wuchang. These three towns are separated by two big rivers since city's formation and are connected by nine bridges and one tunnel. The population in two subcenters of Hanyang and Wuchang take up more than* 40% *of the total, and the trips attracted to the center and two subcenters are about* 48%, 34%, *and* 18% *of the total trips, respectively* (Yang et al., 2018). *The commerce, education, medical care, and public affairs in two subcenters can provide sound services for their residents.*

Hypothesis 2:. *Planning and developing satellite cities are widely applied among rapidly-developing megacities during their urban expansions. It is assumed that commuters located in the satellite cities are associated with smaller commuting CO_2 emissions. A dummy variable, whether commuters are located in the satellite city or not, will be used to reflect the commuting CO_2 emission changes in the satellite cities.*

We consider that a satellite city should have high levels of job-housing balances and a certain degree of size. In this paper, the size of a satellite city is suggested to be larger than 10 km^2 and there is a largest share of job-housing balanced trips, which take up more than 40% of the total trips in the satellite city. In FangShan, ChangPing, HuanRou, ShunYi, PingGu, MiYun and DaXing districts of Beijing, the intra-district commute trips take up more than 60%. These areas are considered as satellite cities in our models. The dummy variable equals to one when commuters are in the above districts. In Wuhan, Xi'an, and Bangalore, we do not find high levels of job-housing balanced trips with more than 40% of the total trips in the surveyed urbanized areas. Thus, dummy variables all equal to zero in these three cities.

Hypothesis 3:. *We intend to examine the adjustment effects of polycentricity on the increased transport CO_2 emissions caused by the high emitters* (*car availability, high income, and households located in the sprawling areas of the city*). *The interaction terms will be added in the models. We assume that polycentric urban forms will reduce the increasing emissions driven by the high emitters.*

Hypothesis 4:. *The interaction terms of satellite city and socio-economic factors will also be considered in the models. We assume that located within the satellite city will reduce the increasing emissions produced by high emitters with car availability and high income.*

Hypothesis 5:. *Due to metro's high potential for providing urban transportation services, plenty of rapidly-developing cities have begun constructing metro lines* (Wang et al., 2013). *Our previous researches show that distances from household to the nearest metro station are not statistically significant factors in reducing transport CO_2 emissions* (Yang et al., 2019; Wang et al., 2017b; Yang et al., 2017). *On the one hand, this may be correlated with the average higher household income in the households near the metro stations. Additionally, longer traveling time when using metros, as opposed to private vehicles, is another possible reason* (Yang et al., 2019). *Besides, the variable of the distance from household to the nearest metro station is disaggregated at the individual and household levels, and in this study, we propose to use an aggregate variable at the city level, a dummy variable of whether metro service exists, to re-examine metro effects in the four case cities. We assume the coefficient of this dummy variable will be negative.*

Hypothesis 6:. *The city's economic growth plays a major role in the transport CO_2 emission increases in developing countries* (Shuai et al., 2018; Timilsina and Shrestha, 2009). *Many researchers find that the city's economics and transport CO_2 emissions are not always linear in relationship and there exits an inverted U-shaped relationship between the level of environmental degradation and economic growth. This inverted U-shaped relationship is identified as the Environmental Kuznets Curve* (*EKC*) *hypothesis* (Kaika and Zervas, 2013; Dinda, 2004). *The economic growth factor can be reflected by per capita income or alternatively per capita GDP* (Kaika and Zervas, 2013). *By using panel data, time-series data or cross-sectional data, many studies choose different countries, periods of time, econometric techniques, and variables to test this EKC hypothesis. However, mixed empirical results and sometimes controversial findings are obtained* (Omri et al., 2015; Kaika and Zervas, 2013; Ozcan, 2013; Coondoo and Dinda, 2008; Azomahou et al., 2006; Jha, 1997). Azevedo et al. (2018) *suggests that the relationship between environmental degradation and economic growth should be examined on a case-by-case basis. Therefore, this study intends to further examine fast-growing cities' economic growth effects on transport CO_2 emissions. We will identify whether they have a positive, negative, or nonlinear relationship in the models. City's per capita GDP and its quadratic and cubic terms will be added in the models. According to the EKC hypothesis, we suppose the coefficient of per capita GDP to be positive, its quadratic term's coefficient to be negative, and its cubic term's coefficient to be zero.*

Based on the Tobit models in Equation (1), the dependent variables in the models are household/individual commuting CO_2 emissions, and the independent variables include dummy variable of mono/polycentric city, dummy variable of whether commuters are located in the satellite city or not, interaction terms of polycentric city and socio-economic factors and household locations, interaction terms of commuters located in the satellite city and socio-economic factors, per capita GDP and its quadratic and cubic terms, and dummy variable of whether the city has metro services or not. Meanwhile, a set of control variables of socio-economic and household location factors will also be included in the models.

4.4. Unifying household locations separated by ring roads

Urban sprawl by ring roads is the most common characteristic in rapidly-growing cities, and previous studies have found that household locations separated by ring roads are statistically significant factors in explaining the commuting CO_2 emissions (Yang et al., 2018; 2019; Wang et al., 2017b; Yang et al., 2017). Since Beijing has a different number of ring roads compared with the other three case cities, the variables of household location separated by ring roads in the four case cities should be unified in the modeling process. Furthermore, in order to apply the model in other cities, average distances from the ring roads to the city centers, or the radiuses of the areas covered by the ring roads, would be better indexes to indicate the locations of the ring roads or travelers' household locations.

In the three typical cities of Beijing, Xi'an, and Wuhan, the average distances from the 2nd Ring Roads to cities' centers are quite similar, about 5~6 km. The average distance from the Outer Ring Road to the city center in Bangalore is about 8 km. Thus, we define a variable of household location inside the ring road with a 5~8 km radius to represent household located in the inner area of the city near the city center.

The average distance from the 4th Ring Road to the city center of Tian'anmen Square in Beijing is about 10 km, and the average distance from the 3rd Ring Rd. to the city center of Bell Tower in Xi'an, to the city center of Wuhan Yangtze Grand Bridge in Wuhan are about 10.5 km and 13 km, and the average distance from Peripheral Ring Rd. to the CBD of Bangalore is about 12.5 km, respectively. Therefore, in Beijing, we combine the variable of household location between the 2nd and 3rd Ring Rd. and the variable of household location between the 3rd and 4th Ring Rd. into one variable. Then, we define a variable of household location between the ring road with a 5~8 km radius and the ring road with a 10~13 radius to represent household located outside the inner area of the city.

Similarly, the variable of household location outside the 3rd / 4th / Peripheral Ring Rd. in the four case cities is defined as 'Outside the ring road with 10~13 km Radius' to represent household located in the outer area of the city. Table 6 shows the definitions of the unified variables of the household locations separated by ring roads.

4.5. Model results and analysis

Table 7 show the results of Tobit model for commuting CO_2 emissions in the four case cities. For the urban form factors, the coefficients of the polycentric city and commuters located in the satellite cities are both negative and statistically significant (-0.147 and −1.185 in the household emission model; −0.190 and −0.835 in the individual emission model). This manifests that polycentric cities are associated with smaller emissions than monocentric cities, and commuters located in the satellite cities emit smaller emissions. These results confirm our 1st and 2nd hypothesis.

The effects of the dummy variable of a city having metro services or not are statistically significant in the models. Both coefficients in the household and individual commuting CO_2 emission models turn out to be negative and statistically significant (−0.203 and −0.158 in the household and individual models, respectively). This manifests that generally metro constructions can reduce the commuting CO_2 emissions, and this aggregate variable at the city level can better explain the general reduction of commuting CO_2 emissions than the disaggregate variable of the distances from household to metro stations. This result indicates that our 5th hypothesis is tenable.

The effects of polycentricity's interaction terms on the commuting CO_2 emissions are also statistically significant. The results show that when the factor of a polycentric city interacts with the socio-economic factors and household location factors, their effects on increasing the commuting CO_2 emissions decrease significantly, and some even turned out to be negative. The coefficients of the interactions of polycentric city and car availability decrease to 0.455 and 0.212 in the household and individual models, respectively, compared to 0.664 and 0.524 when a polycentric urban form does not exist. For the factors of household income, when they interact with the polycentric city, their coefficients also decrease significantly. Specifically, the coefficients of the interactions of the polycentric city and household annual income of more than US $20,000 turn out to be negative and are statistically significant in the household and individual models (−0.692 and −0.266 for the incomes between US $20,000 and $40,000; −0.756 and −0.278 for incomes higher than US $40,000). If a polycentric urban form does not exist, their coefficients are positive, much larger, and statistically significant (0.904 and 0.449 for the incomes between US $20,000 and $40,000; 1.349 and 0.698 for the incomes higher than US $40,000). Also, the factor of a polycentric city can greatly reduce the effects that households located in the outer areas contribute to the commuting CO_2 emission increases. The coefficients of the interactions of polycentric city and household located outside the ring road with 10~13 km Radius are both negative and statistically significant in the household and individual emission models (−0.564 and −0.327); however, if a polycentric urban form does not exist, their coefficients are 0.548 and 0.315.

The coefficients of the interactions of satellite cities and socio-economic characteristics also indicate the reduced effects on the increase of commuting CO_2 emissions. The coefficients of the interactions of satellite cities and car availability decrease to 0.205 and 0.052 in the household and individual models, respectively. Besides, the coefficients of the interactions of satellite cities and household income of more than a US $20,000 drop to be negative and statistically significant (−0.285 and −0.097 for income between US $20,000 and $40,000; −1.435 and −0.942 for income more than US $40,000). These results prove that our 3rd and 4th hypotheses are tenable.

The reason that commuters located in the context of polycentric urban forms and satellite cities tend to produce smaller

Table 6
Unified variables of the household locations separated by ring roads and their definitions.

Unified household location separated by ring roads	Beijing	Xi'an	Wuhan	Bangalore
Inside the ring road (RRd.) with 5–8 km Radius	inside the 2nd Ring Rd.	inside the 2nd Ring Rd.	inside the 2nd Ring Rd.	inside the Outer Ring Rd.
Between the ring roads (RRd.) with 5–8 km Radius and 10–13 km Radius	2nd − 4th Ring Rd.	2nd − 3rd Ring Rd.	2nd − 3rd Ring Rd.	Outer - Peripheral Ring Rd.
Outside the ring road (RRd.) with 10–13 km Radius	Outside 4th Ring Rd.	Outside 3rd Ring Rd.	Outside 3rd Ring Rd.	Outside Peripheral Ring Rd.

Table 7
Tobit model results for commuting CO_2 emissions.

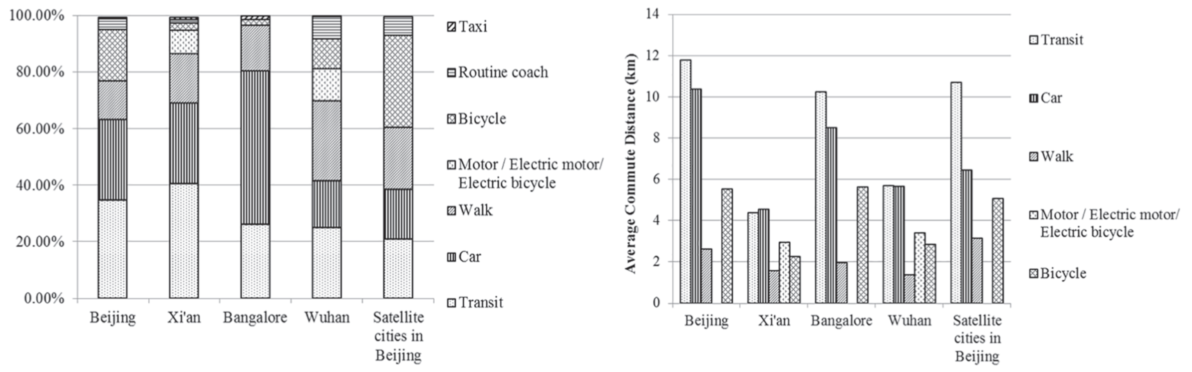
	Household Model (kg/household trips)	Individual Model (kg/per trip)
Polycentric City	−0.147**	−0.190***
	(−1.97)	(−4.08)
Household Car Availability	0.664***	0.524***
	(23.41)	(29.02)
Household Annual Income		
US $6,000–10,000	−0.022	−0.0300
	(−0.59)	(−1.17)
US $10,000–20,000	0.252***	0.102***
	(5.70)	(3.76)
US $20,000–40,000	0.904***	0.449***
	(9.85)	(9.26)
> US $40,000	1.349***	0.698***
	(5.39)	(5.45)
Household Location		
Between RRd. with 5~8 km R and 10~13 km R	−0.015	0.00219
	(−0.51)	(0.12)
Outside RRd. with 10~13 km R	0.548***	0.315***
	(5.52)	(5.82)
Polycentric City*Household Car Availability	0.455***	0.212***
	(5.10)	(4.31)
Polycentric City*US $6,000–10,000	0.108	0.0973**
	(1.47)	(2.10)
Polycentric City*US $10,000–20,000	−0.0431	0.0587
	(−0.49)	(1.11)
Polycentric City*US $20,000–40,000	−0.692***	−0.266***
	(−3.79)	(−2.73)
Polycentric City* > US $40,000	−0.756**	−0.278
	(−2.12)	(−1.46)
Polycentric City*Between RRd. with 5~8 km R and 10~13 km R	0.0846	0.0464
	(1.31)	(1.19)
Polycentric City*Outside RRd. with 10~13 km R	−0.564***	−0.327***
	(−4.45)	(−4.70)
Satellite City	−1.185***	−0.835***
	(−6.79)	(−7.54)
Satellite City*Household Car Availability	0.205	0.052
	(0.95)	(0.38)
Satellite City*US $6,000–10,000	0.460*	0.359**
	(1.90)	(2.29)
Satellite City*US $10,000–20,000	0.439**	0.329**
	(2.07)	(2.41)
Satellite City*US $20,000–40,000	−0.285	−0.097
	(−0.78)	(−0.40)
Satellite City* > US $40,000	−1.435***	−0.942**
	(−4.20)	(−2.08)
City GDP (10 Billion US$)	0.013***	0.006***
	(4.71)	(3.61)
City Has Metro	−0.203***	−0.158***
	(−4.77)	(−6.08)
Obs.	5243	8111
F	80.73	110.53
Prob > F	0.000	0.000
Log Likelihood	−6681.02	−8075.14
Pseudo R^2	0.152	0.145

Note: (a). Data in parentheses are t statistics; (b). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

commuting CO_2 emissions can be mainly contributed to the shorter commute distances and more environmentally friendly transport mode uses, which can be illustrated in Fig. 3.

The polycentric city of Wuhan has lower carbon travel patterns. There are shorter commute distances and more non-motorized mode shares. Also, in the satellite cities of Beijing, the car-trip distances are much shorter than the average level in Beijing, and travelers use more non-motorized modes. While, the average transit-trip distance in the satellite cities is more than 10 km. It draws our attention that the rapidly continuous urban sprawl and the fast developments of rails or metro lines to the suburbs or satellite cities may attract more commuters working in the urban central areas (Yang et al., 2019). This indicates that satellite cities should foster industries during the development process.

The model results show that the effects of the control variables of city's GDP, commuters' socio-economic and household location factors on the commuting CO_2 emissions are similar to the previous study results: city's GDP and car availability has positive effects



(a) Commute mode shares (b) Average commute distances

Fig. 3. Commute mode shares and average commute distances in the four case cities. (Note: The car mode in Bangalore's questionnaires includes both cars and two-wheelers, and two-wheelers account for 77.1% of these two types of vehicles in Bangalore (BT, 2015)).

on the emission increases (Shuai et al., 2018; Wang et al., 2017b; Yang et al., 2017; 2019); commuters with higher household incomes are responsible for higher emissions (Brand et al., 2013; Ko et al., 2011; Brand and Preston, 2010); commuters located in the sprawling areas of the cities produce larger emissions than those located in the inner areas (Wang et al., 2017b; Yang et al., 2017; 2019; Büchs and Schnepf, 2013; Ko et al. 2011).

Table 8 shows the model results when adding the quadratic and cubic terms of per capita GDP. The results show that highly positive correlations exist between the commuting CO_2 emissions and economic growths in the four case cities. All four cities' per capita GDPs (see Table 1) are larger than the turning points of the quadratic equations in household and individual models (US $5,159 and US $5,636, respectively). These indicate a faster increasing speed of the commuting CO_2 emissions compared with that of per capita GDP growths. Also, the calculation results show that the elasticities of household and individual commuting CO_2 emission to per capita GDP are 1.90% and 1.45%, respectively. These results manifest that, presently, transport CO_2 emissions in the four case cities are experiencing faster growths in contrast with economic growths.

Our finding shows the statistically significant nonlinear quadratic growth relationship between transport CO_2 emissions and per capita GDP. This is because, the decreasing effects of per capita GDP's quadratic terms on the commuting CO_2 emissions may be replaced by the variable of existence of metro services, which probably better explain commuting CO_2 emission reductions than the continuous economic growth factor. The reason may stem from the ability to construct metro systems when economic data reaches a higher level, and metro network will be gradually formed.

5. Residents' transport CO_2 emission predictions

5.1. Baseline results

Table 9 shows the estimation results of resident transport CO_2 emissions in the urban areas of the four case cities in the survey year. The baseline estimation method is shown in Equation (2):

$$CO2_i = TripRate_i \times UrbanPop_i \times EPT_i \times 365 \tag{2}$$

where $CO2_i$ is the residents' urban transport CO_2 emissions in city i for the baseline year; $TripRate_i$ is urban resident average trip rate (trips per day) in city i; $UrbanPop_i$ is urban population in city i; EPT_i is the average residents' urban transport CO_2 emissions per trip, derived from the statistical results of the residents' urban transport CO_2 emission calculations in city i in Table 5.

The results show that Wuhan has the lowest level of residents' urban transport CO_2 emissions. Compared with the similar fast-growing provincial city of Xi'an, Wuhan's lower emissions are mainly due to its polycentric urban form. For the more-developed city of Beijing, the residents' urban transport CO_2 emissions turn out to be the largest, reaching nearly 8 times of the other two typical provincial cities, which is mainly caused by its more-developed economics, greater urban and population expansions, and motorization levels. In Bangalore of India, higher transport CO_2 emission levels exist than the similar rapidly-developing cities in China, mainly due to much more motorized two-wheeler uses and longer travel distances.

5.2. Scenario development and prediction method

According to transport and urban development tendencies, governmental policies, and technology improvement trends for transport CO_2 emission reductions in recent decades, we develop seven multi-dimensional scenarios for the potential future developments in fast-growing cities: (i). business as usual (BAU); (ii). development of polycentric urban forms (P); (iii). development of satellite cities (S); (iv). metro network promotion (M); (v). energy efficiency improvement (EI); (vi). electric vehicle promotion (EV); and (vii). electric public bus promotion (EPB). The short-term period for the transport CO_2 emission predictions are from 2010 to

Table 8
Models with the quadratic terms of per capita GDP.

	Household Model (kg/household trips)	Individual Model (kg/per trip)
Polycentric City	−0.129	−0.138***
	(−1.56)	(−2.68)
Household Car Availability	0.897***	0.643***
	(23.50)	(28.39)
Household Annual Income		
US $6,000–10,000	0.160***	0.0958***
	(4.28)	(3.62)
US $10,000–20,000	0.389***	0.201***
	(8.65)	(7.18)
US $20,000–40,000	0.889***	0.459***
	(10.12)	(9.69)
> US $40,000	1.321***	0.713***
	(5.45)	(5.67)
Household Location		
Between RRd. with 5~8 km R and 10~13 km R	0.126***	0.0897***
	(4.42)	(4.71)
Outside RRd. with 10~13 km R	0.456***	0.274***
	(4.70)	(5.10)
Polycentric City*Household Car Availability	0.218**	0.0915*
	(2.37)	(1.81)
Polycentric City*US $6,000–10,000	−0.0756	−0.0290
	(−1.04)	(−0.62)
Polycentric City*US $10,000–20,000	−0.181**	−0.0408
	(−2.08)	(−0.77)
Polycentric City*US $20,000–40,000	−0.678***	−0.277***
	(−3.77)	(−2.86)
Polycentric City* > US $40,000	−0.730**	−0.294
	(−2.08)	(−1.56)
Polycentric City*Between RRd. with 5~8 km R and 10~13 km R	−0.0566	−0.0413
	(−0.88)	(−1.06)
Polycentric City*Outside RRd. with 10~13 km R	−0.473***	−0.286***
	(−3.79)	(−4.13)
Satellite City	−1.047***	−0.738***
	(−6.14)	(−6.76)
Satellite City*Household Car Availability	−0.0334	−0.069
	(−0.16)	(−0.50)
Satellite City*US $6,000–10,000	0.274	0.232
	(1.14)	(1.48)
Satellite City*US $10,000–20,000	0.297	0.228*
	(1.42)	(1.68)
Satellite City*US $20,000–40,000	−0.275	−0.110
	(−0.76)	(−0.45)
Satellite City* > US $40,000	−1.414***	−0.957**
	(−4.22)	(−2.13)
City Has Metro	−0.120***	−0.122***
	(−2.75)	(−4.63)
Per Capita GDP (1,000 US$)	−0.227***	−0.124***
	(−11.67)	(−11.13)
Square of Per Capita GDP	0.022***	0.011***
	(10.94)	(10.13)
Obs.	5243	8111
F	74.51	113.38
Prob > F	0.000	0.000
Log Likelihood	−6584.67	−7991.25
Pseudo R^2	0.165	0.154

Note: (a). Data in parentheses are t statistics; (b). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; (c). The coefficients of cubic term of per capita GDP are zeros and they are omitted in the model results.

2020, in order to be in accordance with the implemented transport and urban planning to 2020 in the three Chinese cities and the Indian city of Bangalore. The middle-term and long-term periods for the transport CO_2 emission predictions are 2020 to 2035 and 2035 to 2050. The definition and values of the parameters in the seven scenarios are shown in Table 10.

(i). Business-as-Usual (BAU): The parameters in the BAU scenario include the growth rates of motor vehicles, residents' annual income, GDP, urban activity radius/urban areas, urban population and residents' average trip rate in short-term and long-term periods. These changes' effects on the individual transport CO_2 emissions are calculated according to the estimated coefficients in the individual Tobit model (Table 7). The BAU scenario does not consider emission reduction policies or technologies. In other scenarios, transport CO_2 emission predictions are based on the BAU scenario, meanwhile adding related parameters' changings in terms of

Table 9
Baseline results of resident transport CO_2 emission estimations in the main urban areas of the four case cities.

City	Urban Resident's Average Trip Rate (trips/day)[a]	Population in the Main Urban Area (million)	Average Resident Transport CO_2 Emissions Per Trip[b] (kg/trip)	Resident Transport CO_2 Emission Estimations in the Urban Areas (million ton) (Baseline Results)
Xi'an	2.540	4.50	0.284	1.185
Wuhan	2.410	5.46	0.241	1.157
Beijing	2.538	12.80	0.681	8.075
Bangalore	1.415	7.30	0.414	1.561

Note: (a). Xi'an's trip rate data is from Xi'an Transport Development Annual Reports in 2012 (XCTMCCU, 2012); Wuhan's trip rate data is from Wuhan Transportation Annual Reports in 2011 (WLRPB & WTDSI, 2011); Beijing's trip rate data is from Beijing Transport Development Annual Reports in 2011 (BTRC, 2011); Bangalore's trip rate data is from Bangalore Mobility Indicators Report 2011–2012 (DULT, 2011). (b). Data come from the statistical results of the commuting CO_2 emission calculations in the four case cities in Table 5.

urban and transport development policy and new energy technology from the short-term to the long-term periods.

(ii). Polycentric Urban Form Development (P): The parameter in this scenario is defined by the realization rate of future polycentric urban forms, which is calculated based on the population percentage of city's sub-center. In our model, polycentric urban forms are reflected by the dummy variable, which refers to the fact that Wuhan city is polycentric, while the other three cities are monocentric. Since Wuhan's sub-center population percentage takes up more than 40%[2], the realization rate of the polycentric urban forms equals to one when the sub-center population percentage reaches 40%. If the populations in the subcenters have great differences from those in the central areas (< 5% of the total population), we will consider the city as a monocentric urban form. Besides, sub-centers can attract working, commercial, and medical care activities to a high extent, otherwise the areas are the sprawls of a monocentric city.

(iii). Satellite Cities Development (S): The parameter in this scenario is defined as the realization rate of future satellite city developments. Satellite cities have the characteristics of job-housing balance in great extents. In our forecast model, if the intra-district commute trip share reaches 40%, the parameter value equals to one. The parameter values in the year of 2015 are calculated according to the intra-district commute trip percentages. The parameter values all equal to one in the year of 2035 according to the four cities' master plans, and will increase progressively from 2015 to 2035.

(iv). Metro Network Promotion (M): The parameter in this scenario is defined by whether a city has metro services or not. The parameter value equals to one if the city has metro services.

(v). Energy Efficiency Improvement (EI): The parameter in this scenario is defined as traditional energy efficiency (fossil fuels) improvement percentage per five-years, referencing the recent research on the energy efficiency by Hao et al. (2017).

(vi). Electric Vehicle Promotion (EV): One parameter in this scenario is determined by the future electric vehicle percentages per five-years, derived from the data in the low carbon emission planning, automobile industry planning, and mobility planning in the four case cities. Another parameter in this scenario is fuel-cycle CO_2 emission factor of EVs. The present value is about 10% lower than conventional cars (Huo et al., 2012). The values in the future years reference the researches by Huo et al. (2010) and will decrease progressively, being 20% lower by 2050.

(vii). Electric Public Bus Promotion (EPB): In this scenario, there are three parameters: one is future electric public bus percentages per five-years, the next is public bus mode share, and the third parameter is the fuel-cycle CO_2 emission factor of EVs, which is similar to that in the EV scenario. The first parameters' values are derived from the data in the new energy vehicle development plan and public bus development plan in the four case cities. The second parameters' values are determined by the tendencies of the public bus mode share changes in recent years, derived from the four case cities' annual transport development reports. According to the decreasing trends of the bus shares and the increasing tendencies of the metro shares in the four cities' transport development reports, we assume that the mode share of public buses in the future years will not have a significant increase.

The residents' urban transport CO_2 emission prediction method for the future scenarios in the four case cites is shown in Equation (3):

$$CO2_{i,t,s} = TripRate_{i,t} \times UrbanPop_{i,t} \times EPT_{i,t,s} \times 365 \tag{3}$$

where $CO2_{i,t,s}$ is the estimation of residents' urban transport CO_2 emissions in city i of year t for scenario s; $TripRate_{i,t}$ is urban residents' average trip rate (trips per day) in city i of year t; $UrbanPop_{i,t}$ is urban population in city i of year t; $EPT_{i,t,s}$ is the average residents' urban transport CO_2 emissions per trip in city i of year t for scenario s. The changes of $TripRate_{i,t}$ and $UrbanPop_{i,t}$ are estimated according to their growth rate tendencies in city i in recent years. The changes of $EPT_{i,t,s}$ under various future scenarios are estimated according to the parameters of the Tobit model for the individual commuting CO_2 emissions (shown in Table 7), and the growing tendencies of GDP, residents' annual income, urban activity radius/urban areas, and motor vehicles in the four case cities, meanwhile considering the governments' urban and transport planning policies (polycentricity, satellite city, metro promotion), and changing tendencies of energy efficiency improvement and EV and EPB promotion planning.

We also make predictions for developing Asian countries according to the four case cities' average changing tendencies in

[2] Apart from Wuhan, subcenters' population in some Chinese megacities also reach about 40%. In Shanghai, population in the five districts of Pudong, Hongkou, Yangpu, Minxing, and Baoshan, which are planned to be city's subcenters, take up 47% of the total in the year of 2017 (SMBS, 2018); In Hangzhou, population in the districts of Xiaoshan and Yuhang, planned to be city's subcenters, take up 38% of the total in the year of 2018 (HMBS, 2019).

Table 10
The definition and values of the parameters in the seven scenarios.

Scenario[a]	Parameter Definition	Parameter Value Description
Business as Usual (BAU)	Annual car growth	The annual growth rates are 3.33%, 13.14%, 13.11%, and 10.47% in Beijing, Wuhan, Xi'an and Bangalore, respectively, calculated based on Beijing Transport Annual Report of 2018 (BTRC, 2018), Wuhan Transport Annual Report of 2018 (WLRPB & WTDSI, 2018), Xi'an Statistical Yearbook 2015–2018 (XMBS, 2016-2019), and Bangalore's vehicle statistics/annual reports (TDK, 2019).
	Annual high-income growth (US $20000-$40000; > US$40000)	The annual growth rates are 8.56%, 9.71%, 10.47%, and 10% in Beijing, Wuhan, Xi'an and Bangalore, respectively, calculated based on Beijing Statistical Yearbook 2018 (BMBS, 2019), Wuhan Statistical Yearbook 2015–2018 (WMBS, 2016–2019), Xi'an Statistical Yearbook 2016–2017 (XMBS, 2017-2018), Mobility for Development, Bangalore of India (TERI, 2008).
	Annual GDP growth	The annual growth rates in Beijing are 9.09% from 2010 to 2020 and 10.00% from 2020 to 2050, calculated based on Beijing Statistical Yearbook 2018 (BMBS, 2019); The annual growth rates are 10.04%, 10.95%, and 10.30% respectively in Wuhan, Xi'an and Bangalore, calculated based on Wuhan Statistical Yearbook 2016–2018 (WMBS, 2017–2019), Xi'an Statistical Yearbook 2018 (XMBS, 2019), and Mobility for Development, Bangalore of India (TERI, 2008).
	Annual urban activity radius growth	The annual growth rates are 2.83% from 2010 to 2020 and 6.01% from 2020 to 2050 in Beijing, 3.53% from 2010 to 2020 and 4.34% from 2020 to 2050 in Wuhan, 3.88% from 2010 to 2020 and 4.30% from 2020 to 2050 in Xi'an, and 2.85% from 2010 to 2020 and 4.50% from 2020 to 2050 in Bangalore, respectively, calculated based on the urban built-up areas in China City Statistical Yearbook 2013–2018 (NBSC, 2014-2019), and Mobility for Development, Bangalore of India (TERI, 2008), Bangalore Mobility Indicators 2010–2011 (DULT, 2011), and Sudhira et al. (2007).
	Annual urban population growth	The annual growth rates are 1.55% from 2010 to 2020 and 2.62% from 2020 to 2050 in Beijing, 2.83% from 2010 to 2020 and 3.11% from 2020 to 2050 in Wuhan, 2.39% from 2010 to 2020 and 3.40% from 2020 to 2050 in Xi'an, and 2.20% from 2010 to 2020 and 3.09% from 2020 to 2050 in Bangalore, respectively, calculated based on Beijing Statistical Yearbook 2018 (BMBS, 2019), Wuhan Statistical Yearbook 2016–2018 (WMBS, 2017-2019), China City Statistical Yearbook 2013–2018 (NBSC, 2014-2019), and Bangalore Mobility Indicators 2010–2011 (DULT, 2011).
	Annual residents' trip rate growth	The annual growth rates are 2.40% from 2010 to 2020 and 3.90% from 2020 to 2050 in Beijing, 2.21% from 2010 to 2020 and 2.60% from 2020 to 2050 in Wuhan, 2.41% from 2010 to 2020 and 3.37% from 2020 to 2050 in Xi'an, and 6.21% from 2010 to 2050 in Bangalore, respectively, calculated based on Beijing Transport Annual Report of 2018 (BTRC, 2018), Wuhan Transport Annual Report of 2018 (WLRPB & WTDSI, 2018), Xi'an Transport Annual Report of 2012 (XCTMCCU, 2012), and Bangalore Mobility Indicators 2010–2011 (DULT, 2011) and Sarath et al. (2019).
Polycentric Urban Form (P)	Realization rate determined by population percentage of the sub-center (Equals to 1 if population% of sub-center greater than 40%)	Population% of four cities' sub-center data refer to Beijing Urban Master Plan 2016–2035 (BMCPNR, 2018), Beijing Sub-Center Control Detailed Planning 2016–2035 (BMCPNR, 2019), Wuhan Urban Master Plan 2017–2035 (WNRPB, 2019), Xi'an Urban Master Plan 2008–2020 (XCPB, 2010), Xi'an High-Tech Industries Development Zone Planning (XHTZMC, 2010), Urban Development Policy for Karnataka (GOK, 2009), and Mobility for Development, Bangalore of India (TERI, 2008). Bangalore's data refers to the similar fast developing city of Xi'an. Based on the above plannings, the realization rates of polycentric urban form are 0.1, 0.12, 0.15, 0.2, 0.25, 0.3, 0.35, and 0.4, respectively in every five-years during 2010–2050 in Beijing; 0.8, 0.85, 0.9, 0.95, 1.0, 1.0, 1.0, and 1.0, respectively in every five-years during 2010–2050 in Wuhan; 0.1, 0.12, 0.15, 0.2, 0.25, 0.3, 0.35, and 0.4 respectively in every five-years during 2010–2050 in Xi'an and Bangalore.
Satellite City Development (S)		Data refer to Beijing Urban Master Plan 2016–2035 (BMCPNR, 2018), Wuhan Urban Master Plan 2017–2035 (WNRPB, 2019),

(*continued on next page*)

Table 10 (*continued*)

Scenario[a]	Parameter Definition	Parameter Value Description
	Realization rate determined by master plan and intra-district commute trip percentage (Equals to 1 in 2035 according to the master plans)	Xi'an Urban Master Plan 2008–2020 (XCPB, 2010), Urban Development Policy for Karnataka (GOK, 2009), and Mobility for Development, Bangalore of India (TERI, 2008). Based on the above plannings, the realization rates of satellite city development are 0.6, 0.7, 0.8, 0.9, 1.0, 1.0, 1.0, and 1.0, respectively in every five-years during 2010–2050 in Beijing; 0.2, 0.4, 0.6, 0.8, 1.0, 1.0, 1.0, and 1.0, respectively in every five-years during 2010–2050 in Wuhan, Xi'an and Bangalore.
Metro Network Development (M)	Equals to 1 if the city has metro service	According to the metro services in Beijing, Wuhan, and Xi'an, the data value is 1.0 during 2010–2050. The metro lines in Bangalore was still under construction during the survey year 2011–2012, thus the data value during 2010–2015 is zero and the data value is 1.0 during 2015–2050.
Energy Efficiency Improvement (EI)	Traditional energy efficiency (fossil fuels) improvement percentage per five-years	Based on the study by Hao et al. (2017), the traditional energy efficiency improvement percentage in Chinese cities is 1% increase every five years, and Bangalore's data referred to the cities in China. To the year of 2050, the traditional energy efficiency improvement percentage is estimated to about 8%.
Electric Vehicle Promotion (EV)[b]	Electric vehicle percentage per five-years	The EV percentages are 2% increase every five years from 1% to 15% during 2010–2050 in Beijing and Wuhan, and 1% increase every five years from 1% to 8% during 2010–2050 in Bangalore, calculated based on Beijing's Battle Plan to Win the Blue Sky (BMG, 2018), Prioritizing the Development of Urban Public Transport in Wuhan (WMG, 2018), and India National Electric Mobility Mission Plan 2020 (GOI, 2012). The EV percentages in Xi'an are 5%, 10%, 20%, 25%, 28%, 30%, 33%, and 35% in every five-years from 2010 to 2025, calculated based on Xi'an Automobile Industry Development Plan 2018–2025 (XMG, 2018).
	Fuel-cycle CO_2 emission factor of EVs	The present value is about 10% lower than the conventional cars (Huo et al., 2012), and in the future years, the values are 10%, 12%, 14%, 15%, 16%, 18%, 19%, and 20% lower in every five-years from 2010 to 2050, calculated based on the research by Huo et al. (2010).
Electric Public Bus Promotion (EPB)[b]	Electric public bus percentage per five-years	The EPB percentage in Beijing is from 10% to 80% during 2010–2050 with the average increase rate of 10% of every five-years, calculated based on the Plans of Development of New Energy Vehicles of Beijing Public Transport (BPTG, 2018); The EPB percentages in Wuhan are 20%, 50%, 70%, 75%, 80%, 85%, 90%, and 90% in every five-years from 2010 to 2025, calculated based on the Opinions on Prioritizing the Development of Urban Public Transport in Wuhan (WMG, 2018); The EPB percentage in Xi'an is from 20% to 90% during 2010–2050 with the average increase rate of 10% of every five-years, calculated based on the Plans of Development of New Energy Vehicles of Xi'an Public Transport (XPTG, 2018); The EPB percentages in Bangalore are 10%, 30%, 50%, 85%, 100%, 100%, 100%, and 100% in every five-years from 2010 to 2025, calculated based on the Implementation Plan for Electrification of Public Bus Transport in Bangalore (CSTEP, 2018).
	Mode share of public bus per five-years	The data in Beijing are 25% during 2010–2035 and 30% during 2030–2050, calculated based on the changing tendency from Beijing Transport Annual Report of 2018 (BTRC, 2018). The data value in Wuhan is from 34% to 40% during 2010–2050 with the average increase rate of about 1% of every five-years, calculated based on the changing tendency from Wuhan Transport Annual Report of 2018 (WLRPB & WTDSI, 2018). The data in Xi'an are 30%, 33%, 36%, 37%, 38%, 39%, 40%, and 40% in every five-years from 2010 to 2050, calculated based on the changing tendency from Xi'an Transport Annual Report of 2012 (XCTMCCU, 2012). The data in Bangalore are 30%, 30%, 32%, 32%, 34%, 34%, 35%, and 35% in every five-years from 2010 to 2050, calculated based on the changing tendency from Bangalore Mobility Indicators 2010–2011 (DULT, 2011).

(a). All the parameters and data in the BAU scenario are also used in other scenarios with urban natural growths and mitigation policy both considered; The annual growth rates after the year 2020 have taken into account the situations of urban agglomeration's fast developments. (b). The data of resident transport CO_2 emission per trip for the EV and EPB scenarios did not consider the transport CO_2 emissions during the battery productions and scraps of EV and EPB.

residents' urban transport CO_2 emissions under various future scenarios. Developing Asian countries include 42 countries in the Central, East, South, and Southeast of Asia, and the Pacific area, which reference the report of Asian Development Outlook 2016 (ADB, 2016)[3]. The calculation method is shown in Equation (4):

$$CO2_{i,t,s} = TripRate_t \times UrbanPop_{i,t} \times EPT_{t,s} \times 365 \tag{4}$$

where $CO2_{i,t,s}$ is the prediction of residents' urban transport CO_2 emission in country i of year t for scenario s; $TripRate_t$ is the average residents' trip rate (trips per day) among the four case cities of year t; $UrbanPop_{i,t}$ is urban population in country i of year t; $EPT_{t,s}$ is the average values of the residents' urban transport CO_2 emissions per trip among the four case cities of year t for scenario s. The urban population data and the growth rates in recent years in developing Asian countries are derived from the dataset of World Development Indicators (WD, 2018).

5.3. Prediction results and analyses

According to the future planning and development tendencies of the four typical fast-growing cities and the model results, we estimate the residents' urban transport CO_2 emissions in the four case cities, China, India, and developing Asian countries under different scenarios. The prediction results in Fig. 4 show that under the cases of six single mitigation policies, residents' urban transport CO_2 emissions will slowly increase. Without mitigation policies, the BAU scenario results show sharp increasing tendencies in the future. For the more-developed city of Beijing, the residents' urban transport CO_2 emissions in 2050 in the BAU scenario will be about 12 times of the base-year level, reaching 184 million tons. Furthermore, in the fast-growing Indian city of Bangalore, the residents' urban transport CO_2 emissions in 2050 in the BAU scenario will be about 41 times that of the base-year emissions, reaching 208 million tons. The average level of residents' urban transport CO_2 emissions in 2050 in the BAU scenario among the four case cities is estimated to reach 144 million tons, nearly 20 times the base-year level. For China, India and developing Asian countries, the estimations in 2050 in the BAU scenario will be approximately 7.4, 8.4, and 8.6 times that of the base-year level, reaching about 4507, 3034, and 12,165 million tons, respectively.

Among the six mitigation scenarios, developing satellite city (S) and polycentric urban forms (P) could generally have the largest effects on mitigating the predicted sharp increases in residents' urban transport CO_2 emissions. Compared with the BAU scenario, their contributions could reduce 75–82% and 51–75%, on average, of the emissions in the four case cities in 2050, respectively. For China, these two policies could reduce about 79% and 64% of the emissions in 2050, respectively. For India, these two policies could reduce about 78% and 58% of the emissions in 2050, respectively. And for developing Asian countries, under the S and P scenarios, about 80% and 64% of the emissions will be reduced in 2050, respectively. Generally, after the implementations of the S or P policies, the residents' urban transport CO_2 emissions in 2050 will be about 2–11 times that of the base-year level.

For the megacity of Beijing, improving energy efficiency (EI) will also have larger effects for mitigating the emission increases, possibly reducing 66% of the emissions in 2050, compared with the BAU scenario; however, in the other three case cities and developing Asian countries, effects of EI are smaller, estimated at an average of 40% and 48% of the reductions in 2050, respectively, compared with the BAU scenario. Under the EI scenario, the residents' urban transport CO_2 emissions in 2050 will be about 4–26 times that of the base-year level.

The scenario analysis results of promotions of electric vehicles (EVs), electric public buses (EPBs), or metro networks (Ms) show that these policies and technologies have similar effects, and their contributions in emission reductions are smaller than scenarios of P and S. EV, EPB, or M policies could reduce approximately 43–62% of the emissions in the four case cities, 55–57% in China, 52–54% in India, and 55–57% in developing Asian countries in 2050, compared with the BAU scenario[4]. Under the EV, EPB, or M scenarios, the residents' urban transport CO_2 emissions in 2050 will be about 4–13 times that of the base-year level.

Fig. 5 shows the estimations under two combined scenarios. We find that P + S are the most effective policy combinations in mitigating transport CO_2 emissions' sharp increases in the future. This combination's contribution could reduce 83–96% of the emissions in the four case cities, 88% in China, 85% in India, and about 88% in developing Asian countries in 2050, compared with the BAU scenario. After the implementations of P + S policy, the residents' urban transport CO_2 emissions in 2050 will be about 1.4–5 times the base-year level.

The next effective policy combinations are S + M or S + EI, showing on average to reduce 80% of the emissions in 2050. After the implementations of S + M or S + EI policy, the residents' urban transport CO_2 emissions in 2050 will be about 2.1–7 times the base-year level.

Thirdly, combined scenarios of P + M or P + EI could on average reduce about 63% of the emissions in the four case cities, 61% in China, 66% in India, and 67% in developing Asian countries in 2050, compared with the BAU scenario. After the implementations of P + M or P + EI policy, the residents' urban transport CO_2 emissions in 2050 will be about 3.5–11 times the base-year level.

[3] Developing Asian country includes: Armenia, Azerbaijan, Georgia, Kazakhstan, Kyrgyz Republic, Tajikistan, Turkmenistan, Uzbekistan (Central Asia); China, Korea Republic, Mongolia (East Asia); Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka (South Asia); Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, Philippines, Singapore, Thailand, Vietnam (Southeast Asia); Fiji, Kiribati, Marshall Islands, Micronesia, Fed. Sts., Nauru, Palau, Papua New Guinea, Samoa, Solomon Islands, Timor-Leste, Tonga, Tuvalu, Vanuatu (The Pacific).

[4] EV and EPB could reduce averagely 52% and 52.2% of the emissions in the four case cities, 55.3% and 56% in China, 52.1% and 52.4% in India, and 55.3% and 56% in developing Asian countries in 2050, compared with the BAU scenario, respectively.

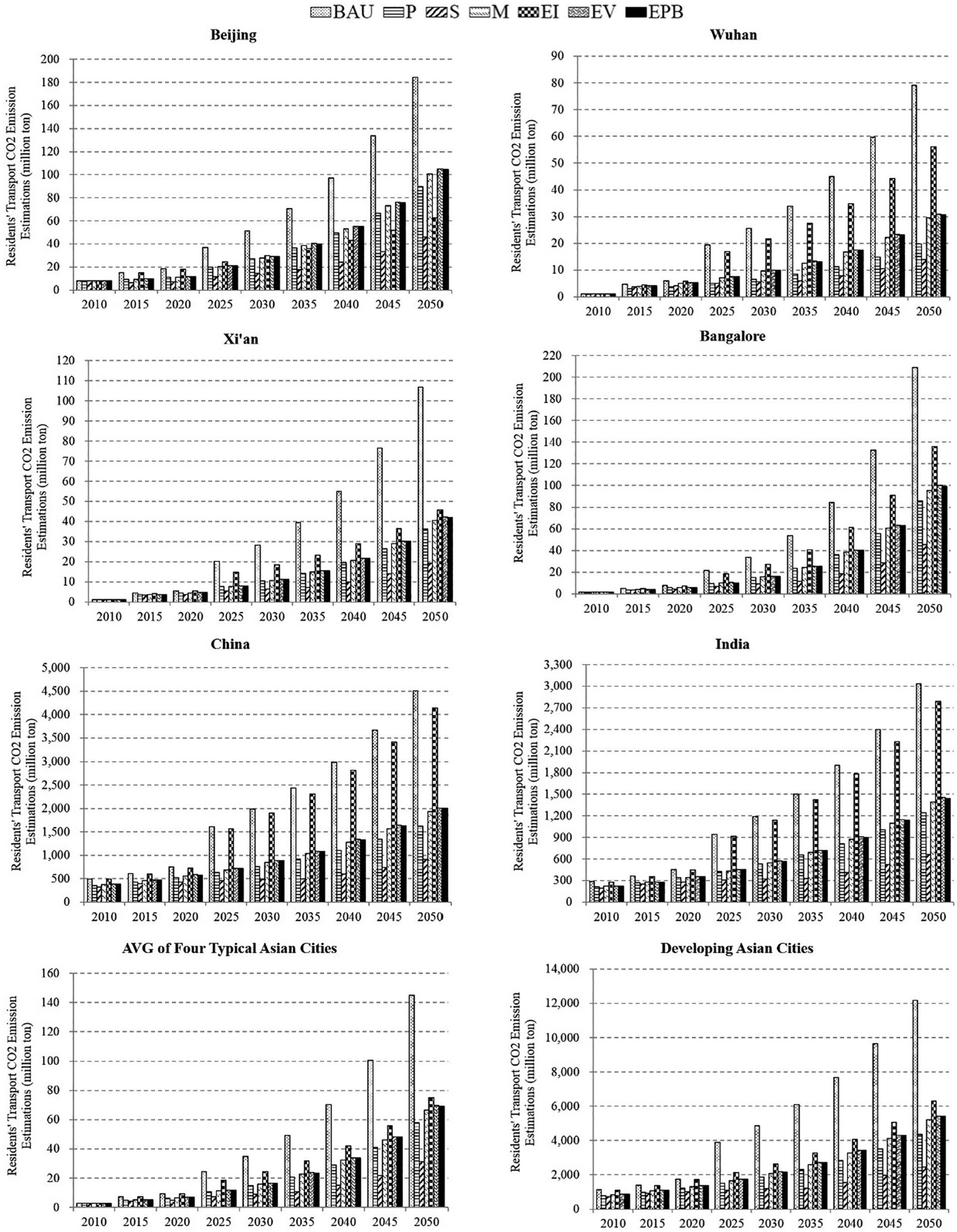


Fig. 4. Residents' urban transport CO_2 emission predictions under seven single scenarios.

Finally, in the combined scenario of EV + EPB or M + EI, their effects could reduce an average of about 55% of the emissions in the four case cities, 58% in China, 55% in India, and 58% in developing Asian countries in 2050, compared with BAU scenario. After the implementations of EV + EPB or M + EI policy, the residents' urban transport CO_2 emissions in 2050 will be about 4–12 times that of the base-year level.

Between 2025 and 2035 in Wuhan, the emissions in a P + S scenario will decrease a lot. This is due to the smallest residents'

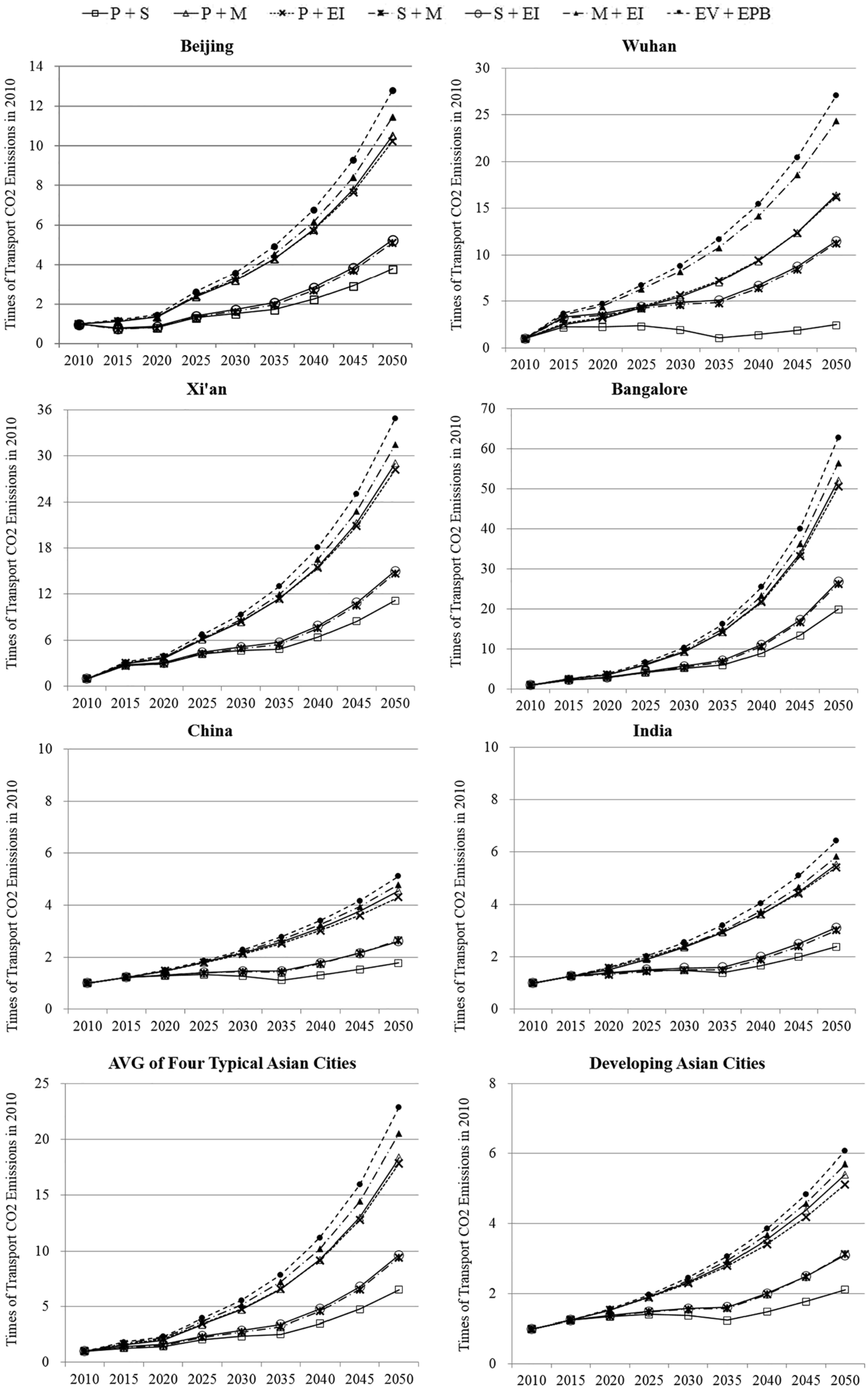


Fig. 5. Times of residents' urban transport CO_2 emissions compared to the year 2010, under two combined scenarios.

urban transport CO_2 emissions per trip in Wuhan in the base year and its decreasing tendency, caused by higher realization ratios of both polycentric urban forms and satellite city development. Therefore, the effects of the increasing economics, travel demands, and urban expansions on emission increases between 2025 and 2035 can be offset by the effects of higher realization ratios of P + S policies. After the realization of polycentric urban forms and satellite city development in 2035, specified in the master plan, the emissions will continue to increase but at a slower pace.

Between 2025 and 2035 in China, India, and developing Asian countries, the emissions in a P + S scenario will also have a slight decrease. This is mainly due to the smaller and continuously decreasing residents' urban transport CO_2 emissions per trip in this scenario, which are calculated using the four case cities' average levels. The effects of the increasing urban population and travel demands on the emission increases between 2025 and 2035 can be offset by the effects of a P + S policy.

Fig. 6 shows the estimations under three or more combined scenarios. We can find that the six combined scenarios with P + S policies (P + S + M, P + S + EI, P + S + EV + EPB, P + S + M + EI, P + S + M + EV + EPB, P + S + M + EI + EV + EPB) have similar effects and are most effective in mitigating transport CO_2 emissions' sharp increases in the future. Their contributions could bring about 84–98% of the emission reductions in the four case cities, 89–92% in China, 86–88% in India, and 89–92% in developing Asian countries in 2050, compared with the BAU scenario. After the implementations of combined policies with P + S, the residents' urban transport CO_2 emissions in 2050 will be about 1.2–4.9 times of the base-year level.

The next effective policy combinations are those scenarios with developing satellite cities (S + M + EI, S + EV + EPB), averagely reducing 75–85% of the emissions in the four case cities, 80–83% in China, 78–81% in India, and 80–83% in developing Asian countries in 2050, compared with the BAU scenario. After the implementations of combined policies of S + M + EI or S + EV + EPB, the residents' urban transport CO_2 emissions in 2050 will be about 2.1–7 times that of the base-year level.

Thirdly, the scenario combinations with developing polycentric urban forms (P + M + EI, P + EV + EPB) could reduce 52–78% of the emissions in the four case cities, 64–68% in China, 59–64% in India, and 64–68% in developing Asian countries in 2050, compared with the BAU scenario. After the implementations of combined policies of P + M + EI or P + EV + EPB, the residents' urban transport CO_2 emissions in 2050 will be about 3.6–11 times the base-year emissions.

Lastly, the combined scenarios of M + EV + EPB or EI + EV + EPB could averagely reduce about 57% of the emissions in the four case cities, 58% in China, 55% in India, and 58% in developing Asian countries in 2050, compared with the BAU scenario. After the implementations of combined policies of M + EV + EPB or EI + EV + EPB, the residents' urban transport CO_2 emissions in 2050 will be about 4–12 times the base-year level.

Similarly, as the prediction results show in Fig. 5, the emissions in the six combined scenarios with P + S policies (P + S + M, P + S + EI, P + S + EV + EPB, P + S + M + EI, P + S + M + EV + EPB, P + S + M + EI + EV + EPB) will decrease a lot between 2025 and 2035 in Wuhan city and have mild decreases in China, India, and developing Asian countries.

Overall, developments of satellite cities and polycentric urban forms are the most effective urban development policies in mitigating the sharp increases of transport CO_2 emissions, compared with metro network promotion, energy efficiency improvement, and EV and EPB promotions. This result is due to the fact that development of satellite cities and polycentric urban forms can greatly reduce high emitters' emissions, which can be concluded from the model results in Table 7. Since the characteristics of the high emitters are car availability, high income, and households located in the sprawling areas of the cities, the percentages of high emitters and their emissions in the future years will increase to large extents with the economics, population, motor vehicles, and urban expansions increase under the BAU scenario. Therefore, when high emitters' transport CO_2 emissions decrease, there will be a greater reduction in the city's total quantities. This could be realized by reduced travel distances and increases of more eco-friendly mode uses under the context of satellite cities and polycentricity. Wuhan city's smaller transport CO_2 emissions and slower increasing tendency in future years provide an empirical reference.

The effect of energy efficiency improvements on emission reduction is about 26% larger in the more-developed megacity of Beijing than other three fast-growing cities. This could possibly be related to the city's master plan, with controlled development policies in future years allowing little increase of the urban population (controlling the urban population increasing limit) and limiting the number of motor vehicles (lottery policy of buying private cars).

To mitigate the sharp increases in transport CO_2 emissions in rapidly-developing cities, it is necessary and effective to develop job-housing balanced satellite cities and form polycentric patterns. Further, if these two urban development policies combined with metro network promotion, energy-related technology improvement, and new energy applications, the effects of transport CO_2 emission reductions will become greater.

5.4. Prediction comparisons with other related work

We use the Tobit method to establish commuting CO_2 emission models and a bottom-up prediction method to estimate the future residents' urban transport CO_2 emissions in fast-growing cities. These are different from previous literatures. Thus, we compare our estimation results with the estimated data listed in the IEA website (IEA, 2019) and World Energy Outlook (IEA, 2018), and some estimation results from existing studies in China and India. Generally, our approach shows reasonable estimations compared with other studies.

Our results also have some differences from the previous results, and we make explanations in the followings. Under the combined scenario of EI + EV + EPB in 2030, our estimations of residents' urban transport CO_2 emissions in China and India and in Asia Pacific are smaller than the on-road transport CO_2 emissions estimated from IEA in their sustainable development scenario (Fig. 7). The differences lie in that our estimations include residents' urban transport CO_2 emissions and transport CO_2 emissions from metros, while the data from IEA's estimations refer to the scope of all on-road transport including cargo transportation.

In Table 11, under the advanced scenario of TDM, transit city and polycentric form, the estimation results in 2020 and 2030 (540 Mt and 590 Mt) in Li et al.'s study, (2018) are larger than our results of the average level of P + M, P + S, and S + M scenarios (420.54 Mt and 509.19 Mt), and their estimation scope is similar to ours. This is probably due to that there is a lack of satellite city's

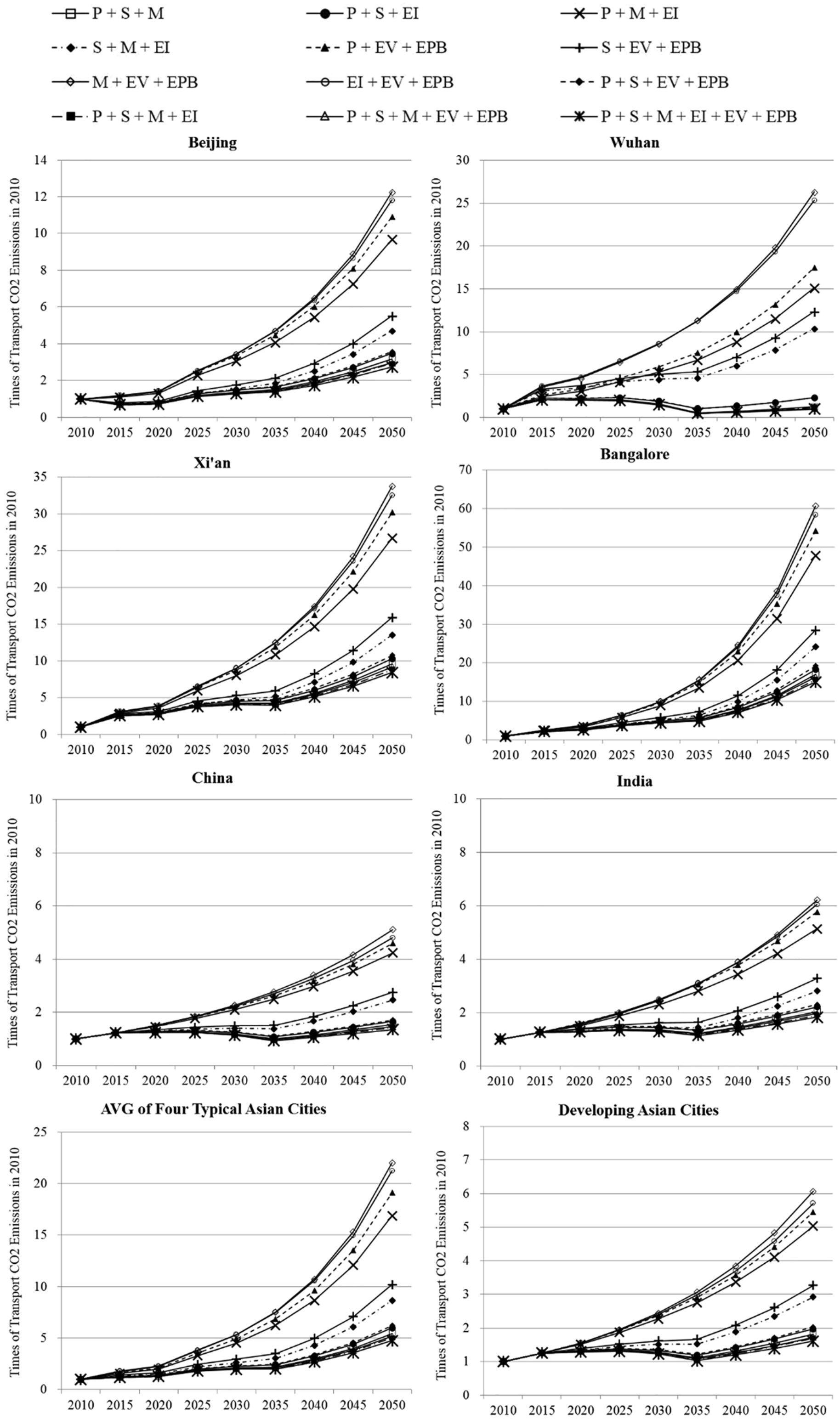


Fig. 6. Times of residents' urban transport CO_2 emissions compared to the year 2010 under three or more combined scenarios.

effects on reducing the emissions in their estimations. Also, in Li et al.'s study (2018), polycentric form's effects are reflected by the effects of bus and car mode share changes, but trip distances' reductions are not considered, which may cause their larger estimations. The estimations in 2050 (610 Mt) are smaller than our results (949.19 Mt). This may be due to that out prediction lacks TDM's long-

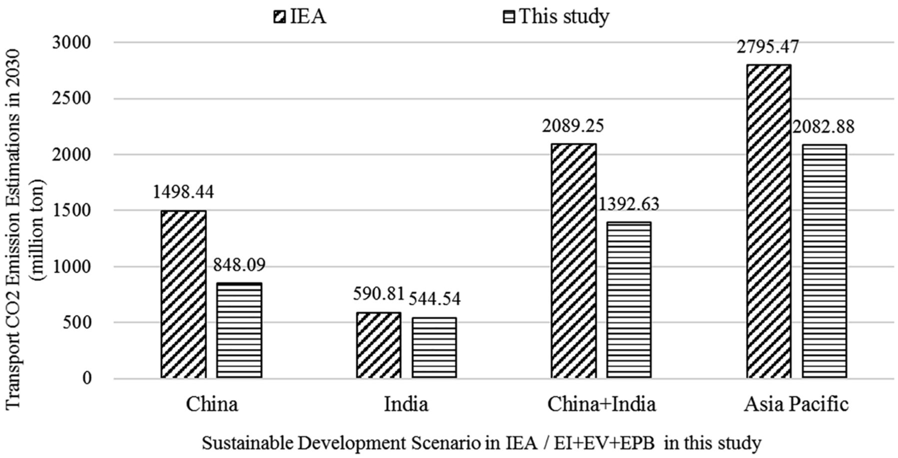


Fig. 7. Comparisons with sustainable development scenario in 2030 by IEA. (Note: (a). IEA's data are calculated from Fig. 1.6, Fig. 2.10, and Fig. 2.16 in World Energy Outlook 2018 (IEA, 2018) and the website of IEA (IEA, 2019); (b). The sustainable development scenario in IEA consider decreased energy intensity and CO_2 intensity, and increased electric vehicles, which is similar as the combined scenario of EI + EV + EPB in this study.)

term effects to slow down the car increase. Under other two scenarios in 2050 in Table 11, estimations in the existing studies (1450 Mt and 1240 Mt) are smaller than our results under the average level of moderate scenarios (M + EI and EV + EPB, 1874.06 Mt) and advanced scenarios (M + EV + EPB and EI + EV + EPB, 1871.95 Mt). These could be explained by that we consider unchanged growth rates of private cars in the estimations.

Presently, China's current policy tends to encourage consumptions and promote electric vehicles. The National Development and Reform Commission wants to forbid the restrictions on car purchase and car usage according to the license plate's number. Besides, the research by the Ministry of Transport of China and World Bank (MOT and WB, 2016) indicate that individual's trip distances per year in China increase quickly, from 3,000 km in 2010 to about 11,000 km in 2020, thus, VKT also increases quickly. Therefore, we consider the factors of electric vehicle promotions, urban size expansions and trip distance increase, but not the factor of restricting car quantity in more and more cities. This is in line with the future trends in Chinese cities. In general, our estimations of residents' urban transport CO_2 emissions are rational and feasible.

6. Limitations and future work

In this study, we establish transport CO_2 emission models by using data from four typical Chinese and Indian cities. This generally reflects the common statistically significant factors for the transport CO_2 emission changes during the rapid economics, transport and urban developments in fast-growing cities. Indeed, each city has unique factors such as socio-economic characteristics, culture, climate, or population behavior, and there exist big gaps of residents' income and large number of two-wheelers in Bangalore of Indian than in Chinese cities. These factors' influences on the transport CO_2 emissions need to be examined in specific cities in future research. The results may not necessarily suit for all the fast-growing cities.

According to the statistical test results in the models, distance to the nearest bus stop and whether a bus stop is within 500 m from the household are not significant factors, thus we exclude these two variables from the models. The reason may lie in widely-covered bus lines and bus stops in city's urbanized areas or statistically significant factors of household income. Service qualities of public buses, such as being crowded, long queues, inconvenient transfer facilities, and poor air-conditioning may also influence the mode choices. These factors' effects need to be examined in future research. Besides, we consider the factor of electric bus vehicle promotions in future's transport CO_2 emission forecasting, and the results show that it can reduce about 43–61% of the emissions by 2050 compared with the BAU.

In Bangalore, we only survey the households and commuters located in the main urban areas inside the Peripheral Ring Rd. In future study, samples in the outer suburbs outside the Peripheral Ring Rd. can be surveyed for analyzing whether there exist satellite cities and for calculating transport CO_2 emissions.

This paper does not address how to align urban planning, investment, transportation planning for the expected polycentricity and satellite cities' urban forms, especially among different cities. These are also important for the desirable urban forms, transport CO_2 emission mitigations and sustainable urban development, and can be further explored in future research.

We find nonlinear quadratic growth relationship between commuting CO_2 emissions and per capita GDP by using the pooled data of the four fast-growing cities selected from Asia. Since we lack of data in developed countries and time-series data in the single case city, we could not conclude whether this relationship could be established or not in developed countries and the single case city. In the future work, we can collect these data and further examine this relationship.

Table 11
Comparison results of China's estimations with existing studies.

		Moderate Scenario	Advanced Scenario	
Scenario description in the related work		fuel efficiency improvement	vehicle related technologies, urban planning, bus rapid transit, road conditions, renewable and clean fuels improvement	TDM, transit city and polycentricity
2020	Related work	727[a]	430[a]	540[g]
	This study	730.98[b]	417.9[c]	420.54[h]
Scenario description in the related work		increased bus shares, non-motorized traffic shares, and mild increased car shares	increased bus shares, non-motorized traffic shares, and decreased car shares	TDM, transit city and polycentricity
2030	Related work	640[d]	480[d]	590[g]
	This study	631.09[e]	499.8[f]	509.19[h]
Scenario description in the related work			Improving energy efficiency, promoting EVs, and collecting additional fuel and CO_2 taxes	TDM, transit city and polycentricity
2040	Related work		1129[l]	605[g]
	This study		1248[k]	653.65[h]
Scenario description in the related work		considering high car growth, clean-energy vehicle promotion, fuel efficiency improvement, fuel and vehicle costs	considering low car growth, clean-energy vehicle promotion, fuel efficiency improvement, fuel and vehicle costs	TDM, transit city and polycentricity
2050	Related work	1450[i]	1240[i]	610[g]
	This study	1874.06[j]	1871.95[k]	949.19[h]

(a). Data come from Wang et al. (2007) and they predict the on-road transport CO_2 emissions; (b). Data refers to the energy efficiency improvement (EI) scenario in Fig. 4 in this study; (c). Data refers to the average level of three or more combined scenarios in 2020 in Fig. 6 in this study; (d). Data come from He et al. (2013) and they predict the urban passenger transport CO_2 emissions, which is similar as our study's scope; (e). Data refers to the average level of two combined scenarios in 2030 in Fig. 5 in this study; (f). Data refers to the average level of three or more combined scenarios in 2030 in Fig. 6 in this study; (g). Data come from Li et al. (2018) and they predict the urban passenger transport CO_2 emissions, which is similar as our study's scope; (h). Data refers to the average level of P + M, P + S, and S + M scenarios in Fig. 5 in this study. (i). Data come from Gambhir et al. (2015) and they predict the on-road transport CO_2 emissions; (j). Data refers to the average level of M + EI and EV + EPB scenario in Fig. 5 in this study; (k). Data refers to the EI + EV + EPB scenario in Fig. 6 in this study; (l). Data come from Wang et al. (2017a) and they predict CO_2 emissions from transport sector.

7. Conclusions

In this paper, we establish the Tobit models for transport CO_2 emissions, quantify the effects of polycentricity and satellite city, re-examine per capita GDP and metro's impacts, and estimate future residents' urban transport CO_2 emissions under various scenarios of different urban and transport policies and new energy technologies in rapidly-growing Asian cities.

Presently, transport CO_2 emissions increase at a speed faster than per capita GDP growths in fast-growing cities selected from Asia. If cities develop polycentric urban patterns and satellite cities, the transport CO_2 emissions will decrease greatly. Furthermore, polycentricity and satellite city can greatly reduce transport CO_2 emissions from the high emitters with car availability, high income, and households located in the outer areas or sprawling suburbs. These can be explained by their shorter trip distances and more eco-friendly transport mode usages under the context of polycentric urban form and satellite cities. In terms of the effects of metro services on the transport CO_2 emissions, a dummy variable of a city having metro services is statistically significant in the model and has a negative coefficient. This indicates that, in general, metro services could reduce transport CO_2 emissions to a certain degree. Compared with the previous study (Yang et al., 2019), the aggregate dummy variable of whether the city has metro services can better explain the emissions' reductions than the disaggregate variable of the nearest distance from households to metro stations.

From the statistical results, it is found that the top 20% of the high emitters produce 50–80% of the total emissions in the four case cities. Thus, there will be massive reductions in the total transport CO_2 emissions in the four case cities, if a city develops a polycentric urban form and job-housing balanced satellite cities. The scenario analysis and predictions show the expected reductions.

Compared with the BAU scenario in 2050, satellite city or polycentric urban form have the largest effects on future emission reductions, and will contribute to reducing 51–82% of the emissions in the four case cities, 64–79% in China, 58–78% in India, and 64–80% in developing Asian countries. If these two policies combined with others (metro network promotion, energy efficiency improvement, and new energy type applications, such as EV and EPB promotions), transport CO_2 emission reductions will become larger, and their contributions could bring about 84–98% of the emission reductions in the four typical case cities, 89–92% in China, 86–88% in India, and 89–92% in developing Asian countries in 2050, compared with the BAU scenario.

The second effective policy for emission reduction is promotions of EVs, EPBs, or metro networks, which could averagely reduce 43–62% of the emissions in the four case cities, 55–57% in China, 52–54% in India, and 55–57% in developing Asian countries in 2050, compared with the BAU scenario. Thirdly, improving energy efficiency could averagely reduce 48% of the emissions in the four case cities and developing Asian countries in 2050, compared with the BAU scenario.

Overall, developing polycentricity and job-housing balanced satellite cities are key factors for effectively reducing future transport CO_2 emissions in rapidly-growing cities, and ultimately mitigating global climate changes. Metro network promotion, energy efficiency improvement, and new energy type applications such as EV and EPB promotions, can also play a role in the reduction of future emissions.

Our findings indicate that great attentions should be paid to foster industries in the beginning developments of polycentricity and satellite cities. And in the meanwhile, more investments should be put in low carbon transportation facilities and energy improvement technologies. Per capita GDP growth, developing polycentric urban form and satellite cities, and metro constructions show the characteristics during the urban developments in fast-growing cities, and thus our study results will help policy makings for reducing transport CO_2 emissions and offer empirical evidence and reference values for other cities.

CRediT authorship contribution statement

Liu Yang: Conceptualization, Methodology, Software, Investigation, Writing - original draft, Funding acquisition. **Yuanqing Wang:** Conceptualization, Supervision, Writing - review & editing, Project administration, Funding acquisition. **Yujun Lian:** Methodology, Software, Validation, Funding acquisition. **Sunsheng Han:** Writing - review & editing, Project administration, Funding acquisition.

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