Key Factors, Planning Strategy and Policy for Low-Carbon Transport Development in Developing Cities of China

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Abstract: Exploring key impact factors and their effects on urban residents’ transport carbon dioxide (CO₂) emissions is significant for effective low-carbon transport planning. Researchers face the model uncertainty problem to seek a rational and better explanatory model and the key variables in the model set containing various factors after they are arranged and combined. This paper uses the Bayesian Model Averaging method to solve the above problem, explore the key variables, and determine their relative significance and averaging effects. Beijing, Xi’an, and Wuhan are selected as three case cities for their representation of developing Chinese cities. We found that the initial key factor increasing transport emissions is the high dependence on cars, and the second is the geographical location factor that much more suburban residents suffer longer commuting. Developing satellite city rank first for reducing transport emissions due to more local trips with an average short distance, the second is the metro accessibility, and the third is polycentric form. Key planning strategies and policies are proposed: (i) combining policies of car restriction based on vehicle plate number, encouraging clean fuel cars, a carbon tax on oil uses, and rewarding public transit passengers; (ii) fostering subcenters’ strong industries to develop self-contained polycentric structures and satellite cities, and forming employment and life circle within 5 km radius; and (iii) integrating bus and rail transit services in the peripheral areas and suburbs and increasing the integration level of multi-modes transferring in transport hubs. The findings will offer empirical evidence and reference value in developing cities globally.

Keywords: transport CO₂ emission; impact factors; variable significance; planning strategy and policy; Bayesian Model Averaging

1. Introduction
The transport sector produces a large amount of CO₂ emissions and is one of the main sources of CO₂ emissions [1,2]. The energy consumption demand for transport will grow rapidly in the coming years. According to the forecast of the International Energy Agency (IEA), the energy consumption demand for transport will increase by 40% by 2035 [1]. In the field of transportation, urban residents’ transport is the main part [3], and its CO₂ emissions account for a large proportion, especially traffic congestion during commuting peak hours will bring more pollutant emissions and other environmental problems [2].
the future, Chinese cities and other developing cities will continue facing challenges of urban and economic growth, motorization level increases, and metropolitan and urban agglomeration developments; thus, we should focus on reducing urban residents’ transport CO\textsubscript{2} emissions. In order to realize this objective, it is necessary to understand and quantify the impact factors of urban residents’ transport CO\textsubscript{2} emissions and to establish a rational explanatory transport CO\textsubscript{2} emission model. Furthermore, on this basis, it is of great significance to identify the key factors and their exact effects on transport CO\textsubscript{2} emissions. Thus, key planning strategies and policies for low-carbon transport developments can be proposed effectively.

Previous studies have examined and modeled the correlations between transport CO\textsubscript{2} emissions and their impact factors. The modeling techniques mainly focus on the methods based on regressions [4–9], and the impact factors mostly include socio-economic characteristics, urban form factors, geographical locations, and metro and transit accessibility.

Research findings in Kenilworth, Southampton, and Cardiff in the United Kingdom (UK) manifest that owning a car will increase household transport CO\textsubscript{2} emissions by about 44% to 59% [7]; owning more than two cars will increase the personal trips’ transport CO\textsubscript{2} emissions by about 13% [8]. Transport CO\textsubscript{2} emissions produced by households with two cars are two times of those with one car [10]. The emissions generated from private cars account for the vast majority of road transport CO\textsubscript{2} emissions in the Netherlands [11]. Meanwhile, higher household income is also an important factor in increasing transport CO\textsubscript{2} emissions. Study results from the UK show that when the annual household income increases by 1%, the annual household transport CO\textsubscript{2} emissions will increase by about 0.59% [9].

The urban form and structure factors’ impact on travel behavior and transport CO\textsubscript{2} emissions have aroused great interest among researchers. Many studies find that, in two Danish city regions, in the state of Maryland, and in the developing cities of Wuhan in China, the polycentric urban form can promote more sustainable travel patterns and reduce transport CO\textsubscript{2} emissions [12–14]. When the ratio of polycentricity or the working population’s proportion is higher, there exists less commuting travel time [6,12]. However, some studies show contrary results, that a polycentric urban form leads to increasing commuting distance, more dependence on cars, and less reduction of transport CO\textsubscript{2} emissions [15–17]. In Italy, the study results show that the polycentric urban form has little help in reducing emissions [15]. Lee and Lee [16] found that in the 125 largest urbanized areas in the United States, the polycentric form has a moderate impact on reducing transport CO\textsubscript{2} emissions. In the San Francisco Bay Area, Cervero and Wu [17] found that great increases in the commuting vehicle kilometers traveled have taken place during the period of rapid suburban employment growth, which could not benefit from reducing the transport CO\textsubscript{2} emissions.

Households’ geographical locations can also influence transport CO\textsubscript{2} emissions. It is found that in most metropolises in China, in the sprawling suburbs, along the ring roads and radial roads, more residents depend on cars for traveling, and the travel distance tends to be much longer; thus, there exist much larger transport CO\textsubscript{2} emissions in these areas [14,18]. However, in the inner city or city center, the residents tend to use more green travel modes such as public transit, bicycle, and walking, which leads to smaller transport CO\textsubscript{2} emissions [18–20]. In the research in Beijing, transport CO\textsubscript{2} emissions in Hutong and other residential areas located in the center of the city are smaller, while the emissions in the suburban areas are larger [20]. Moreover, the trip distances and car uses of the travels in the suburbs have increased greatly due to urban sprawl and there are plenty of long-distance commuting to central urban areas [21]. In Seoul metropolitan area, transport CO\textsubscript{2} emissions in Gyeonggi and Incheon, located in the peripheral area, are larger, while in Seoul, the center of the metropolitan area, the emissions are smaller [22]. Study results in France show that residents in the urban fringe areas and in the rural areas produce larger daily transport CO\textsubscript{2} emissions than those located in the suburbs [23].

In recent decades, plenty of cities have started constructing rails or mass transit to meet urban residents’ travel demands in terms of more time-saving and comfortable. Many
studies focusing on the impacts of rail transit or mass transit on low-carbon travel behaviors and transport emissions indicate positive effects [5,24–26]. Building a rail line can help enhance transit ridership [27]. Proximity to metro stations (commonly referred to within 1 km) had positive effects on the rail transit mode choice [28] and could reduce car trips [29], and vehicle miles traveled [30]. Simultaneously, some new forms of transfer modes greatly promote first-and-last mile access trips to metros, such as shared bicycles, customized shuttle buses, electric bicycles/motors, and electric scooters [31,32]. At the same time, some study results show inconsistency. Some researchers find that better accessibility of rail transit will not influence the transit use of recent movers [33], household’s car ownership [34,35], and commuting by car [34].

From the above studies, it is found that there exist various types of impact factors on urban residents’ transport CO₂ emissions. Supposing there are \( k \) variables that could be placed in the model except for the constant term, then there will possibly be a set of \( 2^k \) models after these variables are arranged and combined. Moreover, if \( k \) equals 10 or more, the number of models in the model sets that could be selected will become a huge quantity. Hence, it is difficult to identify the model with better and reasonable goodness-of-fit and explanatory power. Moreover, it is hard to determine the relative importance among the \( k \) variables and identify the key variables that should be placed in the model. These cause the model uncertainty problem, which will not be helpful in making key planning strategies and policies for reducing transport emissions effectively.

Faced with the trouble of model uncertainty, this paper intends to apply the Bayesian Model Averaging (BMA) technique to solve this problem. This method can identify the relative importance among the \( k \) explanatory variables contributing to the explained variable of urban residents’ transport CO₂ emissions, help choose the key explanatory variables, and calculate the variables’ averaging effects among all the models in the model set. Thus, based on the BMA method, this paper will establish urban residents’ transport CO₂ emission model in the three case developing cities of Beijing, Xi’an, and Wuhan in China, sort the relative importance of the impact factors, identify and quantify the key factors and their averaging effects, and propose the key low-carbon planning strategies and policies effectively. Because commute trips take up a large proportion of urban transportation, and these trips are inflexible, this study will focus on the residents’ commuting CO₂ emissions. The three selected case cities have experienced urban growth, motorization and economic increases, rail transit constructions, and urban agglomeration developments in recent decades, representing the general situations of urban and transport developments in the developing country of China. Meanwhile, the above development situations are important issues for transport emission increases and climate change in other developing cities. Therefore, the study results and the proposed key planning strategies in this paper will offer empirical evidence and reference value in developing cities globally.

2. Data and Methodology

2.1. Data Collection and Description

Beijing, Xi’an, and Wuhan are representative of the most developing metropolises in the eastern, middle, and western inland of China in terms of their economic levels, city grading, urban sprawls by the ring roads, and development of public transport infrastructure. Household travel surveys using the simple random sampling method were implemented in the traffic zones in the urban areas of Beijing, Xi’an, and Wuhan in the years 2010, 2012, and 2010, respectively. In the year 2021, a household travel survey was implemented in the traffic zones in the urban area of Xi’an (Since the beginning of 2020, the COVID-19 epidemic has not ended, which has seriously affected the large-scale residents’ travel surveys. Therefore, up to now, we have only carried out the travel survey in Xi’an, which is less affected by the COVID-19 epidemic). Surveyors implemented face-to-face inquiries in the household neighborhoods. In total, the household travel surveys during the years 2010–2012 interviewed 1400 households and 1915 commuters in Beijing, 1501 households and 2449 commuters in Xi’an, and 1194 households and 2050 commuters in Wuhan. In the
year 2021, the household travel surveys interviewed 1584 households and 2008 commuters in Xi’an.

The household travel surveys included commuting distance, commuting mode, workplace, and households’ and commuters’ socio-economic characteristics, containing car availability, household income, housing tenure, age, work unit type, and educational background. We calculated the commuting path distances from surveyed residents’ homes to workplaces.

Table 1 illustrates the urban built-up areas, population, per capita GDP, motor vehicles, and metro lines in the three case cities in the two periods. In the aspect of the urban form, Beijing and Xi’an each have a strong center and foster monocentric patterns at the beginning. Wuhan fosters a polycentric urban form during the city’s initial formation, with three towns of Hankou, Wuchang, and Hanyang divided by the Yangtze and Han Rivers. Beijing has developed some satellite cities in the outer areas in recent decades, including Changping, Huairou, Shunyi, Miyun, Pinggu, Fangshan, and Daxing. In the recent decade, most of the metropolises in China have constructed several metro lines and formed the skeleton metro network. In 2012, there was only one metro line (Line 2) in Xi’an; after nine years, in 2021, eight metro lines were in operation (Line 1, 2, 3, 4, 5, 6, 9, and 14).

Table 1. General descriptions in the three case cities.

| City   | Urban Built-Up Area (km²) | Population (Million) | Per Capita GDP (US$) | Motor Vehicles (Million) | Metro Lines |
|--------|---------------------------|----------------------|----------------------|--------------------------|-------------|
|        | Year of 2010–2012          |                      |                      |                          |             |
| Beijing| 1268                      | 19.61                | 11,218               | 4.02                     | 8           |
| Xi’an  | 522                       | 9.14                 | 8140                 | 1.38                     | 1           |
| Wuhan  | 520                       | 9.78                 | 10,563               | 1.19                     | 2           |
|        | Year of 2021               |                      |                      |                          |             |
| Xi’an  | 701                        | 13.16                | 11,125               | 3.73                     | 8           |

We calculated the commuting CO₂ emissions, which are equal to the CO₂ emission factor (by mode, fuel type, and occupancy) multiplied by the commuting trip distance (IPCC, 1997). Then, according to the references by Huo et al. [36], we calculated Well-To-Wheel (WTW) CO₂ emission intensities for different fuel types and traffic modes to obtain CO₂ emission factors. Figure 1 reports the statistics and percentiles of individual commuting CO₂ emissions in the three case cities in the years 2010–2012 and in Xi’an in 2021. Beijing has averaged larger commuting CO₂ emissions. The top 25% of the emitters in Beijing produce much more emissions. Generally, Wuhan’s emitters produce smaller commuting CO₂ emissions, and Xi’an’s emitters produce the middle levels of the emissions. The commuting CO₂ emissions at the 50th, 75th, and 90th percentiles in Xi’an in the year of 2021 are 1.7–2.6 times of those in the year 2012.
The unconditional BMA estimates of $\beta$. The reason for partitioning the design matrix $X$ in two subsets of deterministic regressors; and $u \sim N(0, \sigma^2)$, an $n \times 1$ random vector of unobservable disturbances whose elements are independent and identically distributed. It is assumed that $k_1 \geq 1, k_2 \geq 0, k = k_1 + k_2 \leq n - 1$, and the design matrix $X = (X_1, X_2)$ have full column rank $k$. The reason for partitioning the design matrix $X$ in two subsets of regressors is that $X_1$ contains explanatory variables that we want in the model because of theoretical reasons or other considerations about the phenomenon under investigation, whereas $X_2$ contains additional explanatory variables of which we are less certain. The $k_1$ columns of $X_1$ are called focus regressors and the $k_2$ columns of $X_2$ are called auxiliary regressors.

Given the conditional estimates $\hat{\beta}_{1i}$ and $\hat{\beta}_{2i}$ of the regression parameters of model $M_i$ and the model weights $\lambda_i$, the unconditional BMA estimates of $\beta_1$ and $\beta_2$ are computed as

\[
\hat{\beta}_1 = E(\beta_1 | y) = \sum_{i=1}^{I} \lambda_i \hat{\beta}_{1i}
\]

\[
\hat{\beta}_2 = E(\beta_2 | y) = \sum_{i=1}^{I} \lambda_i T_i \hat{\beta}_{2i}
\]
where \( T_i \) are \( k_2 \times k_2i \) matrices are defined by \( T_i^T = (I_{k_2i}, 0) \), or a column permutation thereof, that transform the conditional estimates \( \hat{\beta}_{2i} \) in \( k_2 \times 1 \) vectors by setting to zero the elements of \( \beta_{2i} \), which are excluded from model \( M_i \).

The regressors in the BMA model in this study consist of the following impact factors in seven aspects: household car availability, annual household income, dummy variable of whether the city form is polycentric or has a strong center, dummy variable of whether a commuter is located in the satellite cities, dummy variable of whether the resident’s household is within 1 km from the nearest metro station, dummy variable of whether the resident’s household is within 500 m from the nearest bus stop, dummy variables of household location separated by the ring roads. The outcome variable is individual commuting \( \text{CO}_2 \) emissions. The ordinary least square regression method is used as the model form. In the modeling process, we removed the statistically unrelated factors, including the commuter’s age, gender, education level, work unit type, household type, road network, and intersection density around the commuter’s neighborhood. The model is established as the following:

\[
y = \alpha + X\beta + u
\]  

where \( \alpha \) is the constant term; \( X \) are \( n \times k \) matrices of observations of the independent variables, including the above seven aspects of the impact factors; \( \beta \) are \( k \times 1 \) vectors of unknown regression parameters; and \( u \) is an \( n \times 1 \) random vector of unobservable disturbances whose elements are independent and identically distributed.

Table 2 presents the definitions and the summary statistics of the regressors in the BMA model. Car availability is the dummy variable that 1 indicates the household owns at least a car, and 0 refers to no car in the household. Variables of HAInc refer to annual household income levels in US$, and they are dummy variables. Polycentric urban form is the dummy variable where 1 refers to commuter’s city having a polycentric urban form, and 0 refers to the monocentric urban form. Satellite city is the dummy variable where 1 refers to the commuter is located in the satellite city of Beijing, and 0 refers to not. The variable of the bus within 500 m is the dummy variable where 1 refers to the commuter’s household being within 500 m of the nearest bus stop, and 0 refers to not. The variable of metro within 1 km is the dummy variable where 1 refers to the commuter’s household being within 1 km of the nearest metro station, and 0 refers to not.

Because Beijing has a different number of ring roads compared to the other two case cities, we unify the variables of household location separated by the ring roads in the three case cities in the modeling process using the three cities’ pooled sample. Average distances from the ring roads to the city centers, or the radiuses of the areas covered by the ring roads, are used as an index to indicate the locations of the ring roads or commuters’ household locations. In the three typical developing cities of Beijing, Xi’an, and Wuhan, the average distances from the 2nd ring roads to the cities’ centers are quite similar, about 5~6 km. Thus, a variable of household location inside the ring road with a 5~6 km radius is defined to represent that the household is located in the inner area of the city near the city center. In Beijing, the average distance from the 4th ring road to the city center of Tian’anmen Square is about 10 km. The average distance from the 3rd ring road to the city center of Bell Tower in Xi’an and to the city center of Wuhan Yangtze Grand Bridge in Wuhan are about 10.5 km and 13 km, respectively. Therefore, a variable of household location between the ring road with a 5~6 km radius and the ring road with a 10~13 km radius is defined to represent households located in the middle part and outside the inner area of the city. Then, the variable of outside the ring road with a 10~13 km radius is defined to represent the households located in the outer areas of the cities.
Table 2. Statistics of the regressors in the BMA models.

| Statistics                          | Beijing 2010 | Xi’an 2012 | Wuhan 2010 | Pooled Sample 2010–2012 | Xi’an 2021 |
|------------------------------------|--------------|------------|------------|--------------------------|------------|
| Car availability                   | 0.438        | 0.403      | 0.243      | 0.362                    | 0.708      |
| HAInc $6000–10,000                 | 0.181        | 0.184      | 0.392      | 0.251                    | 0.032      |
| HAInc $10,000–20,000               | 0.397        | 0.651      | 0.288      | 0.448                    | 0.356      |
| HAInc $20,000–40,000               | 0.256        | 0.090      | 0.286      | 0.077                    | 0.140      |
| HAInc > $40,000                    | 0.039        | 0.025      | 0.022      | 0.029                    | 0.029      |
| HAInc $40,000–60,000               |              |            |            |                          | 0.175      |
| HAInc $60,000–80,000               |              |            |            |                          | 0.045      |
| Polycentric urban form             | 1.000        | 0.025      | 0.015      | 0.022                    | 0.029      |
| Satellite city                     | 0.193        | 0.371      | 0.967      | 0.945                    | 0.984      |
| Bus stop within 500 m              | 0.838        | 0.367      | 0.469      | 0.550                    | 0.660      |
| Metro station within 1 km          | 0.236        | 0.424      |            |                          |            |
| Household between ring roads with 2 km and 5–6 km radius | | | | | |
| Household inside ring road with 5–6 km radius | | | | | |
| Household between ring roads with 5–6 km and 10–13 km radius | | | | | |
| Household outside ring road with 10–13 km radius | | | | | |
| Observations                       | 1863         | 1952       | 1863       | 5678                     | 2004       |

In the modeling process using Xi’an data in the year 2021, the household locations separated by the ring roads are defined as the household between ring roads with a 2 km and 5–6 km radius, households between ring roads with a 5–6 km and 10–13 km radius, and household outside ring road with a 10–13 km radius.

3. Bayesian Model Averaging Results, Discussions, and Policy Suggestions

3.1. Model Results and Analysis

Table 3 shows the Bayesian Model Averaging results in the three developing cities of Beijing, Xi’an, and Wuhan by using the survey data of the year 2010–2012. The column of Coef. calculates the averaging effects of the corresponding factor on individual commuting CO₂ emissions; the column of Std. Err and t-value calculate the averaging standard errors and t ratios of each corresponding coefficient; and the column of pip refers to the posterior inclusion probabilities, which means the posterior probability that a variable $x_i$ is included in the model or the total proportion that the corresponding variable $x_i$ contained in the model space, which can help identify the relative importance of the variables. If the t-ratio of a regressor is greater than one in absolute value, then it is considered to be robustly correlated with the outcome; alternatively, pip values can also judge the robustness of the regressors, and a pip value of 0.5 corresponds approximately to a t-ratio of one in absolute value [37].
Table 3. Bayesian Model Averaging results in the three developing case cities (2010–2012).

| Individual Commuting CO₂ Emissions (kg/trip) | Coef.  | Std. Err. | t-Ratio | Pip  |
|--------------------------------------------|--------|-----------|---------|------|
| Constant                                   | 0.092 *** | 0.021 | 4.24 | 1.00 |
| Car availability                           | 0.650 *** | 0.019 | 33.8 | 1.00 |
| Polycentric urban form                      | −0.079 *** | 0.022 | −3.55 | 0.98 |
| Satellite city form                         | −0.278 *** | 0.040 | −6.89 | 1.00 |
| Household between ring roads with 5–6 km and 10–13 km radius | 0.007 | 0.018 | 0.38 | 0.15 |
| Household outside ring road with 10–13 km radius | 0.247 *** | 0.025 | 9.82 | 1.00 |
| Bus stop within 500 m                       | −0.001 | 0.009 | −0.12 | 0.02 |
| Annual household income between $10,000 and $20,000 | −0.0001 | 0.002 | −0.03 | 0.01 |
| Annual household income between $20,000 and $40,000 | 0.309 *** | 0.026 | 11.74 | 1.00 |
| Annual household income >$40,000             | 0.440 *** | 0.052 | 8.33 | 1.00 |

Model space: 512 models

Note: * indicates the t-ratio value is more than one, and the corresponding variable is robustly correlated with the outcome variable. *** p < 0.01.

It can be seen from the results that the pip value of residents’ car availability, household location in the outer areas of the city, higher levels of household income, polycentric urban form, and satellite city form are all equal to one, which means that all possible 512 models contain these variables. This indicates the high importance of these variables contributing to the commuting CO₂ emissions.

In terms of the statistical significance and the averaging effects of the variables, car availability, household location outside the ring road with a 10–13 km radius, and annual household income of more than $20,000 have robust statistically significant positive effects on increasing the emissions. Their coefficients manifest that if the resident has a car available, the individual commuting CO₂ emissions will increase on average by 0.65 kg, which is the largest increasing effect among all the factors. Secondly, if the resident’s annual household income is between $20,000 and $40,000 and even more than $40,000, the individual commuting CO₂ emissions will increase by 0.309 and 0.44 kg, respectively. Thirdly, if the residents’ household is located in the outer areas of the city, the individual commuting CO₂ emissions will increase by 0.247 kg.

In terms of the urban form factors, polycentric urban form and satellite city form could reduce individual transport CO₂ emissions, and they are robust and statistically significant. Their coefficients manifest that if the city has a polycentric urban form, the individual commuting CO₂ emissions will averagely reduce by 0.079 kg, and if the resident is located in the satellite cities, the emissions will averagely reduce by 0.278 kg.

On average, the variable of bus stops within 500 m from the household location does not have a robust statistically significant effect in reducing commuting CO₂ emissions.

Table 4 shows the Bayesian Model Averaging results in Xi’an by using the recent data in 2021. Similar to the results in 2010–2012, the pip value of residents’ car availability and a higher level of household income are all equal to one, which means that all 256 possible models contain these variables. This indicates the high importance of these variables contributing to the commuting CO₂ emissions.

Notably, the pip value of the metro station within 1 km reaches 0.86, indicating the high importance of this variable. While in the years 2010–2012, this variable is not a statistically significant factor. This result can be probably attributed to the fact that the metro skeleton networks have been formed in Chinese metropolises in the past decade, which promotes the metro mode uses among the nearby residents. In 2021, metro lines in Xi’an amounted to eight lines, while in 2012, there was only one metro line. This situation takes place in many rapidly developing provincial cities in China.
Table 4. Bayesian Model Averaging results in Xi'an (2021).

| Individual Commuting CO₂ Emissions (kg/trip) | Coef.  | Std. Err. | t-Ratio | Pip |
|---------------------------------------------|--------|-----------|---------|-----|
| Constant                                    | 0.171 ** | 0.080 | 2.12 | 1.00 |
| Car availability                            | 0.638 *** | 0.044 | 14.27 | 1.00 |
| Household between ring roads with 2 km and 5–6 km radius | 0.001 | 0.009 | 0.11 | 0.03 |
| Household outside ring road with 10–13 km radius | 0.002 | 0.013 | 0.09 | 0.03 |
| Metro station within 1 km                   | −0.114 * | 0.058 | −1.93 | 0.86 |
| Bus stop within 500 m                       | 0.012 | 0.060 | 0.20 | 0.06 |
| Annual household income between $10,000 and $20,000 | 0.002 | 0.013 | 0.15 | 0.04 |
| Annual household income between $40,000 and $60,000 | 0.085 * | 0.082 | 1.03 | 0.58 |
| Annual household income between $60,000 and $80,000 | 0.206 * | 0.148 | 1.39 | 0.73 |

Model space: 256 models

Note: * indicates the t-ratio value is more than one, and the corresponding variable is robustly correlated with the outcome variable. ** p < 0.01, *** p < 0.05, **** p < 0.01.

It can be seen from the averaging effects and the statistical significance that car availability and annual household income of more than $40,000 have robust and statistically significant positive effects on increasing emissions. When the resident has a car available, the individual commuting CO₂ emissions will averagely increase by 0.638 kg, which is the largest increasing effect. Secondly, when the resident’s annual household income is between $40,000 and $60,000, and between $60,000 and $80,000, the individual commuting CO₂ emissions will increase by 0.085 and 0.206 kg, respectively.

In terms of the factors that could reduce the emissions, when the residents’ households are within 1 km from the metro stations, the individual commuting CO₂ emissions will decrease by 0.114 kg. Similar to the situation in the years 2010–2012, the variable of bus stops within 500 m from the household location does not have a robust and statistically significant effect in reducing emissions.

Model results in Tables 3 and 4 manifest that the significant impact factors that have great effects on increasing the emissions are similar in the two periods. They are residents’ car availability, households located in the outer areas of the cities, and residents with a higher level of income. Probably due to the large-scale metro network that has been formed in the developing metropolises, residents located within 1 km of the metro stations use more metro modes than those far away from the stations, which contributes to reducing commuting CO₂ emissions. Since we only surveyed one city of Xi’an in the recent year 2021, we could not place the urban form factors (polycentric city and satellite city) in the model, which could be further studied when we survey the residents’ travel data in the polycentric city.

We use the significant factors’ coefficients in the model results and the average increasing situations of the motor vehicles, urban built-up area, per capita GDP, and metro network construction in Xi’an from 2012 to 2021 to estimate the changing percentages of resident’s commuting CO₂ emissions in the six scenarios in the future years of 2025 and 2030. The six scenarios represent the impacts on commuting CO₂ emissions from car availability, urban sprawl, economic growth, metro accessibility, and developing a polycentric urban form and satellite city.

According to Xi’an city’s data in 2012 and 2021 in Table 1 and Xi’an urban rail transit construction plan [38], we calculate the average yearly increasing rates of the motor vehicles, urban built-up area, per capita GDP, and metro network, which are 11.68%, 3.33%, 3.53%, and 9.97%, respectively. The individual commuting CO₂ emission per trip in Xi’an at the 50th percentile in the year 2021 (0.169 kg) is used as the base level. Figure 2 shows the results of the changing percentages of individual commuting CO₂ emissions per trip in 2025 and 2030. It can be seen that, due to the fastest growth rate of motor vehicles and the largest coefficient of car availability in the BMA model results, residents’ car availability contributes much more to increasing emissions. Secondly is the household in the outer areas/suburbs and the higher household income. Developing satellite cities and metro
accessibility rank first for reducing individuals’ commuting CO\textsubscript{2} emissions, and next is fostering polycentric urban form.

![Figure 2. The estimated changing percentages of the individual commuting CO\textsubscript{2} emissions per trip in 2050 and 2030 in developing city of Xi’an.](image)

### 3.2. Discussions and Policy Suggestions

By comparison with the study results in other developed cities, it is found that, in Seoul metropolitan area and in Kenilworth, Southampton, and Cardiff in the UK, a household’s income has more effects on increasing transport CO\textsubscript{2} emissions than owning cars [7,22]. However, in typical developing Chinese cities, households owning cars contribute more significantly to increasing transport CO\textsubscript{2} emissions than household income. During cities’ economic growth in the future, car ownership levels will evidently continuously increase. This will lead to much more dependency on cars for traveling, which will cause surges in transport CO\textsubscript{2} emissions in the coming years. Based on the pip value and the averaging effect of the car availability variable on transport emissions in the model results, the increasing ownership of private cars and, thus, high dependency on cars for traveling is the initial key factor that needs to be focused on in the process of achieving transport emission reduction and sustainable development.

Generally, larger transport CO\textsubscript{2} emissions existing in the suburban areas are consistent with the previous study results in other developed cities [17,22]. Study results in Beijing by Xiao et al. [20] and Zhao et al. [21] manifest that there exist longer travel distances and larger transport CO\textsubscript{2} emissions in the suburban areas. Furthermore, we find that in Beijing, due to the continuous urban sprawls in the nearby suburbs inside the 6th ring road, there exist the longest travel distances and the largest transport CO\textsubscript{2} emissions, while, in the satellite cities in the exurb areas, due to the self-contained lifestyle, there exist more local trips with short travel distances and thus smallest transport CO\textsubscript{2} emissions. In the sprawling suburbs of the developing Chinese cities, due to the lack of rail stations, sparse bus stops, slow bus operation speed, long waiting times, and other reasons for low bus service levels, most residents in these areas prefer to drive. Moreover, suburbs are far away from the central urban area where employment is concentrated, which leads to a significant increase of commuting distance and time. Furthermore, in recent years in Chinese cities, the urban population’s distribution has shown a trend of decentralized expansion to sprawling areas and suburbs. These situations result in sharp increases in the total travel demands, travel distances, travel time consumption, traffic pollution, and transport CO\textsubscript{2} emissions. The model results of the pip value and the averaging effect show that household location
in the outer areas of the city will contribute to increasing transport CO$_2$ emissions. These manifest that with the household geographical location factor, that many more residents located in the sprawling suburbs suffering much longer distances and time for commuting is another key factor for increasing transport CO$_2$ emissions.

In terms of the factors that could reduce transport CO$_2$ emissions, it is found that in the polycentric city of Wuhan and satellite cities of Beijing, residents’ travel distances are generally shorter, and there exist more local trips within the subcenters and satellite cities with the average distances of 4.1 km and 5.43 km, respectively. Thus, there exist more public transport and non-motorized travel mode uses (71.7% and 79.4%, respectively), and thus less transport CO$_2$ emissions. The urban form factors’ pip values and coefficients in the model results also manifest that polycentric and satellite city urban forms have more advantages in reducing transport CO$_2$ emissions compared with other factors. Thus, the urban form factor is a significant factor in reducing transport CO$_2$ emissions and is quantified to have great contributions.

The rapid development of the rail transit network has a significant impact on residents’ travel behaviors. In the model results, the pip value and coefficient of the variable of the metro station within 1 km from the household indicate that convenient rail transit facilities have robust and statistically significant effects in promoting metro mode uses and thus reducing transport emissions. This result is consistent with some previous research in developed cities [5,29]. With the formation of the urban rail transit skeleton network, the rail transit passenger number has significantly increased. Furthermore, in most developing metropolises in China, with the development of internet technology and mobile communication application software, more trips are made by public bicycles and shared bicycles combined with rail transit. However, although metro mode uses have increased greatly in recent years, at the same time, many cities are facing the serious problem of a sharp decrease in bus users due to the reason that the service levels of normal buses have dropped seriously. Most of the normal bus users move to use the rail transit mode. These changing tendencies have not been studied in the existing literature. Rail transit facilities conveniently combined with public bicycles and buses can attract more divers to abandon their cars. This is another important key factor for reducing transport CO$_2$ emissions.

In Suzhou city of China, eight bus lines integrating public bus and rail transit networks have been opened since June 2022. These bus lines connect multiple metro stations. Among these bus lines, the strongest connecting line is 9021M. The time of the first and last bus of this connecting line is basically synchronized with rail transit, and the operation time is extended from 5:10 to 23:10, accurately matching the service time of rail transit. In rush hour during commuting, the same departure frequency is used as that of rail transit. Suzhou will continue to run 14 connecting bus lines integrating bus and metro networks. It is estimated that about 50 rail transit stations can be seamlessly connected, providing more efficient and convenient transit services for commuters [39].

Moreover, non-motorized traffic is restricted by a large number of on-road parking, without the consideration of people-oriented active traveling, resulting in an unsmooth and unsafe riding and walking environment. Thus, the principles of public transport priority and people-oriented transport planning, design, and management are crucial to promote the low-carbon and green travel modes used.

According to the model result analyses and discussions, this paper proposes the following key strategies and policy suggestions for reducing transport CO$_2$ emissions in three aspects:

1. Continuing and strengthening to implement traffic demand management by restricting the car use policy based on vehicle plate number, controlling the proportion of traditional fuel cars, and promoting clean fuel cars. On the other hand, increasing the travel cost of driving through a carbon tax, for example, a carbon tax on oil uses, and meanwhile, rewarding public transit passengers.
2. Fostering strong industries in the subcenters to develop a polycentric structure and forming an employment circle and life circle within 5 km radius. The formation of the polycentric structure and the satellite city requires the high-quality industrial developments within the subcenters, combing with the necessary education, medical, and commercial service facilities, which can attract more residents both working and living within the subcenters or satellite cities. This is the key step to form self-contained polycentric structures. According to the statistical results in the subcenters of Wuhan and satellite cities of Beijing, the local trips’ distances are on average 4.8 km, and the public transport and non-motorized travel mode uses amount to an average of 75.6%, thus, it is suggested to form an approximately 5 km radius employment and life circle.

3. Strengthening the integration of public bus and rail transit services in the peripheral areas and suburbs and improving the integrated service level of multi-modes transferring in transport hubs in order to save travel time consumption when drivers abandon their cars. On the one hand, it is significant to arrange short-distance feeder bus lines in the suburbs to connect rail transit services according to the passenger flow demand. Simultaneously, this should be combined with building bus lanes, bay stations, and transit depots; otherwise, the bus operation efficiency and environment could not be improved, and the needs of residents for convenient, time-saving, and comfortable commuting could not be satisfied, and thus, the proportion of driving could not be reduced. On the other hand, it is urgent to guarantee bicycle lane facilities for non-motorized traffic, reduce the number of parking spaces on the road, and ensure the safety, continuity, and smoothness of the walking and bicycling environment in traffic design and management. Last but not least, it is necessary to encourage park-and-ride around the rail stations in the suburbs by constructing enough parking lots and reducing parking fees.

4. Conclusions

It is important to identify urban residents’ transport CO\textsubscript{2} emissions’ key impact factors and their effects for the effective low-carbon transport planning strategy and policy making. Previous studies have found several aspects of the impact factors, and there exists a huge quantity of explanatory models containing the various factors after they are arranged and combined. However, if these variables’ relative significance in all possible models can be further determined and their averaging effects can be quantified, this will be beneficial to making the key planning strategies and policies and thus will have effective implementing results in reducing transport emissions. To realize this, we are more likely faced with the problems of which model has better and reasonable goodness-of-fit and explanatory power, what are the key variables, and what is the relative importance of the variables. Thus, the model uncertainty problem arises. This paper applies Bayesian Model Averaging method to solve this problem. It provides a way to settle the choice of the explanatory variables and models and to identify the relative significance of the variables. It is found that, because of household car availability, high dependence on cars for commuting is commonplace. Household geographical location factor that much more residents located in the outer areas and suburbs suffer much longer commuting distances and travel time is the second key factor for increasing transport emissions. For reducing transport emissions, polycentric and satellite city structure factor play a great role, due to there being many more local trips with an average distance of 4.8 km and 75.6% of green modes used. Moreover, the rail transit facility conveniently combined with public buses and bicycles around residents’ households is also an important factor. According to the study results, three aspects of key planning strategies and policies are proposed in this paper, including (i) combinations of car restriction based on vehicle plate number, clean fuel car uses’ promotions, a carbon tax on oil uses, and rewards for public transit passengers; (ii) fostering subcenters’ high-quality industries to develop a self-contained polycentric pattern and satellite cities and forming an
employment circle and life circle within about a 5 km radius; and (iii) integrating public bus and rail transit in the peripheral areas and suburbs and improving the integrated service level of multi-modes transferring in transport hubs.

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