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LETTER

Public and private transportation in Chinese cities: impacts of population size, city wealth, urban typology, the built environment, and fuel price

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Abstract

The development of urban transportation is affected by city population size, wealth, urban typology, the built environment, and fuel price, and has significant implications for urban sustainability. We analyze data of 297 Chinese cities between 2017 and 2019 using both simple regressions to examine the relationships between metrics of public and private transportation and city size, and multiple regressions to examine the impacts of the above urban factors on public transit use and private vehicle number. Both public transit use and private vehicle number scale super-linearly with population and sub-linearly with gross regional product. We find that the impacts of population size, city wealth, the built environment, and fuel price on transportation vary across city groups (industrial, mixed-economy, and commercial cities). We find that the relationships between urban transportation metrics and their factors extracted from intra-city variations over time are different from those derived from pooling data of multiple cities over time, indicating the importance of choosing appropriate analyses to inform local policymaking. A key finding is that to reduce private vehicle ownership, enhancing land use diversity, increasing rail transit, and expanding taxi fleets are more effective than increasing density in already dense Chinese cities. Our findings improve understanding of the drivers of public and private transportation in urban China which are needed to promote sustainable growth of Chinese cities.

1. Introduction

Cities occupy less than 3% of land globally, but accommodate more than half the global population, contribute 80% of global gross domestic product, and are responsible for 70% of global energy-related carbon emissions (Dhakal *et al* 2014). Urban areas, especially those in developing countries, will increasingly be hotspots of carbon emissions and are critical to decarbonize. Building the infrastructure in existing and future cities in developing countries to the same level as cities in developed countries would emit 226 Gt of CO_2 (Nagendra *et al* 2018). This equals four times the emissions from building existing urban infrastructure and half of the carbon budget consistent with the 1.5 °C warming target (Masson-Delmotte *et al* 2021). However, if appropriately managed, huge opportunities exist in developing cities to leapfrog carbon intensive urbanization and lock in positive climate responses through low-carbon infrastructure and sustainable urban design (Ürge-Vorsatz *et al* 2018).

How urban characteristics evolve with development across cities is critical to the understanding of urban systems. Many urban characteristics (e.g. city wealth, material and energy uses) increase with urban population following a power-law scaling relation (Bettencourt *et al* 2007, Bettencourt 2013). Equation (1) shows the relationship, where Y is an urban characteristic, N is population, and Y_0 and β are constants. Depending on the scaling factor β, urban scaling relations can be categorized into super-linear ($\beta > 1$), linear ($\beta = 1$), and sub-linear ($\beta < 1$). Characteristics related to innovation and wealth creation scale with population super-linearly, which social network theories attribute to the super-linear scaling of human interactions with city size; Characteristics associated with infrastructure and public goods scale with population sub-linearly, reflecting economies of scale (Bettencourt 2013, Pan *et al* 2013, Schläpfer *et al* 2014). Although the values of scaling factors vary across countries, this power law is shown to be universal (Bettencourt *et al* 2007, Keuschnigg *et al* 2019, Zünd and Bettencourt 2019),

$$Y = Y_0 N^{\beta}. \tag{1}$$

While most studies on urban scaling conduct cross-sectional analyses (i.e. a snapshot of multiple cities in time), temporal scaling analyses (i.e. tracking individual cities over time) are rare. Recent literature (Depersin and Barthelemy 2018, Keuschnigg 2019, Bettencourt *et al* 2020) has started to compare the two types of scaling mathematically and empirically, suggesting that the cross-sectional scaling patterns of multiple cities do not necessarily represent the development trajectories of individual cities. Based on this divergence, we employ both a pooled model and a fixed effect model to understand urban transportation development from cross-sectional and temporal perspectives.

Patterns of urban scaling in China, the largest developing country, have great global implications and have received much research attention (Ramaswami *et al* 2018, Zünd and Bettencourt 2019, Lei *et al* 2021). These studies confirm that urban scaling patterns of many variables found in cities around the world also apply to China. However, the scaling relations of transportation variables in Chinese cities have not been extensively investigated. To our knowledge, there is no city-level study focusing on the scaling of public and private transportation in China. Since transportation is a central part of urban systems and pivotal to urban sustainability and wellbeing (Ramaswami 2020), how urban transportation grows with city size should be better explored.

Aside from population size, other urban factors also affect the scale and characteristics of urban transportation. Increase in wealth leads to higher private vehicle ownership, more vehicle use, and higher carbon footprint both at regional (Yang *et al* 2018, Li *et al* 2019, Ma *et al* 2019) and household (Minx *et al* 2013, Jones and Kammen 2014, Mi *et al* 2020) levels. Additionally, factors in the built environment are also related to total travel demand and transportation mode. For instance, compact urban development (CUD) is promoted as a sustainable urbanization strategy that features improvements in 5 inter-related dimensions abbreviated as '5Ds' (population/job density, land use diversity, street network design, destination accessibility, and distance to transit) (Global Platform for Sustainable Cities 2020). Abundant empirical evidence (Newman and Kenworthy 1989, Cervero 1996, 2002, Cervero and Kockelman 1997, Kockelman 1997, Ewing and Cervero 2001, 2010, Clark 2007, Karathodorou *et al* 2010, Zegras 2010) has shown that making cities more compact could lower private vehicle ownership, reduce car use, facilitate walking and public transit, therefore reducing VKT (vehicle kilometers travelled) and the associated emissions. Moreover, it has been demonstrated theoretically and empirically that fuel price (fuel tax) affects urban form and transportation, with higher fuel prices associated with more public transit use and less transportation energy use (Creutzig 2014, Creutzig *et al* 2015, Borck and Brueckner 2018).

Previous analyses of transportation in Chinese cities focus on the associations between private vehicle ownership and the built environment features reflected in the '5Ds' (Li *et al* 2010, Cao and Huang 2013, Wu *et al* 2016, Sun *et al* 2017, Yang *et al* 2017, Yin and Sun 2017, Du and Lin 2019). These studies draw similar conclusions as studies on cities in developed countries, indicating the importance of the urban built environment to automobile dependence. However, there are several limitations with existing studies. First, none of them explore the potential effects of urban typology by economic structure (industrial, mixed-economy, commercial) on transportation as well as its associations with population, wealth, the built environment, and fuel price. As revealed by Ramaswami *et al* (2018), the scaling patterns in Chinese cities depend largely on economic structure. Second, existing findings on how built environment features affect vehicle ownership are still inconclusive (Sun *et al* 2017, Yang *et al* 2017, Yin and Sun 2017). Furthermore, the differences between results derived from inter-city and intra-city variations are not explored. Therefore, the relationships between private transportation and its determinants in Chinese cities are worth revisiting.

Here we address gaps in the previous literature by examining the scaling relations of metrics of public and private transportation of 297 Chinese cities, in conjunction with the impacts of city wealth, urban typology based on economic structure, built environment variables, and fuel price on transportation. Figure 1 illustrates our conceptual model. We posit that all the factors above, as well as local policies on transportation and urban planning, are important in the development of urban public and private transportation. We focus on three questions: (1) what are the scaling patterns of public and private transportation across Chinese cities in 2017–2019? (2) Are the impacts of the built environment on public

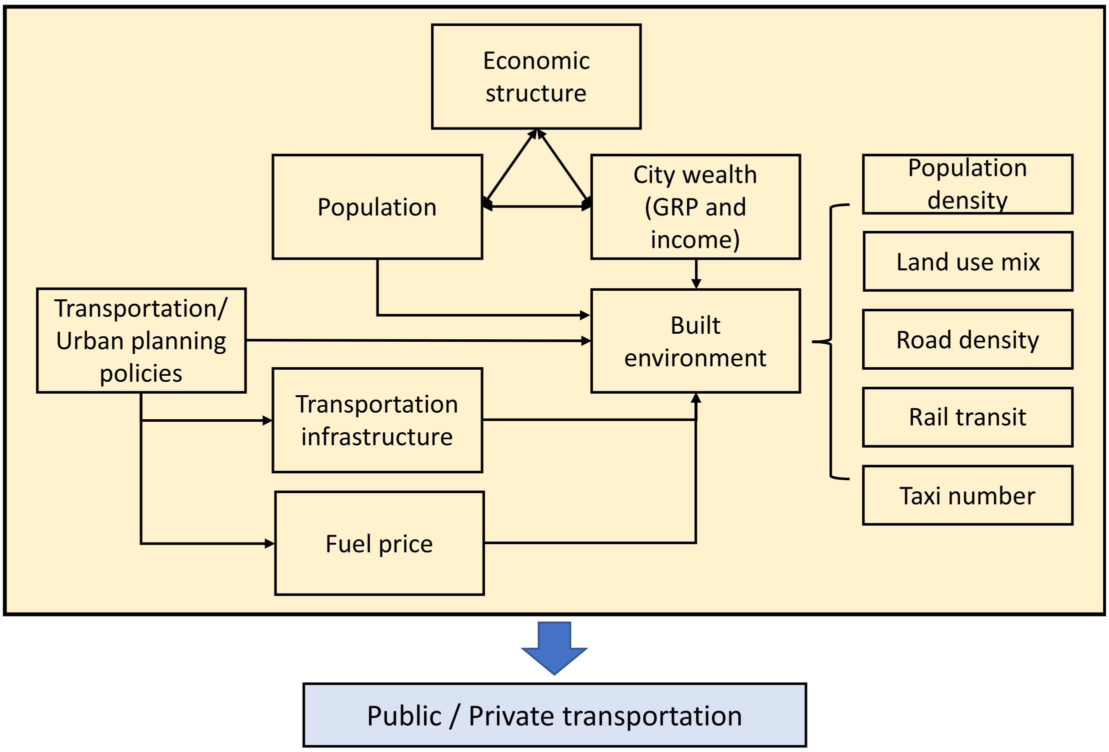

Figure 1. Conceptual modeling framework of public and private transportation and their factors in Chinese cities.

transit use and private vehicle number in Chinese cities consistent with CUD theory? (3) How do patterns of urban transportation metrics vary if analyzed from cross-sectional and temporal perspectives? A better understanding of these issues is needed to inform sustainable transportation and urban planning.

2. Method

We collect data of 297 Chinese cities, with 4 municipalities (Beijing, Tianjin, Shanghai, and Chongqing) and 293 prefecture-level cities. Following the methodology of (Ramaswami *et al* 2018), we focus on 'city propers' instead of entire cities, since city propers are the central areas of cities and better represent urban development patterns.

For the analyses of urban public transportation (bus and rail transit), dependent variables include bus number, annual public transit trip number, and annual public transit passenger kilometers travelled (PKT). While the bus numbers, bus trip numbers, rail transit trip numbers, and rail transit PKT of cities are officially reported, there is no available city-level bus PKT data. Only Shaanxi and Jiangxi provinces report city-level total bus operation mileages in their yearbooks. Based on data from the two provinces from 2017 to 2019, we find a linear relationship between the total bus mileage per year and the number of buses in a city (see figure S1) that can be applied to other cities. We find the average mileage per bus per year is 54 680 km, consistent with the national average value from recent literature (Huo *et al* 2012). Assuming that the average bus mileage and load factor (taken from an integrated assessment model GCAM-China (Tong *et al* 2020)) are approximately the same across cities in China, we estimate bus PKT in each city proper and sum with the rail transit PKT to calculate the PKT of public transit.

For the analyses of urban private transportation, the dependent variable is private vehicle number. Previous studies (Li *et al* 2010, Cao and Huang 2013, Sun *et al* 2017, Yang *et al* 2017, Yin and Sun 2017) on private transportation in Chinese cities usually take private vehicle number or ownership as the dependent variable, since vehicle activity data such as VKT are not available at the city level except for some megacities (e.g. Beijing, Shanghai). One exception is (Du and Lin 2019), which estimates automobile energy consumption based on vehicle number, vehicle type, and average fuel use data. However, it fails to consider the heterogeneity of VKT across cities with different urban forms, which is a key part of CUD theory (Ewing and Cervero 2010). Therefore, here we continue to use private vehicle number as the dependent variable.

Table 1. Summary statistics of data.

Variable	Unit	Mean	Standard deviation	Minimum	Maximum
Population	10 000-persons	195	299	4.6	2567
GRP	10 000-Chinese Yuan	2.5×10^7	4.4×10^7	4.9×10^6	3.8×10^8
Disposable income per capita	Chinese Yuan	35 381	9032	21 370	73 849
Population density	10 000-persons km^{-2}	1.27	0.69	0.20	11.52
Land use mix index	N/A	0.85	0.05	0.63	0.98
Road density	km km^{-2}	6.24	2.33	0.31	16.23
Existence of rail transit	N/A	0.12	0.33	0	1
Taxi number per capita	Taxies/10 000-persons	17.6	14.0	0.33	142.3
Total bus number	N/A	1838	3089	16	25 624
Annual public transit trip number	10 000-trips yr^{-1}	29 759	78 877	56	713 386
Annual public transit PKT	10 000-person km yr^{-1}	269 913	663 733	1750	6104 695
Private vehicle number	10 000-vehicles	72.6	76.0	3.2	497.4
Gasoline price	Chinese Yuan/L	6.65	0.54	5.66	8.38

Note: N/A means 'not applicable'.

The independent variables are described as follows:

(1) **Population:** There are two types of population data in China. Resident population refers to the population living in a city within a period, while registered population refers to people with hukou (officially registered) in a city without necessarily living there (Beijing Municipal Bureau of Statistics 2021). Here, the urban population is defined as the resident population (pop) in city propers, as the resident population better characterizes the real scales and dynamics of cities.

(2) **City wealth:** We use gross regional product (GRP) of city propers to quantify the wealth of cities. However, as pointed out by (Ramaswami *et al* 2018), GRP cannot be exactly converted to urban household income and this conversion depends highly on urban typology. Therefore, we also include the disposable income per capita of urban residents (income) in our analyses.

(3) **The built environment:** The urban form factors considered include population density (pop den, resident population/urban built-up area (constructed area with basic infrastructure within urban administrative divisions)), land use diversity (land use mix, represented by an entropy-like index (Cao and Yang 2017, Xu *et al* 2018)), and road density (road den, total road length/urban built-up area). To capture the level of urban public transit provision, we also add a dummy variable indicating whether a city has urban rail transit (rail), and taxi number per capita (taxi num, total taxi number/resident population). These variables are included to explore the effects of '5D' parameters in CUD theory on transportation in the Chinese urban context.

(4) **Fuel price:** We use the regulated price of standard gasoline, type 92, to represent the fuel price (fuel price). The fuel price in China is regulated at the provincial level by the National Development and Reform Commission, and the retail fuel price in a province fluctuates around the regulated price by less than 5% based on local cost (National Energy Administration 2011).

All data are collected from official sources, including China City Statistical Yearbooks, China Urban Construction Statistical Yearbooks, the website of China Association of Metros (China Association of Metros 2021), databases of national oil price (CNGold 2023, EastMoney 2023), provincial statistical yearbooks, and city-level statistical bulletins. We focus on the data from 2017 to 2019 to investigate the recent patterns of urban transportation development in China. To exclude the impacts of COVID-19 on transportation, we do not include data after 2019. After excluding missing data, we get 858 city-year observations for public transportation and 778 for private transportation. Table 1 lists the summary statistics of our data.

Based on existing urban theories, we propose the following hypotheses:

H1. Both public transit use and private vehicle number scale super-linearly with urban population (due to the super-linear scaling of human social interactions in cities (Bettencourt 2013)).

H2. Both public transit use and private vehicle number are positively associated with city wealth.

H3. Public transit use is positively associated with population density, land use diversity, road density, and the existence of rail transit, while negatively associated with taxi number per capita.

H4. Private vehicle number is negatively associated with population density, land use diversity, road density, and public transit provision (the existence of rail transit, and taxi number per capita).

H5. Public transit use is positively associated with fuel price, while private vehicle number is negatively associated with fuel price.
H6. The impacts of population, wealth, the built environment, and fuel price on public transit use and private vehicle number vary across cities with different economic structures.

To examine the hypotheses above, we conduct three types of analyses:

(1) **Simple population-scaling and GRP-scaling relationships of all cities.** We assess how transportation variables scale with urban population and GRP separately. Through simple log-log regressions, we determine the scaling patterns of these variables.
(2) **Simple scaling relationships in different categories of cities.** We explore whether the scaling relations of transportation variables with population and GRP are dependent on urban typology. We categorize cities into three types by economic structure (industrial, mixed-economy, and commercial) based on the GRP shares of different industries and build the categorical regression model following the method of (Ramaswami *et al* 2018).
(3) **Bivariate multiple regressions of transportation in different categories of cities**. We further employ multiple log-log regressions to examine the combined impacts of population, wealth, urban typology, the built environment, and fuel price on public transit PKT and private vehicle number. The variance inflation factor analysis shows there is no strong collinearity between independent variables. Besides the regressions where we simply pool all data across cities and years together ('the Pooled model'), we also perform two sets of fixed effect regressions ('the City model' and 'the Year model'), where the city or year fixed effects are included. The fixed effect regression is preferred over random effect regression based on the result of Hausman test. As an example, the categorical regression equation of the City/Year model is as follows:

$$\begin{aligned}\ln\left(\left[\text{pub PKT}_{it},\ \text{veh num}_{it}\right]\right) = &\sum\nolimits_{j=1}^{3}\left[a_j \times I_j + b_j \times I_j \times \ln\left(\text{income}_{it}\right) + c_j + I_j \times \ln\left(\text{pop}_{it}\right) + d_j \times I_j\right.\\ &\times \ln\left(\text{pop den}_{it}\right) + e_j \times I_j \times \ln\left(\text{land use mix}_{it}\right) + f_j \times I_j \times \ln\left(\text{road den}_{it}\right)\\ &\left.+ g_j \times I_j \times \text{rail}_{it} + h_j \times I_j \times \ln\left(\text{taxi num}_{it}\right) + k_j \times I_j \times \ln\left(\text{fuel price}_{it}\right)\right]\\ &+ \delta_i \text{ or } \tau_t + \varepsilon_{it}. \qquad (2)\end{aligned}$$

In equation (2), $[\text{pub PKT}_{it}, \text{veh num}_{it}]$ is a vector of public transit PKT and private vehicle number in city i and year t, I_j are the dummy variables of city type, δ_i is a city-specific term absorbing all factors constant over time (city fixed effect), τ_t is a year-specific term absorbing all factors constant across cities (year fixed effect), and ε_{it} denotes the error term. While the Pooled model estimates coefficients based on both inter-city and intra-city variations of variables over time, the coefficients of the City model are derived from intra-city variations over time and averaged across cities, and the coefficients of the Year model are derived from inter-city variations within a specific year and averaged over years.

3. Results

3.1. Simple regression of public transit use

Table 2 shows the population- and GRP-scaling relationships for public transit use analyzed using number of buses, number of public transit trips, and public transit PKT.

The results of the non-categorical model (all cities grouped together) demonstrate that all three dependent variables scale super-linearly with urban population (supporting hypothesis H1). This implies that public transit use has similar scaling patterns as urban characteristics related to wealth creation and innovation. Due to the agglomeration effect, residents in cities with larger populations take public transit more frequently. Scaling relations with GRP are sub-linear or linear, as GRP represents city wealth and scales super-linearly with urban population.

The results of the categorical model (cities grouped by economic structure, see figures 2 and S2) illustrate the differences in scaling patterns across groups of cities. For population-scaling, the scaling factors of transit trip number and PKT differ by city type (supporting hypothesis H6), with commercial cities having the highest scaling factors and industrial cities having the lowest (figures 2(a) and S2(c)). We also perform regressions against normalized population size for each city group and find similar results, suggesting that the scaling difference across city groups is not due to difference in city size distributions (supplementary note 1). In addition, we find that the linearity of population-scaling also depends on city

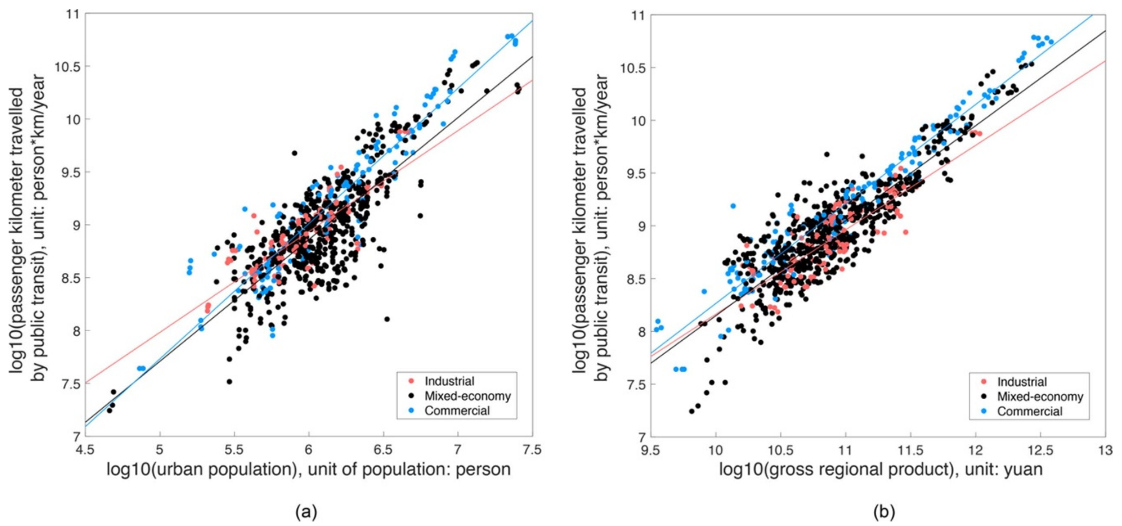

Figure 2. Scaling relationships of public transit PKT with respect to (a) population and (b) GRP in industrial, mixed-economy and commercial cities. Regressions within each category are indicated by the colored lines.

type. Mixed-economy and commercial (industrial) cities show super-linear (linear) scaling of public transit use with population. Thus the agglomeration effect in Chinese industrial cities is not strong enough to generate super-linear growth in public transit, perhaps due to relatively small city sizes (Ramaswami *et al* 2018). When we use GRP as the scaling metric, however, the effect of city type on transit use is smaller. For GRP-scaling, although the relative relationship of scaling factors across city groups remains essentially the same (figures 2(b), S2(b) and (d)), the inter-group differences are generally insignificant (table 2) due to the different GRP-population scaling relations across city groups in China (Ramaswami *et al* 2018). Therefore, it is likely that cities with more commercial activities experience faster scaling of GRP with population and hence faster scaling of public transit use.

3.2. Multiple regression of public transit PKT

The multiple regression results of public transit PKT against various variables are summarized in figure 3 and table S1. The Year model and the Pooled model produce similar results for most independent variables except for fuel price, while the City model results are quite different. The coefficient change in fuel price in the Year model is because the fuel prices of all cities vary similarly over time and absorb much of the year fixed effect. We therefore just compare the results of the Pooled (the most common scaling approach) and the City models. We find the City model better controls for omitted city-level variables and thus better explains public transit PKT (greater R^2) variations than the Pooled model.

In the Pooled model (figure 3(a)), the two dominant drivers of public transit PKT are population and income which both show positive correlations with PKT (supporting hypothesis H2). The coefficient of population is significantly larger than 1, demonstrating that the super-linear scaling of transit PKT with population remains solid after controlling for other factors. Results for the impacts of the built environment are unexpected. First, population density and land use mix are negatively associated with transit PKT. This is opposite to hypothesis H3 and the finding of a study on US cities (Wu *et al* 2019a). We find that in Chinese cities, if other variables are held constant, transit PKT decreases by 0.5% for each 1% increase in population density. A possible explanation is that in denser cities, driving is replaced by walking and mechanical and electric cycling rather than by buses and subways. Additionally, the densities of most Chinese cities may be higher than a threshold over which density has less impact on public transit use. Second, we find a positive correlation between taxi number per capita and transit PKT, implying that taxies and public transit are complements in Chinese cities.

There are four notable differences between the City (figure 3(b)) and the Pooled models. First, the coefficient of population for all cities grouped together drops to 0.48 (sub-linear scaling). It shows that only 40% of the scaling of transit PKT with population measured from the pooled data can be attributed to population growth within individual cities, while the rest 60% are associated with city heterogeneity. This echoes the finding of recent literature that the scaling forms of urban variables derived from pooling data of multiple cities and years cannot be directly applied to the dynamics of individual cities (Depersin and Barthelemy 2018). Second, the coefficient of income is much less for mixed-economy cities and even becomes negative for industrial cities in the City model. This might be ascribed to two competing effects of

Table 2. Population- and GRP-scaling relationships of public transit use in industrial, mixed-economy, and commercial cities.

Dependent variable		All cities ($n = 858$)			All cities categorized into different types						
					Industrial ($n = 118$)		Mixed-economy ($n = 592$)		Commercial ($n = 148$)		
		b	Linearity	Adjusted R^2	b	Linearity	b	Linearity	b	Linearity	Adjusted R^2
Scaling factors with respect to population	Bus number	1.090^{***} (0.025)	Super-linear	0.694	0.948 (0.084)	Linear	1.085 (0.032)	Super-linear	1.137 (0.042)	Super-linear	0.707
	Public transit trip number	1.243^{***} (0.035)	Super-linear	0.599	$0.891^{\$\$}$ (0.116)	Linear	1.196 (0.045)	Super-linear	$1.396^{\$\$\$}$ (0.058)	Super-linear	0.630
	Public transit PKT	1.180^{***} (0.026)	Super-linear	0.713	$0.954^{\$\$}$ (0.087)	Linear	1.152 (0.033)	Super-linear	$1.280^{\$\$}$ (0.043)	Super-linear	0.731
Scaling factors with respect to GRP	Bus number	0.852^{***} (0.014)	Sub-linear	0.802	0.798 (0.054)	Sub-linear	0.856 (0.018)	Sub-linear	0.841 (0.024)	Sub-linear	0.816
	Public transit trip number	0.962^{***} (0.023)	Linear	0.680	$0.751^{\$\$}$ (0.084)	Sub-linear	0.947 (0.028)	Linear	1.002 (0.037)	Linear	0.708
	Public transit PKT	0.914^{***} (0.015)	Sub-linear	0.810	$0.800^{\$}$ (0.056)	Sub-linear	0.900 (0.019)	Sub-linear	0.943 (0.024)	Sub-linear	0.828

Note: Values in parentheses are the standard deviations. Asterisks (*) in the columns under the non-categorical model show whether the scaling factors are significant (*: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$). Section marks (§) in the columns under the categorical model show whether the scaling factors of industrial and commercial cities are significantly different from mixed-economy cities ($^{\$}$: $p < 0.1$; $^{\$\$}$: $p < 0.05$; $^{\$\$\$}$: $p < 0.01$). The linearities of scaling relationships are determined at a 95% confidence level.

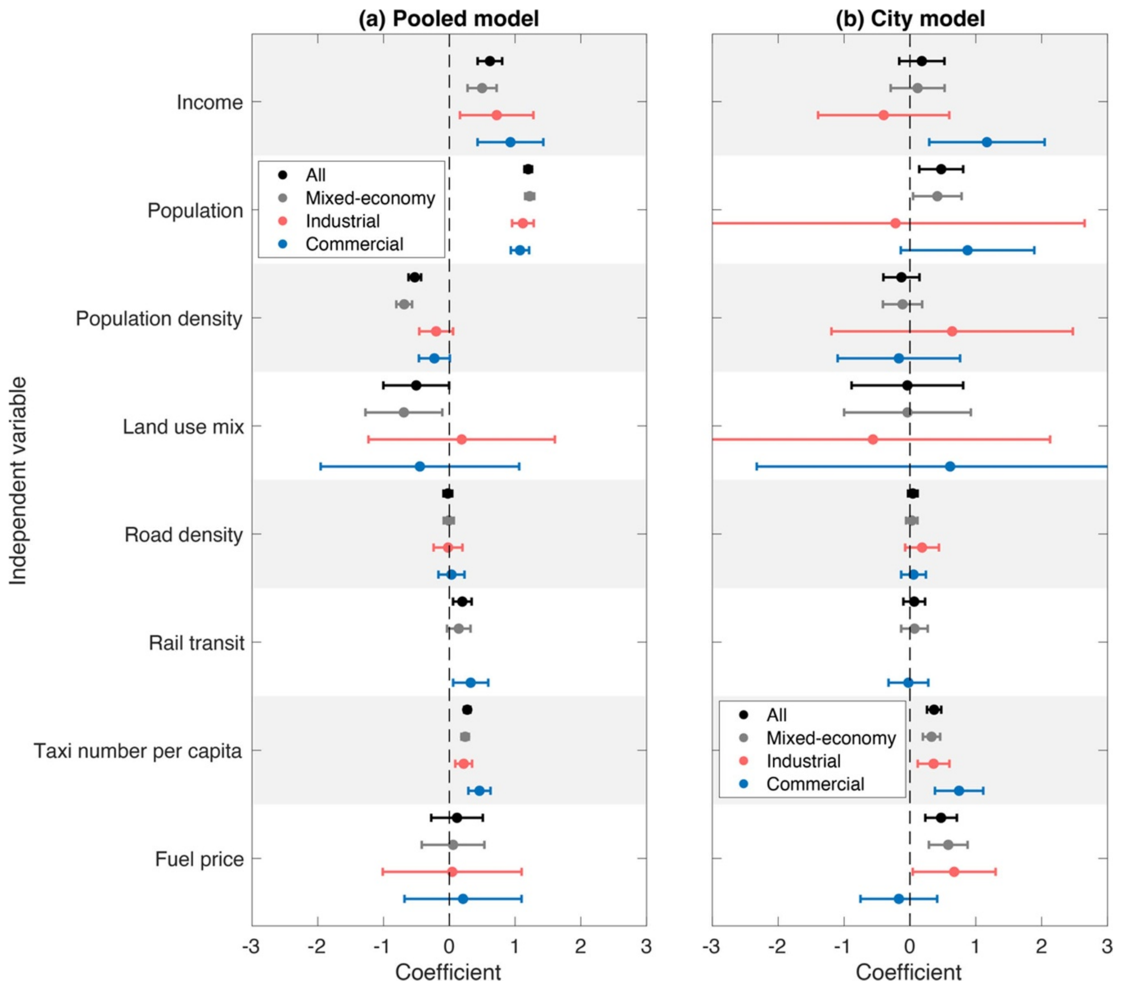

Figure 3. Regression results of (a) the Pooled model and (b) the City model of public transit PKT. The points indicate the coefficient values while the ranges show the 95% confidence intervals. Black, grey, red, and blue plots represent all, mixed-economy, industrial, and commercial cities, respectively.

city wealth on resident preference over transportation modes. On one hand, wealthier cities have better developed transit infrastructure, promoting more public transit use. On the other hand, income increases would enable car purchases and lead to a shift from using public transit to driving. While the latter impact should be homogeneous in the two models, the former impact reflects city-level path dependence due to the lock-in effect of urban infrastructure and is hence more dominant when inter-city variations are included (the Pooled model). Third, the coefficients of population density and land use mix become insignificant, implying that improving the '5Ds' within individual cities may not enhance public transit use significantly, although there may be a threshold density above which transit and taxi uses become widespread (Global Platform for Sustainable Cities 2020). Fourth, fuel price becomes positively associated with public transit PKT (supporting hypothesis H5) in industrial and mixed-economy cities, which suggests that increased fuel price makes public transit more economically favorable in these two city groups. In commercial cities, however, the effect of fuel price is likely attenuated due to higher income.

3.3. Simple regression of private vehicle number

Table 3 and figure 4 present the population- and GRP-scaling relations of two sets of private vehicle numbers. The officially reported vehicle numbers (uncalibrated) correspond to the registered populations of entire Chinese cities (Moody *et al* 2019), while in this study urban population refers to the resident populations of city propers. To address this mismatch between vehicle numbers and populations, we calibrate the vehicle numbers (equation (3)) assuming the vehicle numbers per capita of the two kinds of populations are the same

$$\text{veh num}_{\text{calib}} = \text{veh num} * \frac{\text{resident pop of city proper}}{\text{registered pop of city}} \tag{3}$$

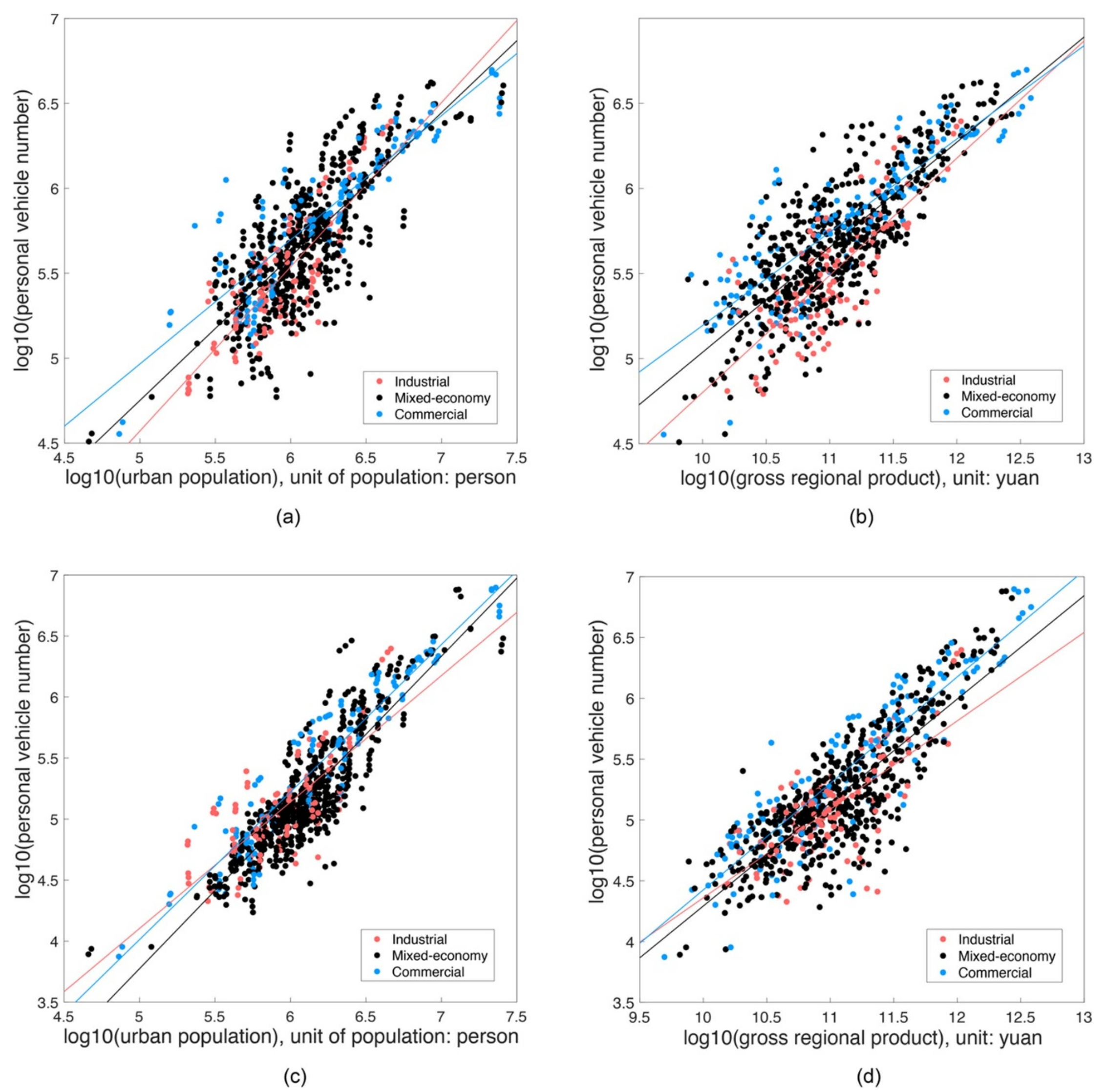

Figure 4. Scaling relationships of (a), (b) uncalibrated and (c), (d) calibrated private vehicle number with respect to (a), (c) population and (b), (d) GRP in industrial, mixed-economy, and commercial cities. Regressions within each category are indicated by the colored lines.

The calibration substantially increases the scaling factors in both the non-categorical and the categorical models and appears to better characterize the scaling relations of private vehicle number (improved R^2 in table 3). The population-scaling relationship in the non-categorical model even turns from sub-linear to super-linear. This is because large cities tend to have higher resident population than registered population, while the opposite is true for small cities. In addition, the calibration changes the rank of scaling factors in different city groups. The uncalibrated vehicle number scales faster with urban size in industrial cities than in mixed-economy and commercial cities, while the calibrated vehicle number scales faster in commercial and mixed-economy cities. Like public transit use, private vehicle number also scales super-linearly with population (supporting hypothesis H1) and sub-linearly with GRP, implying a common scaling pattern of transportation in Chinese cities.

3.4. Multiple regression of private vehicle number

The multiple regression results of private vehicle number are presented in figure 5 and table S2. Again, the Pooled and City models yield contrasting results.

The Pooled model (figure 5(a)) demonstrates that wealth and population have substantially higher influences than built environment factors and fuel price. The scaling of private vehicle number with population remains super-linear. Income is positively correlated with vehicle number in all types of cities (supporting hypothesis H2), but the rates of fleet growth are significantly different across city groups. Vehicle number has a high sensitivity to income growth for industrial cities, with the income coefficient (2.1) more than twice the value for commercial cities (0.8). This echoes the findings of previous studies on vehicle

Table 3. Population- and GRP-scaling relationships of private vehicle number in industrial, mixed-economy, and commercial cities.

Dependent variable		All cities ($n = 778$)			All cities categorized into different types						
					Industrial ($n = 112$)		Mixed-economy ($n = 529$)		Commercial ($n = 137$)		
		b	Linearity	Adjusted R^2	b	Linearity	b	Linearity	b	Linearity	Adjusted R^2
Scaling factors with respect to population	Private vehicle number (uncalibrated)	0.836^{***} (0.023)	Sub-linear	0.639	0.967 (0.075)	Linear	0.847 (0.030)	Sub-linear	$0.731^{\S\S}$ (0.038)	Sub-linear	0.654
	Private vehicle number (calibrated)	1.233^{***} (0.023)	Super-linear	0.787	$1.036^{\S\S\S}$ (0.075)	Linear	1.280 (0.030)	Super-linear	1.209 (0.038)	Super-linear	0.802
Scaling factors with respect to GRP	Private vehicle number (uncalibrated)	0.612^{***} (0.017)	Sub-linear	0.637	0.689 (0.056)	Sub-linear	0.617 (0.020)	Sub-linear	$0.548^{\S\S}$ (0.029)	Sub-linear	0.671
	Private vehicle number (calibrated)	0.858^{***} (0.020)	Sub-linear	0.708	$0.727^{\S}$ (0.068)	Sub-linear	0.851 (0.025)	Sub-linear	0.875 (0.035)	Sub-linear	0.725

Note: Values in parentheses are the standard deviations. Asterisks (*) in the columns under the non-categorical model show whether the scaling factors are significant ($^{*}: p < 0.1$; $^{**}: p < 0.05$; $^{***}: p < 0.01$). Section marks (§) in the columns under the categorical model show whether the scaling factors of industrial and commercial cities are significantly different from mixed-economy cities ($^{\S}: p < 0.1$; $^{\S\S}: p < 0.05$; $^{\S\S\S}: p < 0.01$). The linearities of scaling relationships are determined at a 95% confidence level.

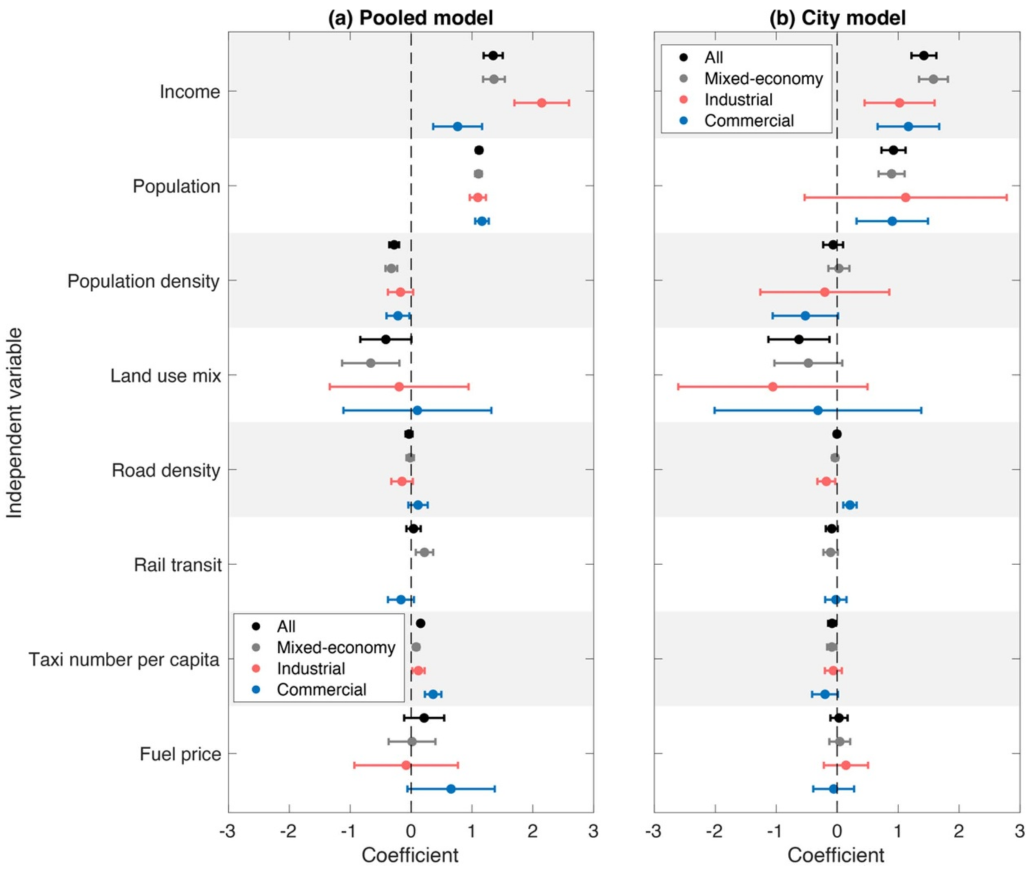

Figure 5. Regression results of (a) the Pooled model and (b) the City model of private vehicle number. The points indicate the coefficient values while the ranges show the 95% confidence intervals. Black, grey, red, and blue plots represent all, mixed-economy, industrial, and commercial cities, respectively.

ownership expansion rates across countries (Dargay and Gately 1999, Dargay *et al* 2007). With lower base vehicle ownership and larger potential of fleet expansion, wealth increase in industrial cities drives more residents to purchase cars than in the other two city groups. Additionally, the Pooled model shows that more compact urban form (i.e. higher density and land use mix) is associated with lower private vehicle number, especially in mixed-economy cities. This supports part of hypothesis H4 and is consistent with CUD theory and existing studies on Chinese cities (Li *et al* 2010, Cao and Huang 2013, Sun *et al* 2017, Yin and Sun 2017). Moreover, we find a positive association between private vehicle number and taxi number per capita. This contradicts with part of hypothesis H4 and implies that there are omitted variables determining the total travel demand by vehicle within a city.

In the City model (figure 5(b)), however, while population and income remain the dominant factors, the scaling of vehicle number with population becomes linear instead. Besides, the impact of population density is attenuated and only weakly significant for commercial cities. It shows that densification may not lead to a shrinking fleet in individual Chinese cities, consistent with the finding of (Cao and Huang 2013) that the negative effect of population density on private car ownership in China varied across years and became insignificant after 2005. Nevertheless, it should not be interpreted as that densification is ineffective to reduce auto dependence in general, as the densities of many Chinese cities are already high compared to their global counterparts (Güneralp *et al* 2020) and probably above the threshold to effectively influence travel behaviors (Wu *et al* 2019b). Moreover, we find that other CUD strategies (i.e. improving land use diversity and building rail transit) could contain fleet growth within a city. For street network design, although we find no correlation between road density and fleet size when all cities are grouped together, there are significant and different associations between the two variables across city groups (supporting hypothesis H6). Increasing road density is associated with larger vehicle number in commercial cities but smaller fleet size in industrial cities, indicating a dual role of road density. On one hand, high road density represents denser street networks and more intersections, which promotes walking and cycling rather than driving. On the other hand, high road density also implies better road infrastructure (e.g. more parking lots), enhancing the convenience of driving. Our results indicate that the former influence is stronger in industrial cities, while the latter overtakes the former in commercial cities, probably due to their relatively high vehicle ownerships. Additionally, expanding taxi fleet in individual cities could significantly reduce residents' dependence on private vehicles, supporting the idea of developing alternative transportation to improve urban sustainability. Finally, higher fuel price is not significantly associated with lower private vehicle number but may still make driving less preferable than taking public transit (see section 3.2).

4. Discussion

China has a huge vehicle fleet, making up 14% of global automobiles (Li *et al* 2017) with numbers increasing by over 200% in the past decade (China Association of Automobile Manufacturers 2022). However, private vehicle ownership in China is still much lower than many developed countries. There are only 0.17 private vehicles per capita in China (National Bureau of Statistics of China 2022), while that number in the US is 0.75 (US Federal Highway Administration 2022). Thus, the vehicle number in China is likely to keep increasing over the next few decades (Li *et al* 2019, Ma *et al* 2019). Although Chinese cities are more compact than many cities in developed countries, they witnessed a sharp decline in population density between 1970 and 2010 (Güneralp *et al* 2020). If the urban sprawl in China continues, residents will increasingly rely on private vehicles and the fleet growth will accelerate further.

Transportation is a major contributor to CO_2 and air pollutant emissions in China, accounting for 10% and 23% of Chinese CO_2 and NO_x emissions (Zheng *et al* 2018). Transportation also contributes indirectly to PM (particulate matter) formation and is the largest source of PM in some major Chinese cities (Li *et al* 2017). Since China pledges to achieve carbon neutrality by 2060, future growth in vehicle numbers will require rapid fleet electrification. If sustainable urban planning could reduce auto dependence, it would slow increases in private vehicle ownership and use, facilitate transportation decarbonization, improve urban street life, and bring considerable climate and air quality co-benefits.

Using aggregated data of 297 Chinese cities in 2017–2019, we explore the impacts of population, wealth, urban typology, the built environment, and fuel price on urban transportation. We find that both public transit use and private vehicle number scale super-linearly with population and sub-linearly with GRP. As urban population increases, although the agglomeration of people and capital catalyzes economic growth, it also intensifies transportation activities and incurs environmental impacts. This implies that the decarbonization of transportation in megacities is particularly critical and requires more effort.

Through multiple regressions we further demonstrate that wealth, the built environment, and fuel price have significant associations with urban transportation. We find that wealthier, less compact cities tend to have more private vehicles. Specifically, the private vehicle number scales super-linearly with income, implying a potential explosive increase in vehicle number with future economic development. We find that currently improving land use diversity and providing rail transit and taxies are more effective strategies than further increasing population density to reduce auto dependence in Chinese cities, probably due to the threshold effect of density. The impact of taxies implies that promoting similar transportation modes (e.g. dynamic ride sharing) might be promising as well to contain the fleet growth. Additionally, we find higher fuel price is associated with more transit use within a city, suggesting that fuel tax is a potentially effective policy to promote public transit use. However, we also find that residents in cities with higher density and land use diversity take less public transit. This implies that the travel behavior of Chinese urban residents is more complicated than the theories built upon observations in developed countries (table S3).

Categorizing cities based on economic structure yields interesting results. We find that different types of cities (industrial, mixed-economy, commercial) have different speeds of scaling. Moreover, the sensitivities of transportation to some factors vary significantly across city groups. Densifying road networks could effectively contain the size of private vehicle fleets within an industrial or a mixed-economy city, but may only incentivize car purchases in a commercial city. Therefore, transportation policies should not be universal across cities but should be contingent on urban typology.

Additionally, we find striking differences between the Pooled and the City model results. The scaling of transit use and vehicle number with population is no longer super-linear when the analysis focuses on intra-city variations over time. For private vehicle ownership, teasing out intra-city variations attenuates the negative density effect and reverses the taxi effect from positive to negative. These differences imply strong city-specific historical inertia or policy heterogeneity of transportation development. While many studies on urban transportation extrapolate results from inter-city variations (Li *et al* 2010, Sun *et al* 2017, Yin and Sun 2017, Lei *et al* 2021, Wu *et al* 2021), here we show that a pattern generalized from a snapshot of multiple cities cannot be used to predict the evolution of a specific city. To inform policymaking, care must be taken to ensure that the analysis approach matches the policy goal. For emergent city planning based on general urban development patterns, cross-sectional analysis that captures inter-city variations is of great value. For optimizing transportation in existing cities, city heterogeneity should not be ignored, and temporal analysis of intra-city variations is preferred.

Our results are subject to the following limitations. First, as city-level VKT data are unavailable for most Chinese cities, we use vehicle number to characterize private transportation without considering the variations of vehicle use intensity. Previous studies indicate that compact urban form could also reduce private VKT in China (Cao and Yang 2017, Chen *et al* 2017, Jiang *et al* 2017). Therefore, our results underestimate the potential of optimizing the built environment to reduce personal travels. Second, when calibrating the private vehicle number, we assume that the probability for residents without *hukou* to own a car is the same as registered residents. Since people without *hukou* are generally less financially capable of owning a car (Yao and Wang 2018), the vehicle numbers of cities with high in-migration are overestimated. Third, due to the lack of city-level data, variables characterizing other travel modes (walking, cycling, ride-hailing, etc) are not included. However, these travel modes are likely to affect the uses of public transit and private vehicles.

5. Conclusions

Our study reveals that urban transportation is shaped collectively by population, city wealth, urban typology, the built environment, and fuel price. We demonstrate that the urban transportation development patterns derived from pooling data of multiple cities, as previous studies have done, does not characterize the evolution of individual cities over time. We find that diversifying land use and promoting rail transit and taxies are effective in reducing private vehicle ownership in Chinese cities. Our findings support the idea of improving urban transportation through compact growth. While in this paper we only include the impacts of bus, rail transit, and taxies, future work should consider exploiting data of other urban travel modes (e.g. ride-hailing, bicycle-sharing) to further examine how land use and transportation infrastructure influence the travel choices of urban residents. Future work should also explore currently feasible policies to improve urban planning in China. Given the long-term implications of urban land use and infrastructure, early planning is necessary to ensure a sustainable future of cities.

Data availability statement

All data analyzed during this study are available from publicly accessible sources stated in the manuscript. The codes that support the findings of this study are available from the corresponding authors on reasonable request.

No new data were created or analyzed in this study.

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References

Beijing Municipal Bureau of Statistics 2021 Resident population and registered population (available at: http://tjj.beijing.gov.cn/zwfw/sjbs/ndbfw/zbjd_31416/202003/t20200321_1723817.html)

Bettencourt L M A 2013 The origins of scaling in cities *Science* **340** 1438–41

Bettencourt L M A, Lobo J, Helbing D, Kühnert C and West G B 2007 Growth, innovation, scaling, and the pace of life in cities *Proc. Natl Acad. Sci. USA* **104** 7301–6

Bettencourt L M A, Yang V C, Lobo J, Kempes C P, Rybski D and Hamilton M J 2020 The interpretation of urban scaling analysis in time *J. R. Soc. Interface* **17** 20190846

Borck R and Brueckner J K 2018 Optimal energy taxation in cities *J. Assoc. Environ. Resour. Econ.* **5** 481–516

Cao X and Huang X 2013 City-level determinants of private car ownership in China *Asian. Geogr.* **30** 37–53

Cao X and Yang W 2017 Examining the effects of the built environment and residential self-selection on commuting trips and the related CO_2 emissions: an empirical study in Guangzhou, China *Transp. Res.* D **52** 480–94

Cervero R 1996 Mixed land-uses and commuting: evidence from the American Housing Survey *Transp. Res.* A **30** 361–77

Cervero R 2002 Built environments and mode choice: toward a normative framework *Transp. Res.* D **7** 265–84
Cervero R and Kockelman K 1997 Travel demand and the 3Ds: density, diversity, and design *Transp. Res.* D **2** 199–219
Chen F, Wu J, Chen X and Wang J 2017 Vehicle kilometers traveled reduction impacts of transit-oriented development: evidence from Shanghai City *Transp. Res.* D **55** 227–45
China Association of Automobile Manufacturers 2022 Number of cars in China 2011–2021 (available at: www.caam.org.cn/chn/11/cate_120/con_5235354.html)
China Association of Metros 2021 Statistics of urban rail transportation in China (available at: www.camet.org.cn/)
Clark S D 2007 Estimating local car ownership models *J. Transp. Geogr.* **15** 184–97
CNGold 2023 National oil price reported by CNGold (available at: www.cngold.org/crude/city_all.htm)
Creutzig F 2014 How fuel prices determine public transport infrastructure, modal shares and urban form *Urban Clim.* **10** 63–76
Creutzig F, Baiocchi G, Bierkandt R, Pichler P-P and Seto K C 2015 Global typology of urban energy use and potentials for an urbanization mitigation wedge *Proc. Natl Acad. Sci. USA* **112** 6283–8
Dargay J and Gately D 1999 Income's effect on car and vehicle ownership, worldwide: 1960–2015 *Transp. Res.* A **33** 101–38
Dargay J, Gately D and Sommer M 2007 Vehicle ownership and income growth, worldwide: 1960–2030 *Energy J.* **28** 143–70
Depersin J and Barthelemy M 2018 From global scaling to the dynamics of individual cities *PNAS* **115** 2317–22
Dhakal S, Seto K, Bigio A, Blanco H, Delgado Ramos G C and Dewar D 2014 AR5 climate change 2014: mitigation of climate change *Human Settlements, Infrastructure and Spatial Planning* (IPCC) ch 12 (available at: www.ipcc.ch/report/ar5/wg3/)
Du Z and Lin B 2019 Changes in automobile energy consumption during urbanization: evidence from 279 cities in China *Energy Policy* **132** 309–17
EastMoney 2023 National oil price reported by EastMoney (available at: https://data.eastmoney.com/cjsj/oil_default.html)
Ewing R and Cervero R 2001 Travel and the built environment: a synthesis *Transp. Res. Rec.* **1780** 87–114
Ewing R and Cervero R 2010 Travel and the built environment: a meta-analysis *J. Am. Plan. Assoc.* **76** 265–94
Global Platform for Sustainable Cities 2020 A review of integrated urban planning tools for greenhouse gas mitigation (World Bank) (available at: www.thegpsc.org/knowledge-products/integrated-urban-planning/review-integrated-urban-planning-tools-greenhouse-gas)
Güneralp B, Reba M, Hales B U, Wentz E A and Seto K C 2020 Trends in urban land expansion, density, and land transitions from 1970 to 2010: a global synthesis *Environ. Res. Lett.* **15** 044015
Huo H, Zhang Q, He K, Yao Z and Wang M 2012 Vehicle-use intensity in China: current status and future trend *Energy Policy* **43** 6–16
Jiang Y, Gu P, Chen Y, He D and Mao Q 2017 Influence of land use and street characteristics on car ownership and use: evidence from Jinan, China *Transp. Res.* D **52** 518–34
Jones C and Kammen D M 2014 Spatial distribution of U.S. household carbon footprints reveals suburbanization undermines greenhouse gas benefits of urban population density *Environ. Sci. Technol.* **48** 895–902
Karathodorou N, Graham D J and Noland R B 2010 Estimating the effect of urban density on fuel demand *Energy Econ.* **32** 86–92
Keuschnigg M 2019 Scaling trajectories of cities *PNAS* **116** 13759–61
Keuschnigg M, Mutgan S and Hedström P 2019 Urban scaling and the regional divide *Sci. Adv.* **5** eaav0042
Kockelman K 1997 Travel behavior as function of accessibility, land use mixing, and land use balance: evidence from San Francisco Bay Area *Transp. Res. Rec.* **1607** 116–25
Lei W, Jiao L, Xu G and Zhou Z 2021 Urban scaling in rapidly urbanising China *Urban Studies* p 00420980211017817
Li J, Walker J L, Srinivasan S and Anderson W P 2010 Modeling private car ownership in China: investigation of urban form impact across megacities *Transp. Res. Rec.* **2193** 76–84
Li M *et al* 2017 Anthropogenic emission inventories in China: a review *Natl Sci. Rev.* **4** 834–66
Li Y, Miao L, Chen Y and Hu Y 2019 Exploration of sustainable urban transportation development in China through the forecast of private vehicle ownership *Sustainability* **11** 4259
Ma L, Wu M, Tian X, Zheng G, Du Q and Wu T 2019 China's provincial vehicle ownership forecast and analysis of the causes influencing the trend *Sustainability* **11** 3928
Masson-Delmotte V *et al* 2021 Climate change 2021: the physical science basis *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge University Press) (https://doi.org/10.1038/s41597-021-00916-9)
Mi Z, Zheng J, Meng J, Ou J, Hubacek K, Liu Z, Coffman D, Stern N, Liang S and Wei Y-M 2020 Economic development and converging household carbon footprints in China *Nat. Sustain.* **3** 529–37
Minx J, Baiocchi G, Wiedmann T, Barrett J, Creutzig F, Feng K, Förster M, Pichler P-P, Weisz H and Hubacek K 2013 Carbon footprints of cities and other human settlements in the UK *Environ. Res. Lett.* **8** 035039
Moody J, Wang S, Chun J, Ni X and Zhao J 2019 Transportation policy profiles of Chinese city clusters: a mixed methods approach *Transp. Res. Interdiscip. Perspect.* **2** 100053
Nagendra H, Bai X, Brondizio E S and Lwasa S 2018 The urban south and the predicament of global sustainability *Nat. Sustain.* **1** 341–9
National Bureau of Statistics of China 2022 China statistical yearbook 2021 (available at: www.stats.gov.cn/tjsj/ndsj/2021/indexch.htm)
National Energy Administration 2011 Reform plan on crude oil and refined oil prices (available at: www.nea.gov.cn/2011-08/16/c_131051983.htm)
Newman P W G and Kenworthy J R 1989 Gasoline consumption and cities *J. Am. Plan. Assoc.* **55** 24–37
Pan W, Ghoshal G, Krumme C, Cebrian M and Pentland A 2013 Urban characteristics attributable to density-driven tie formation *Nat. Commun.* **4** 1961
Ramaswami A 2020 Unpacking the urban infrastructure nexus with environment, health, livability, well-being, and equity *One Earth* **2** 120–4
Ramaswami A, Jiang D, Tong K and Zhao J 2018 Impact of the economic structure of cities on urban scaling factors: implications for urban material and energy flows in China *J. Ind. Ecol.* **22** 392–405
Schläpfer M, Bettencourt L M A, Grauwin S, Raschke M, Claxton R, Smoreda Z, West G B and Ratti C 2014 The scaling of human interactions with city size *J. R. Soc. Interface* **11** 20130789
Sun B, Zhang T, He Z and Wang R 2017 Urban spatial structure and motorization in China *J. Reg. Sci.* **57** 470–86
Tong D *et al* 2020 Dynamic projection of anthropogenic emissions in China: methodology and 2015–2050 emission pathways under a range of socio-economic, climate policy, and pollution control scenarios *Atmos. Chem. Phys.* **20** 5729–57
Ürge-Vorsatz D, Rosenzweig C, Dawson R, Sanchez-Rodriguez R, Bai X, Barau A S, Seto K and Dhakal S 2018 Locking in positive climate responses in cities *Nat. Clim. Change* **8** 174–7
US Federal Highway Administration 2022 2017 National household travel survey (available at: https://nhts.ornl.gov/)

Wu H *et al* 2021 Urban access across the globe: an international comparison of different transport modes *npj Urban Sustain.* **1** 1–9
Wu H, Levinson D and Sarkar S 2019a How transit scaling shapes cities *Nat. Sustain.* **2** 1142–8
Wu N, Zhao S and Zhang Q 2016 A study on the determinants of private car ownership in China: findings from the panel data *Transp. Res.* A **85** 186–95
Wu X, Tao T, Cao J, Fan Y and Ramaswami A 2019b Examining threshold effects of built environment elements on travel-related carbon-dioxide emissions *Transp. Res.* D **75** 1–12
Xu L, Cui S, Tang J, Yan X, Huang W and Lv H 2018 Investigating the comparative roles of multi-source factors influencing urban residents' transportation greenhouse gas emissions *Sci. Total Environ.* **644** 1336–45
Yang K, Shi Y, Luo Y, Xia D and Zhou X 2018 The spatiotemporal characteristics of Chinese civil vehicles' possession in the context of rapid economic development from 1996 to 2015 *Sustainability* **10** 2999
Yang Z, Jia P, Liu W and Yin H 2017 Car ownership and urban development in Chinese cities: a panel data analysis *J. Transp. Geogr.* **58** 127–34
Yao M and Wang D 2018 Mobility and travel behavior in urban China: the role of institutional factors *Transp. Policy* **69** 122–31
Yin C and Sun B 2017 Disentangling the effects of the built environment on car ownership: a multi-level analysis of Chinese cities *Cities* **74** 188–95
Zegras C 2010 The built environment and motor vehicle ownership and use: evidence from Santiago de Chile *Urban Stud.* **47** 1793–817
Zheng B *et al* 2018 Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions *Atmos. Chem. Phys.* **18** 14095–111
Zünd D and Bettencourt L M A 2019 Growth and development in prefecture-level cities in China *PLoS One* **14** e0221017