OPEN ACCESS

ARTICLE

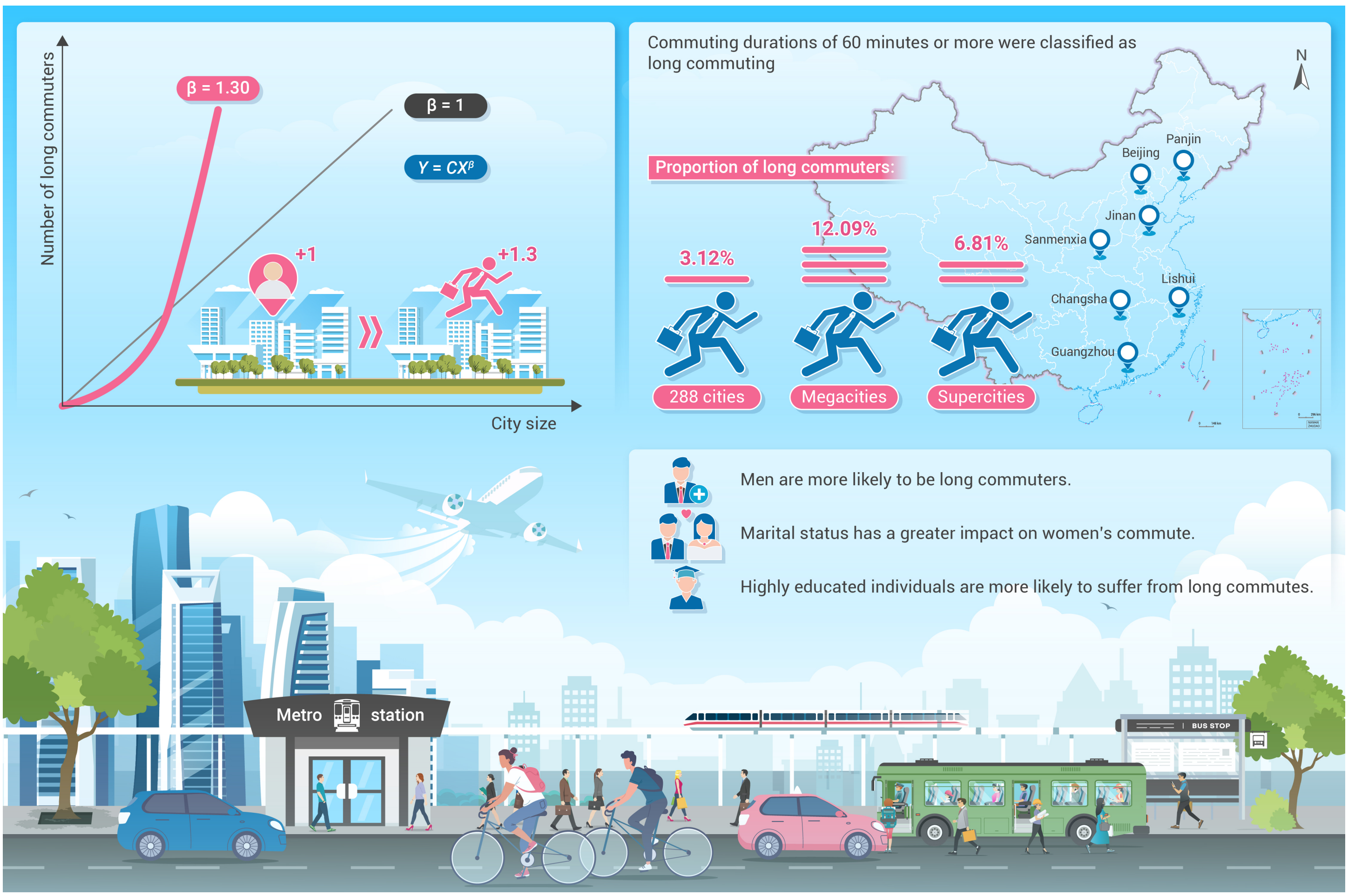
Long commuting, social inequality, and urban development with scaling laws in China

Jie Huang,[1,2] Wenying Fan,[1,2] Jiaoe Wang,[1,2,*] Becky P.Y. Loo,[3] and Wei Qi[1,2]

*Correspondence: wangje@igsnrr.ac.cn

Received: January 20, 2025; Accepted: July 29, 2025; Published Online: August 6, 2025; https://doi.org/10.59717/j.xinn-geo.2025.100164

GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- There is a super-linear relationship between city size and the number of long commuters.
- The super-linear relationship suggests an optimal city size from the perspective of commuting efficiency.
- Long commutes reflect gender, education, and housing inequality, ultimately impacting urban sustainability.

ARTICLE

Long commuting, social inequality, and urban development with scaling laws in China

Jie Huang,[1,2] Wenying Fan,[1,2] Jiaoe Wang,[1,2,*] Becky P.Y. Loo,[3] and Wei Qi[1,2]

[1]Key Laboratory of Regional Sustainable Development Modeling, Institute of Geographic Sciences and Natural Resources Research, CAS, Beijing 100101, China

[2]College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China

[3]Department of Geography, The University of Hong Kong, Hong Kong SAR 999077, China

*Correspondence: wangje@igsnrr.ac.cn

Received: January 20, 2025; Accepted: July 29, 2025; Published Online: August 6, 2025; https://doi.org/10.59717/j.xinn-geo.2025.100164

Citation: Huang J., Fan W., Wang J., et al. (2025). Long commuting, social inequality, and urban development with scaling laws in China. *The Innovation Geoscience* **3**:100164.

Long commuting is associated with negative consequences on the environment, economy, society, and ultimately on urban sustainability. It is still unclear to what extent long commuting, one of the most frequent daily activities for urban dwellers, can be explained with scaling laws. In this paper, we examine whether the number of people suffering from long commuting (LC) disproportionately grows as the city size (population) increases. We employ a census dataset of 811,452 participants, covering details of individual commutes and socioeconomic background in 288 cities in China. By identifying the most sensitive threshold of commuting time, this paper defines commute no less than 60 minutes as LC and explores the scaling laws accordingly. We find that there is a strong super-linear relationship in cities with more than 1.3 million people, suggesting that there exists an optimal city size from the perspective of commuting efficiency. For cities with more than 1.3 million people, this paper reveals that a 1% increase in the population of a city implies an increase of 1.57% in the number of commuters with LC. According to our model calculation, in 2022, the number of long-time commuters in cities with population over one million was 19.06 million in China. With the investigation of various urban attributes and LC, we conclude that mega-cities or above tend to have more LC, the more LC. Moreover, we find that long commuting can reflect on social inequality about gender, income, education, and housing issues, which can offer policy implications for future urban sustainability.

INTRODUCTION

Urban systems present some universal patterns in spatial structures,[1] human mobility[2-5] and city size,[6,7] despite cities being highly complex and diverse.[6] Scaling laws, which describe power-law relationships between city size and various urban attributes,[8] provide a fundamental framework for understanding urban growth, efficiency, and productivity. By bridging urban science with multiple disciplines, including biology and social science,[9-11] scaling laws offer a systematic approach to exploring urban phenomena, particularly in relation to mobility and commuting patterns.

Long commuting (LC) is an urban challenge in daily life, influencing environmental sustainability, economic productivity, and social equity. In urban systems, commuting is essential in individual life, and it can reflect the daily rhythm and spatial structures of an entire city.[12] A plethora of discussions about LC identify it as having negative impacts on the environment,[13] economy,[14,15] interpersonal relationship,[16] personal health[17,18] and well-being.[19-21] Commuting duration significantly affects individuals' well-being and daily routines,[19,20] while also shaping traffic flows and urban morphology.[22-23] Following this stream, job accessibility, a commute-related indicator, is widely recognized as critical to urban sustainable development, ecologically and socially.[24] Despite its significance, little research has examined LC through the lens of urban scaling laws. Existing studies on commuting often focus on individual cities or transportation network analyses, without capturing a generic relationship between commuting time and city size.

Scaling law theory offers a unique perspective compared to conventional transportation models. Traditional models analyze commuting through network structures, congestion dynamics, or spatial mismatch theories.[25,26] In contrast, scaling laws provide a generalized, nonlinear framework that reveals how commuting behavior scales with urban population size. This approach enables comparative analysis across different urban contexts, allowing for the identification of universal trends and thresholds that impact urban efficiency. Following this stream, LC is linked to rapid population growth and urban expansion.[27,28] Given the rapid urbanization observed in both developed and developing countries,[19,29-32] understanding how LC scales with city size is essential for policy-making and urban planning. Addressing three fundamental questions will enhance our understanding of urban mobility from a systemic perspective: Is commuting more efficient in larger cities? How does commuting time scale with city size? Which groups of the population are most affected by LC? To this end, this study employs a large-scale dataset covering 288 cities in China in 2015 to investigate the scaling properties of LC, providing empirical insights into its relationship with urban expansion and socio-economic disparities.

In terms of LC, many studies define it by commute distance or duration, and some of them uncover that commuters are more sensitive to time than distance.[33] 45-minute commute has emerged as a time threshold where the behavioral preference of residential location and workplace changes.[16,34] Meanwhile, commuting time over 60 minutes is found to be associated with negative life satisfaction.[35] Moreover, the definition of LC tends to be different among population sub-groups and in cities of different sizes.[36] Some studies scrutinize cities with more than five million population, proposing 90 minutes as the LC divider.[35,36] Up to date, the most proper threshold for defining LC is still inconclusive.

Urban scaling laws underline the ability and function of cities to generate economic growth and innovation.[8] In general, scaling laws suggest underlying nonlinear relationships between population size (or city size) and urban indicators, such as gross domestic product (GDP) and electrical cable length. More empirical evidence suggests super-linear relationships for socio-economic indicators while sub-linear relationships for infrastructure indicators.[8] Also, those nonlinear relationships turn out to be robust in different countries and periods.[8,11,37,38] Furthermore, various urban scaling laws have been validated across disciplines, including but not limited to economics,[39-41] environment,[13] physics,[42] transportation,[22,43] and human mobility.[44] However, the extent to which commuting, one of the most frequent activities of urban dwellers, adheres to scaling laws remains an open question. We hypothesize that LC indicators, as socio-economic functionalities of cities, exhibit super-linear relationships with city size. By empirically testing this hypothesis, our study contributes to a deeper understanding of urban commuting dynamics and offers policy implications for sustainable urban development.

Moreover, previous studies suggest that LC is linked to socio-economic factors such as income disparities, housing affordability, and demographic characteristics.[45-47] This implies that LC is not only an urban efficiency issue but also a matter of social inequality, necessitating further investigation into the socio-demographic characteristics of long commuters (LCers). By integrating urban scaling laws with socio-demographic analyses, this research aims to provide a comprehensive understanding of LC and its broader implications for urban sustainability and social equity.

MATERIALS AND METHODS

Before analyzing scaling laws for commute, we revisit the urban scaling law of GDP in 288 cities in 2015 in China, utilizing urban population and GDP data (data details see Figures S1–S2). It is important to note that in China's urban statistical yearbooks, population figures are reported at multiple statistical scales due to the country's household registration (hukou) system. This

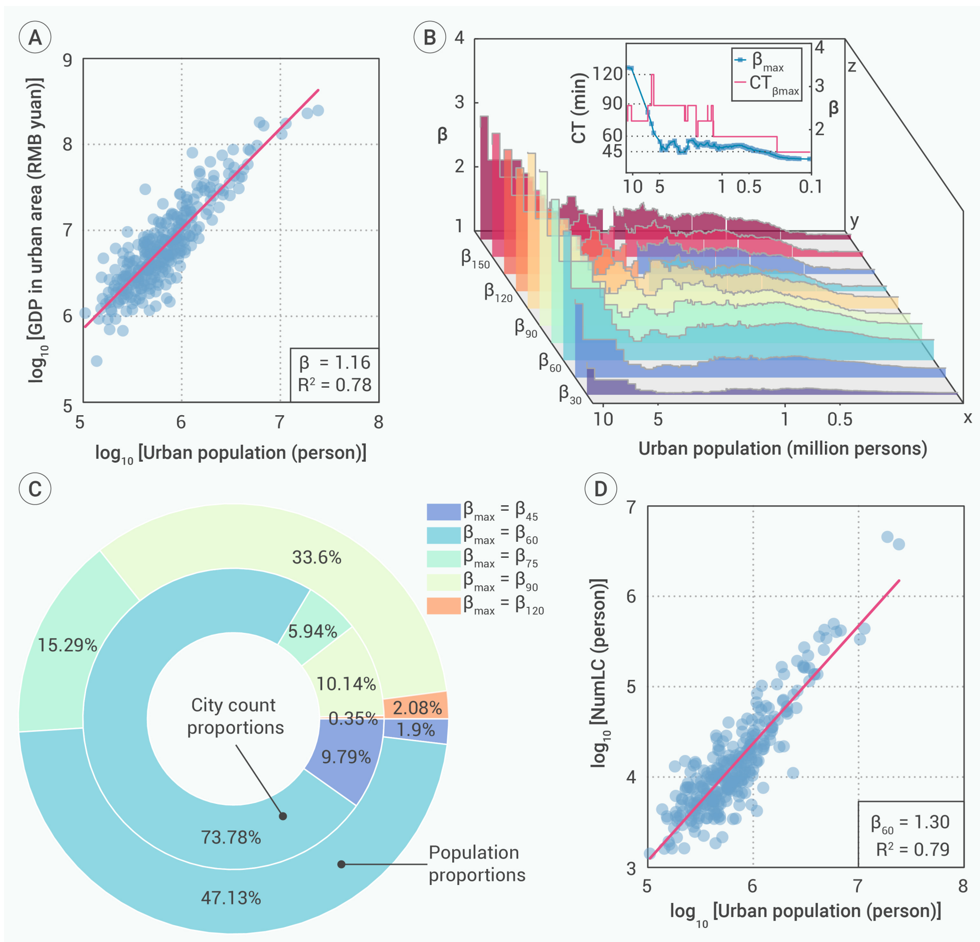


Figure 1. Scaling laws verified for 288 cities of China in 2015 (A) Verification between urban population and GDP. Urban population is used as a proxy of city size and β is reported as 1.16. Note that quantities are expressed in base-10 logarithmic scale. (B) Commuting time threshold calibration with scaling law. A series of regression tests is performed for different commuting time thresholds that ranged from 15 to 150 minutes by 15-minute intervals. β_{15} represents the value of β when the commuting time threshold is 15 minutes. β_{max} indicates the maximum of β values for a city size represented by the urban population. $CT\beta_{max}$ denotes the commuting time corresponding to β_{max}. Here, it verifies $\beta_{max} = \beta_{60}$. A robustness analysis to define that the long commuting is longer than 60 minutes is included in Figure S3. (C) The number of cities and the size of urban population for $CT\beta_{max}$. (D) Verification between urban population and the number of commuters whose commuting time are 60 minutes or more in a city.

variation necessitates careful selection of an appropriate population metric for scaling law analysis. By validating that the relationship between population and GDP follows the classical scaling law, we can demonstrate that the chosen population data is suitable for this study. The urban scaling states that GDP(Y) can be expressed as a power-law function of the urban population(X),[8] that is,

$$Y = C \cdot X^{\beta}$$

$$Y \sim X^{\beta}$$

where β is the urban scaling exponent. Specifically, for $\beta \neq 1$, it means that an increment in urban population may result in a disproportionate percentage change in an urban indicator accordingly. As shown in Figure 1A, the super-linear relationship ($\beta > 1$) between population and GDP has been well validated, with $\beta = 1.16$. This value is comparable to 1.15 in the existing study.[8] The result shows the usability of the dataset.

To explore the relationship between LC and city size, we calculate three LC indicators, including average commuting time (ACT) as shown in Table 1, the number of commuters whose commuting time are 60 minutes or more (NumLC), and the percentage of long commuters (LCshare). In this study, we consider long commuting as a special part of intra-urban traveling. This study excludes inter-city commuting from its analysis. Then, we substitute NumLC for Y in the urban scaling function. Regression tests are performed with different commuting time thresholds that ranged from 30 to 90 minutes by 15-minute intervals (Table 2). Parameters of the models are estimated by ordinary least-squares.

Then we classify cities into seven categories based on the size of urban population.[48-50] The scaling laws are further scrutinized with the inclusion and exclusion of cities of different sizes. To delve into urban characteristics, we perform the principal component analysis (PCA) with various urban attributes.[51] These variables are related to economic development, urban transportation, energy consumption and environmental quality, and the physical features of a city.

RESULTS

The threshold of long commuting

First, we revisit the urban scaling law of GDP in 288 cities in China, figuring out that the super-linear relationship ($\beta > 1$) between population and GDP is well validated, with $\beta = 1.16$ (Figure 1A), comparable to 1.15 in ref[8]. To identify the most appropriate time threshold for defining LC, we obtain the scaling exponents at a set of different thresholds ranged from 30 to 90 minutes by every 15-minute interval (Table 2). This range covers most of the commonly used commuting time definitions. Figure 1B shows that different LC time thresholds (y-axis) correspond to various fitting coefficients (z-axis) by city size (x-axis). A larger β indicates a stronger sensitivity of NumLC to urban growth. Thus, the time threshold corresponding to the largest β can be considered as the most appropriate to define LC. Our findings underscore that, in a significant majority of cities (73.78%), a 60-minute threshold of commuting time is the most sensitive to urban population growth (Figure 1C). Studies have proven the negative correlation between commutes longer than 60 minutes and life satisfaction as well as the inequalities across different demographic groups.[35,36,52] Therefore, the following analysis uses 60 minutes as a threshold of LC. A robustness analysis to confirm the long commuting time parameter can be seen in Figure S3. The respective scaling relationship is shown in Figure 1D.

Population size and the coverage of urban area are two common indicators to represent city size. In this regard, our work also uses urban area as a proxy variable for city size. Similarly,, we find a super-linear relationship between NumLC and city size. Specifically, a 1% increase in the urban area of a city implies an increase of 1.26% in NumLC ($R^2 = 0.70$, see Figure S1), while a 1% increase in the population size of a city implies an increase of 1.30% in NumLC ($R^2 = 0.79$). In a nutshell, there is a more than proportional increase of LC with urban expansion and population growth of cities. Given the consistent results, we choose urban population as a proxy for urban size in our following analysis, which is in line with the literature.[8] We also extend the understanding of Zipf's Law, which is closely associated with scaling laws. The mathematical connection between Zipf's Law and the scaling law is proved in the Text S1. Figure 2A verifies the Zip's Law between the rank of the city and urban population as well as NumLC. With our dataset, the slop parameters are 1.07 and 0.74, respectively. In both cases, the model fit is good with R^2 above 0.95. With the analysis by Zipf's Law, we argue that LC indicators are key for studying urban scaling laws.

Table 1. Differences in commuting time by city size.

City size	ACT(min)	LCshare(%)	n
Megacity	26.03	12.09	4
Supercity	22.67	6.81	3
Big city (Type I)	22.16	5.89	12
Big city (Type II)	18.04	2.90	52
Medium-size city	16.81	1.83	96
Small city (Type I)	16.97	1.89	105
Small city (Type II)	17.84	2.01	16
All cities	18.21	3.12	288

According to the size of urban population, cities are divided into megacities (> 10 million), supercities (5 to 10 million), big cities (Type I of 3 to 5 million and Type II of 1 to 3 million), medium-size cities (0.5 to 1 million) and small cities (Type I of 0.2 to 0.5 million and Type II < 0.2 million). In each group, n denotes the number of cities.

Table 2. Scaling laws by city size.

City size	β_{30}	R^2	B_{45}	R^2	B_{60}	R^2	B_{75}	R^2	B_{90}	R^2
Megacity and Supercity	1.26	0.80	1.56	0.71	1.72	0.72	1.87	0.71	1.92	0.71
Big city (Type I) and above	1.16	0.90	1.36	0.80	1.46	0.78	1.50	0.72	1.51	0.71
Big city (Type II) and above	1.29	0.88	1.53	0.81	1.57	0.76	1.51	0.70	1.52	0.68
Medium-size city and below	0.92	0.76	1.01	0.57	0.90	0.43	0.75	0.22	0.74	0.20
Small city (Type I and II)	0.82	0.58	0.94	0.35	0.78	0.21	0.60	0.08	0.53	0.06
All cities	1.15	0.92	1.32	0.85	1.30	0.79	1.19	0.66	1.18	0.64

This table shows the scaling exponents between the number of people whose commuting time is equal to (or beyond) a certain time limit and the size ofurban population in cities included (more details see Tables S1–S2)

Scaling law of commuting time by city size

Table 1 indicates that the average commuting time (ACT) increases from small cities to megacities. The larger a city, the longer the ACT. For instance, the ACT for megacities (26.03 minutes) is 1.5 times longer than that in medium-sized cities (16.81 minutes). Despite the good performance of the fit to the scaling law (Figure 1D), we observe some deviations as urban scaling tends to underestimate NumLC for large cities (observations above the best-fit line). Hence, city size may matter in understanding the underlying scaling law.

The relationship between commuting time and city size can be further examined by related statistics (see Table S1). Table 2 indicates that β generally exhibits a positive correlation with city size, independent of different LC thresholds. Moreover, we find that the percentage of long commuters (LCshare) is much higher for larger cities, with 12.09% LCers in megacities. When the population of cities is less than 1.3 million, such super-linearity is replaced by sub-linearity ($\beta < 1$) with lower R^2 in many cases (see Figure S3). For cities with more than 1.3 million people, $\beta_{60} = 1.57$, which means a 1% increase in the population size of a city implies an increase of 1.57% in NumLC. It is worth noting that a sensitivity analysis is conducted to verify the population threshold of 1.3 million (see Figure S4). This disproportional relationship is stronger for cities with larger sizes. In particular, for megacities and supercities, a 1% increase in the city size, represented by urban population, implies an increase of 1.72% in NumLC. In Figure 1B, we also see stable strong and positive relationships between β and city size (x-axis, in descending city size) across all long commuting time dividers. Generally, β falls when smaller cities are included, while β tend to increase disproportionally among larger cities. These results confirm a paradox of urban growth and traffic flow, namely, commuting time is longer in large cities despite denser roads and more substantial public transportation services.[22]

The super-linear relationship between LC and population in large cities can be explained by job-housing imbalance. Given that economic activities and higher-income jobs are concentrated in central areas, rising housing costs reinforces long commuting trends, as lower-income individuals are priced out of central locations and must travel longer distances to access employment opportunities.[53,54] In addition, transportation infrastructure expansion struggles to keep pace with demand, resulting in severe congestion and longer commute times. The "fundamental law of road congestion" suggests that increased road supply is quickly absorbed by additional traffic, exacerbating commuting inefficiencies in larger cities.[55,56]

Across the scale of increasing city size, a U-shaped trend between city size and commuting time can be observed, which can offer insights about the evolution of cities.[23] At an early stage, city size is relatively small, and the transportation infrastructure is under the process of improvement,[57] so the commuting time of urban dwellers can be shortened with the growth of the city. Also, economics of scale can be realized for transportation network expansion. Yet, as the city size further increases beyond a critical value, the population growth tends to be a burden and traffic congestion arises. In such cases, the growth of commuting time in larger cities can be seen as urban dwellers' compromise with the city's socio-economic activities. In large cities, growth and productivity are generated through a more detailed subdivision of production. Hence, people tend to suffer from job and housing mismatch in larger cities.[45,58] Although a well-developed transportation network helps commuters to travel faster, the increasing separation of jobs and housing still plays a major role in commuting time variations.

Based on the super-linear relationship, we can predict the NumLC for 2021 and 2022. First, we compare the forecasted results with the known actual LC numbers and find that the fit is quite good (Figure 3). The predict results are in consistence with the report about the long-time commuters in major cities of China in 2021 and 2022, which is jointly published by the China Academy of Urban Planning and Design and Baidu Maps. Furthermore, we extend our calculation to other medium-size cities and small cities where the NumLC data is missing in 2021 and 2022. In summary, by 2021, the NumLC nationwide reached 19.85 million, and the number by increased to 20.88 million by 2022. According to our estimates, in 2022, the NumLC in cities with popula-

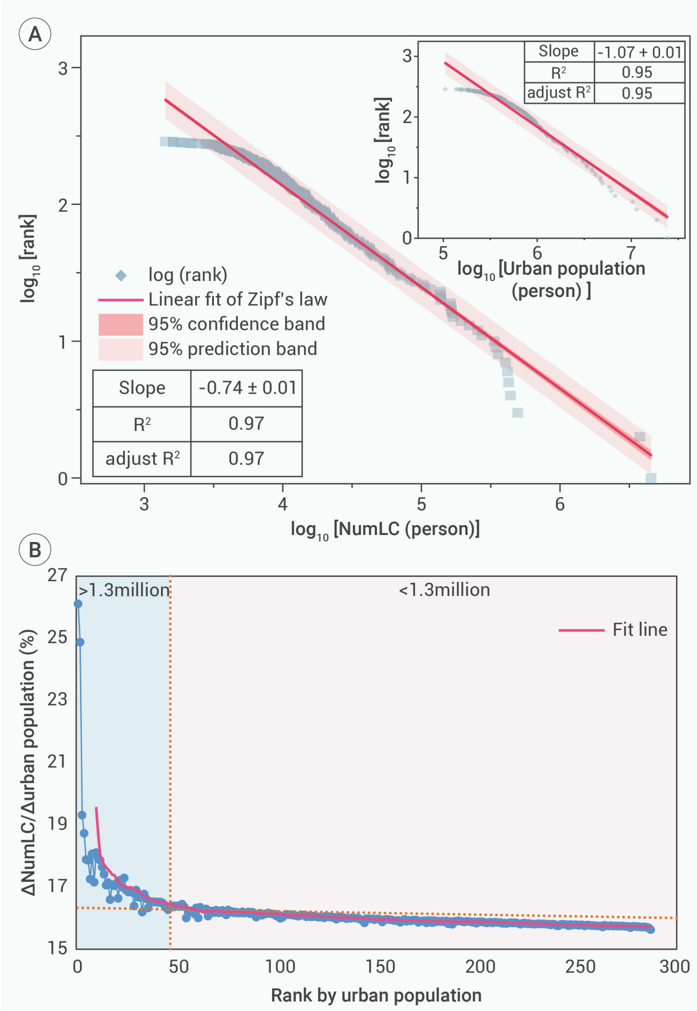


Figure 2. The relationship between LC and city size (A) Zipf's law by NumLC. The slope is 1.07 for population and 0.74 for NumLC, implying that the growth of NumLC follows a consistent pattern with the growth of the urban population. (B) The changing percentage of NumLC within the incremental population. The fit line is smoother on the right end, indicating that NumLC grows in a slow rate in small cities. As the urban population grows, the proportion of NumLC in the newly added population gradually increases, and the inflection point where the growth rate surges corresponding to a population size of around 1.3 million, which can be further verified with a sensitivity analysis in Figure S4.

tion over one million was 19.06 million in China. It is also worth noting that 91% of long-time commuters living in large cities rather than small cities.

Long commuting and urban development

To further identify which cities are more probable to have LC, we examine the results from the principal component analysis (PCA) with various urban attributes in terms of urban development. As shown in Table 3, most urban attributes are associated with average commuting time. Overall, urban attributes related to the level of economic development and transportation infrastructure show a significant and positive relationship with commuting time (Factor 1). Consistent with the jobs-housing literature, GDP, population, urban area, the area of green space, the total amount of CO_2 emissions, housing price, and average wage are highly relevant to commuting time. A more developed urban transportation system (RL, RA, NBr, NIB, TN, and NBu) tends to be associated with longer commuting time, suggesting a complex and potentially bidirectional relationship between urban transportation systems and commuting time. While increased transportation infrastructure may improve mobility options, it can also reflect higher urban densities and spatial mismatches that contribute to longer commutes.

Similarly, urban topography is positively associated with LC but with less weight (Factor 2). Notably, for urban expansion, the higher the value of Factor 2, the more unsuitable the topography is for human activities. In addition, the

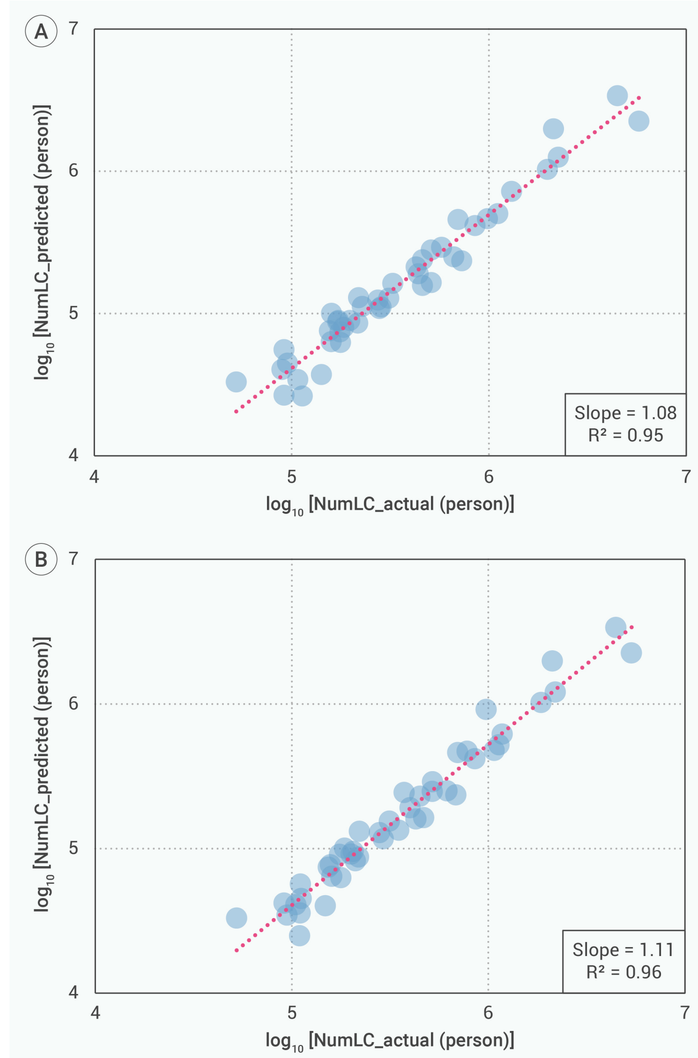


Figure 3. The predication of the number of long-time commuters in 2021 and 2022 with the super-linear relationship captures.

speed of urban economic development has a negative correlation with commuting time (Factor 4). Some attributes representing air quality are not of statistical significance (Factor 3 at p=0.01 level). Overall, the results of PCA highlight the interdependence between urban development and commuting time, reinforcing the need for a nuanced interpretation that considers mutual influences rather than unidirectional causality.

Additionally, we have incorporated case studies from various city size groups—including megacities (Beijing), supercities (Guangzhou), big cities (Changsha, Jinan), and medium/small cities (Panjin, Sanmenxia and Lishui)—to illustrate how urban development patterns and transportation infrastructure interact with commuting dynamics (Figure 4). Megacities and supercities exhibit the highest levels of long commuting, consistent with their extensive but congested transportation networks. The PCA results indicate that high population density, strong economic activity, and high housing prices contribute to significant commuting inefficiencies, aligning with the super-linear relationship. While big cities also experience increasing commuting time, their urban planning and transport policies, such as transit-oriented development, show some mitigating effects. The PCA analysis suggests that cities with well-integrated public transportation may exhibit more efficient commuting patterns despite population growth. Medium and small cities demonstrate shorter commuting times on average, with the PCA analysis indicating that lower population density and reduced spatial mismatch contribute to this trend. However, as these cities continue to expand, their scaling behavior suggests a potential increase in commuting inefficiencies over time. These examples provide empirical support for our

Table 3. Commuting time by urban attribute.

Urban attribute	Factor1	Factor2	Factor3	Factor4
GDP	**0.1017**	−0.0251	0.0137	0.0215
Population (Pop)	**0.0994**	0.0272	0.0035	−0.0829
Road length (RL)	**0.0970**	−0.0194	0.0177	0.0202
Road area (RA)	**0.0957**	−0.0143	0.0533	0.0359
Number of intersection bridges (NIB)	**0.0956**	0.0685	0.0564	−0.0102
Green space area (GA)	**0.0954**	−0.0266	−0.0854	−0.0219
Number of taxis (NT)	**0.0941**	0.0580	0.0775	−0.1788
Urban area (UA)	**0.0939**	0.0376	0.0567	0.0722
Number of buses (NBu)	**0.0898**	−0.0579	−0.0954	0.0788
Number of bridges (NBr)	**0.0898**	−0.0579	−0.0954	0.0246
Housing price (HP)	**0.0835**	−0.0615	−0.2046	0.1484
CO_2 emission	**0.0737**	−0.0156	0.1858	−0.1471
Average wage (AW)	**0.0665**	−0.0729	−0.2517	0.0062
Extreme elevation (EE)	0.0068	**0.4083**	0.0678	0.0264
Average elevation (AE)	−0.0026	**0.3639**	0.0376	−0.1083
Average slope (AS)	−0.0048	**0.3149**	−0.1429	0.0923
Air quality index (AQI)	0.0028	0.0245	**0.5257**	−0.1023
Population density (PD)	0.0038	−0.0469	**0.3699**	0.3279
GDP growth rate (GGR)	−0.0005	0.0038	−0.0182	**0.8234**
Dependent variables	Factor1	Factor2	Factor3	Factor4
ACT	0.626***	0.271***	0.008	−0.171***
NumLC	0.752***	0.093***	−0.057	−0.178***
LCshare	0.730***	0.231***	0.012	−0.141***

R^2 = 0.394 for ACT, R^2 = 0.526 for the number of long-time commuters (NumLC), and R^2 = 0.501 for percentage of long commuters (LCshare). Abbreviations used in Figure 4 are given. *** indicates p<0.01.

findings and demonstrate the real-world implications of scaling laws across different urban contexts.

Long commuting by demography

By dividing the population into two groups (LCers vs. non-LCers), a series of t-tests have been conducted to verify whether the two groups differ by the key demographic variables of age, gender, marital status, and parental status. First, the literature suggests that LC is more common among younger individuals.[34] This is confirmed in Figure 5A (p < 0.01). In line with previous findings,[34] Figure 5B shows males have longer commuting time among the LCers (p < 0.01). In comparison, the non-LCers show little difference in commuting time between genders.

Furthermore, marital status has a more significant impact on female commuting time than that of males (Figure 5C). With the between-group t-test in the LCers, the average commuting time (ACT) of single men (ACT of LCers of m_1, $ACTLm_1$ = 86.26 minutes) is longer than that of single women ($ACTLf_1$ = 82.78 minutes), then married women ($ACTLf_2$ = 78.67 minutes) (p < 0.01). Similarly, the commuting time of single men (m_1) is longer than that of married men ($ACTLm_2$ = 83.45 minutes), then married women (f_2) (p < 0.01). Among the non-LCers, single persons have longer commutes compared to those who are married, with the disparity being greater between single and married women (ΔACT = 2.05 minutes) than that between single and married men (ΔACT = 0.50 minutes).

As for LCshare, 3.51% men have LC whereas 2.59% women do, which emphasizes the gender difference of marital status on varying commuting time once again. As for parental status, our results indicate that women without children commute longer (p < 0.01) than women with children. In brief, our observation indicates that both marital and parental status have a significant impact on women. Women tend to take on more responsibility for caring in marriage. That can help to explain why women are more sensitive to LC.[58,59] Marriage requires more time and effort from women, so household decisions tend to shorten women's commutes. When women have no choice but to commute long distances, they face both work and family pressures, although this seems to manifest itself in the fact that long commutes have a more negative impact on women.[59]

Long commuting and social inequality

Group heterogeneities can be seen from residential income level, educational background, and housing tenure. First, inspired by the positive relationship between GDP and commuting time, we examine the relationship between the average income level and commuting time. Here, the average income level is used as an additional urban attribute. Overall, the increase in income levels corresponds to long commuting. There is a super-linear relationship between the disposable income per capita and the NumLC in cities. Second, among LCers, the educational level is notably higher than non-LCers. The proportion of LCers who have at least bachelor's degree was 24.97%, while that proportion of non-LCers was 6.44%. This finding confirms that the higher educational level, the job selection tends not to be restricted by commuting time. Third, regarding housing types, 68.53% of non-LCers hold self-owned housing, while this rate of LCers is only 36.59%. The rate of LCers who benefited from affordable housing policy is 6.5%, while this rate of non-LCers is 17.19%. In a nutshell, long commuting can reflect on social inequal-

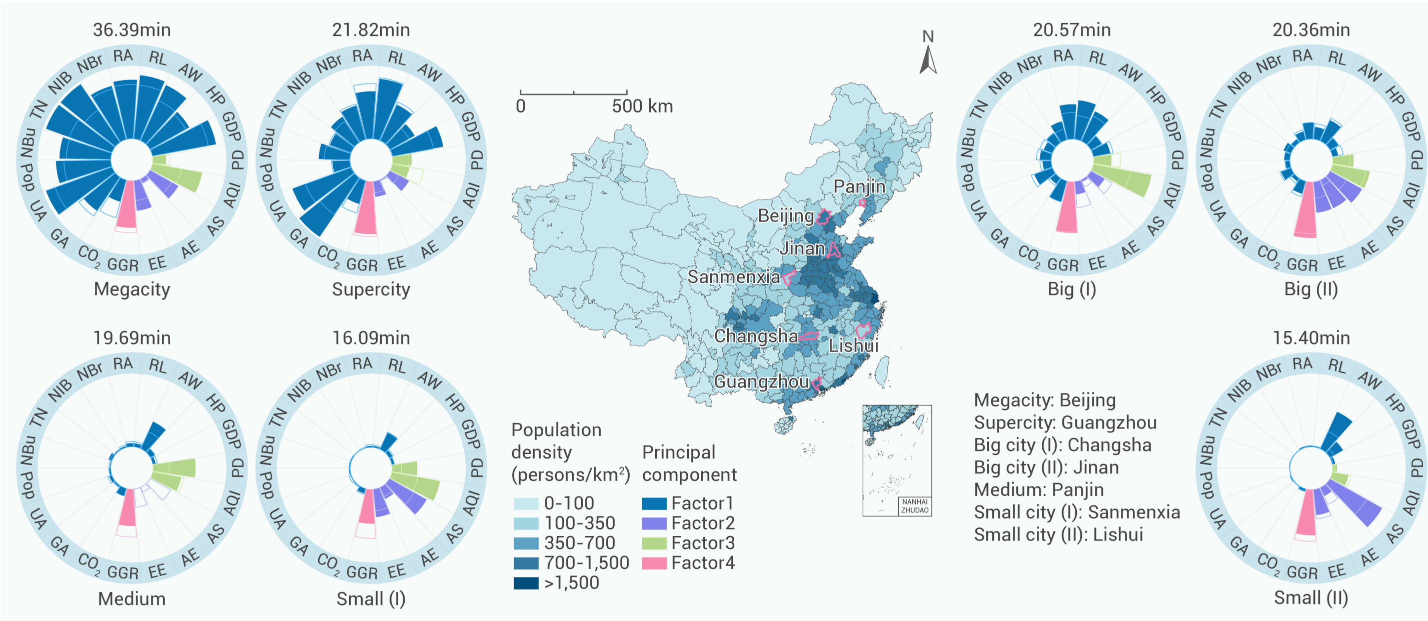


Figure 4. Examples for various city sizes The abbreviations for these urban attributes are consistent with those in Table 3. For each city, every attribute value is standardized and shown as a radius of the sector, and the average commuting time (ACT) is also given as a number. For each group of cities, the traced sectors show the mean value of each attribute. Example cities are randomly selected here and the map in the center shows the spatial location of selected cities. In the case study cities, the ACT increases as city size expands, reflecting the synergistic growth relationship between commuting and urban scale. Beijing, representing a megacity, has a high Factor 1 value, corresponding to a high level of economic development, and Guangzhou, representing a supercity, exhibits a similar pattern. In contrast, the three case cities representing medium and small cities show the opposite trend.

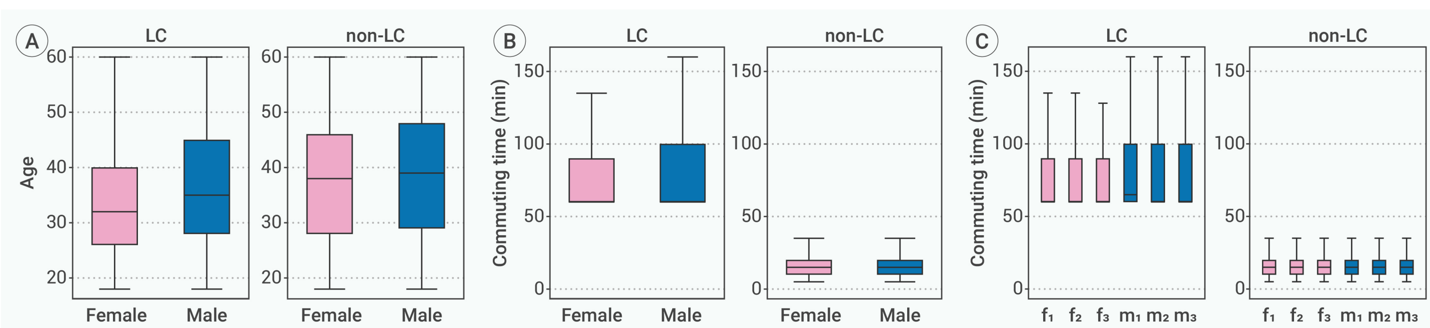


Figure 5. LCers and non-LCers by demography (A) reports the age distribution. (B) shows the differences in commuting time between genders. (C) is a comparison for marital status. Note that f denotes female and m denotes male. Specifically, f_1 refers to single women, f_2 refers to married women and f_3 is for divorced and widowed. The red bars represent results for females, while the blue ones are for males. Demographic differences are confirmed by statistical tests.

ity about income, education, and housing issues.

Furthermore, we expanded the analysis to explicitly link social inequalities with scaling law dynamics, showing that larger cities exhibit more pronounced disparities in commuting burdens across age, gender, income, and education. Our analysis reveals that while demographic structures such as age and gender are generally similar across city sizes, disparities—especially in gender composition and educational attainment—are amplified among long-distance commuters in larger cities. These findings reinforce the relationship between urban scale and social stratification, with detailed results provided in the supplementary materials (Tables S4–S7).

CONCLUSION

In summary, we systematically analyzed commuting time in 288 cities across China using a large census dataset in 2015, revealing a super-linear relationship between LC and city size. It emphasizes the social organization of cities when we extend the understanding of scaling laws from a social activity view.[8] We conclude that the increasing rise in LCers corresponds to more urban energy consumption, indicating an exacerbation of negative effects if city size expands without limits.[13,60] Research has shown that as cities grow, economic productivity and innovation scale non-linearly with population, but so do negative externalities such as congestion and housing shortages, which disproportionately affect commuting patterns.[8,22] Our findings indicate that the relationship between LC and population size follows a super-linear scaling law only when cities reach a certain size threshold, suggesting that efficiency may decline with excessive growth. Furthermore, using the commuting data, we recognize the population threshold as 1.3 million. However, to find out the underlying mechanisms of this phenomenon, further examination needs to be conducted with data in other countries and regions. Whether similar thresholds exist in cities of other countries are intriguing questions that remain open for further discussion.

Here, we identified a LC time threshold of 60 minutes. Daily commuting can be regarded as a trade-off between mobility efficiency of urban dwellers and collective efficiency of the entire urban structure.[22] We use this threshold to explain the scale effect of human mobility and then explore the urban structure evolution process.[1,5,11] However, this study focuses exclusively on intra-city commuting, leaving a gap in research on inter-city commuting. Considering the growing population commuting between cities, further investigation into inter-city commutes can be valuable and will contribute to a more comprehensive understanding of urban dynamics.

Also, this paper distinguishes different scaling laws between LC and seven city types by urban population size. We find that city diversity according to various urban attributes make cities expand at different rates. Theoretically, the lifetime of a single city includes periods of fast growth, slow growth and even periods of shrinkage.[57,61] Hence, we argue that the scaling law between urban expansion and LC needs to be seen from the perspective of different stages of urban development, depending on the actual city size and other attributes. This argument is in line with theories related to the life circle of cities.[62] In addition, long- and short-distance commuting reflect fundamentally different urban dynamics: the former often results from spatial and economic mismatches, while the latter indicates a better job-housing balance. Short commutes are typically enabled by compact urban planning strategies such as mixed-use development and transit-oriented development.[63,64] In contrast, long commutes are driven by housing affordability issues, inadequate infrastructure, and urban sprawl.[53-55]

In the identification of LCers, we highlighted gender, marital status, and age as three crucial variables. Our findings imply that married women may be socially disadvantaged given the traditional gender roles, where women often take up more household responsibilities, thus necessitating shorter commutes. Moreover, younger individuals who generally have less savings and lower social status, are suffering from job-housing imbalance.[65,66] Such within-city inequalities associated with urban scaling laws is worth more investigation.[62]

Here, this paper can offer some policy implications on social inclusion. First, the LC threshold and its impact on society need to be more carefully studied to avoid transport-related exclusion. Second, different urban attributes should be considered in understanding and trying to reduce the negative impact of LC on the environment and individual well-being. Still, it is noted that China has been undergoing rapid urbanization and Chinese cities are densely populated. Hence, one possible limitation is that our study uses a 60-minute threshold for LC, which could potentially increase in countries where population is sparser.

REFERENCES

1. Louf R. and Barthelemy M. (2013). Modeling the polycentric transition of cities. *Phys. Rev. Lett.* **111**:198702. DOI:10.1103/PhysRevLett.111.198702
2. González M.C., Hidalgo C.A. and Barabási A.L. (2008). Understanding individual human mobility patterns. *Nature* **453**:779–782. DOI:10.1038/nature06958
3. Simini F., González M.C., Maritan A., et al. (2012). A universal model for mobility and migration patterns. *Nature* **484**:96–100. DOI:10.1038/nature10856
4. Schläpfer M., Dong L., O'Keeffe K., et al. (2021). The universal visitation law of human mobility. *Nature* **593**:522–527. DOI:10.1038/s41586-021-03480-9
5. Alessandretti L., Aslak U. and Lehmann S. (2020). The scales of human mobility. *Nature* **587**:402–407. DOI:10.1038/s41586-020-2909-1
6. Barthelemy M. (2019). The statistical physics of cities. *Nat. Rev. Phys.* **1**:406–415. DOI:10.1038/s42254-019-0054-2
7. Verbavatz V. and Barthelemy M. (2020) The growth equation of cities. *Nature* **587**:397–401. DOI:10.1038/s41586-020-2900-x
8. Bettencourt L.M.A., Lobo J., Helbing D, et al. (2007). Growth, innovation, scaling, and the pace of life in cities. *Proc. Natl. Acad. Sci. U. S. A.* **104**:7301–7306. DOI:10.1073/pnas.0610172104
9. West G.B. and Brown J.H. (2005). The origin of allometric scaling laws in biology from genomes to ecosystems: Towards a quantitative unifying theory of biological structure and organization. *J. Exp. Biol.* **208**:1575–1592. DOI:10.1242/jeb.01589
10. Banavar J.R., Moses M.E., Brown J.H., et al. (2010). A general basis for quarter-power scaling in animals. *Proc. Natl. Acad. Sci. U. S. A.* **107**:15816–15820. DOI:10.1073/pnas.1009974107
11. Li R., Dong L., Zhang J., et al. (2017). Simple spatial scaling rules behind complex cities. *Nat. Commun.* **8**:1841. DOI:10.1038/s41467-017-01882-w
12. Loo B.P.Y. and Huang Z. (2021). Delineating traffic congestion zones in cities: An effective approach based on GIS. *J. Transp. Geogr.* **06**:103108. DOI:10.1016/j.jtrangeo.2021.103108
13. Ribeiro H.V., Rybski D. and Kropp J.P. (2019). Effects of changing population or density on urban carbon dioxide emissions. *Nat. Commun.* **10**:3204. DOI:10.1038/s41467-019-11184-y
14. Besser L.M., Marcus M. and Frumkin H. (2008). Commute time and social capital in the US. *Am. J. Prev. Med.* **34**:207–211. DOI:10.1016/j.amepre.2007.12.004
15. Ommeren J.N.V. and i Puigarnau E.G. (2011). Are workers with a long commute less productive. *An empirical analysis of absenteeism. Reg. Sci. Urban. Econ.* **41**:1–8. DOI:10.1016/j.regsciurbeco.2010.07.005
16. Sandow E. (2014). Til work do us part: The social fallacy of long-distance commuting. *Urban Stud.* **51**:526–543. DOI:10.1177/0042098013498280
17. Sandow E., Westerlund O. and Lindgren U. (2014). Is your commute killing you. *On the mortality risks of long-distance commuting. Environ. Plan. A* **46**:1496–1516. DOI:10.1068/a46267
18. Raza A., Pulakka A., Hanson L.L.M., et al. (2021). Commuting distance and behavior-related health: A longitudinal study. *Prev. Med.* **150**:106665. DOI:10.1016/j.ypmed.2021.106665
19. Lyons G. and Chatterjee K. (2008). A human perspective on the daily commute: Costs, benefits and trade-offs. *Transp. Rev.* **28**:181–198. DOI:10.1080/01441640701559484
20. Friman M., Gärling T., Ettema D., et al. (2017). How does travel affect emotional well-being and life satisfaction. *Transp. Res. Part A Policy Pract.* **106**:170–180. DOI:10.1016/j.tra.2017.09.024
21. Lorenz O. (2018). Does commuting matter to subjective well-being. *J. Transp. Geogr.* **66**:180–199. DOI:10.1016/j.jtrangeo.2017.11.019
22. Louf R. and Barthelemy M. (2014). How congestion shapes cities: from mobility patterns to scaling. *Sci. Rep.* **4**:5561. DOI:10.1038/srep05561
23. Batty M. (2008). The Size, Scale, and Shape of Cities. *Science* **319**:769–771. DOI:10.1126/science.1151419
24. Stokes E. and Seto K. (2018). Tradeoffs in environmental and equity gains from job accessibility. *Proc. Natl. Acad. Sci. U. S. A.* **115**:201807563. DOI:10.1073/pnas.1807563115
25. Mahmassani H.S. (1990). Dynamic models of commuter behavior: Experimental investigation and application to the analysis of planned traffic disruptions. *Transp. Res. Part A* **24**:465–484. DOI:10.1016/0191-2607(90)90036-6
26. Huang J., Hu Y., Wang J., et al. (2021). A tale of two cities: Jobs–housing balance and urban spatial structures from the perspective of transit commuters. *Environ. Plan B Urban Anal. City Sci.* **48**:1543–1557. DOI:10.1177/2399808320938803
27. Sultana S. and Weber J. (2007). Journey-to-work patterns in the age of sprawl: Evidence from two midsize southern metropolitan areas. *Prof. Geogr.* **59**:193–208. DOI:10.1111/j.1467-9272.2007.00607.x
28. Travisi C.M., Camagni R. and Nijkamp P. (2010). Impacts of urban sprawl and commuting: A modelling study for Italy. *J. Transp. Geogr.* **18**:382–392. DOI:10.1016/j.jtrangeo.2009.08.008
29. Mitchelson R.L. and Fisher J.S. (1987). Long distance commuting and income change in the towns of upstate New York. *Econ. Geogr.* **63**:48–65. DOI:10.2307/143850
30. Moeinaddini A. and Habibian M. (2025). Investigating the role of attitude toward transit safety on the effectiveness of transportation demand management measures: A Tehran case study. *Case Stud. Transp. Policy* **20**:101434. DOI:10.1016/j.cstp.2025.101434
31. Apichon W., and Athispat P. (2024). Development of Large-scale Trip Analysis Toolkits for Vehicle-based GPS Trajectories using Apache Spark and Open Data: A Case Study of Taxis in Bangkok, Thailand. *Int. J. Geoinformatics* **21**:1–14. DOI:10.52939/ijg.v21i1.3783
32. Carriel V., Lufín M. and Pérez-Trujillo M. (2022). Do workers negative self-select when they commute. *Evidence for the Chilean case of long-distance commuting. Ann. Reg. Sci.* **69**:255–279. DOI:10.1007/s00168-022-01121-1
33. Sandow E. and Westin K. (2010). The persevering commuter–Duration of long-distance commuting. *Transp. Res. Part A Policy Pract.* **44**:433–445. DOI:10.1016/j.tra.2010.03.017
34. Zhao P., Liu D., Yu Z., et al. (2020). Long commutes and transport inequity in China's growing megacity: New evidence from Beijing using mobile phone data. *Travel Behav. Soc.* **20**:248–263. DOI:10.1016/j.tbs.2020.04.007
35. Sha F., Li B., Law Y.W., et al. (2019). Associations between commuting and well-being in the context of a compact city with a well-developed public transport system. *J. Transp. Health* **13**:103–114. DOI:10.1016/j.jth.2019.03.016
36. Allen J., Palm M., Tiznado-Aitken I., et al. (2022). Inequalities of extreme commuting across Canada. *Travel Behav. Soc.* **29**:42–52. DOI:10.1016/j.tbs.2022.05.005
37. Hamilton M.J., Milne B.T., Walker R.S., et al. (2007). Nonlinear scaling of space use in human hunter–gatherers. *Proc. Natl. Acad. Sci. U. S. A.* **104**:4765–4769. DOI:10.1073/pnas.0611197104
38. Ortman S.G., Cabaniss A.H., Sturm J.O., et al. (2015). Settlement scaling and increasing returns in an ancient society. *Sci. Adv.* **1**:e1400066. DOI:10.1126/sciadv.1400066
39. Gomez-Lievano A., Patterson-Lomba O. and Hausmann R. (2016). Explaining the prevalence, scaling and variance of urban phenomena. *Nat. Hum. Behav.* **1**:0012. DOI:10.1038/s41562-016-0012
40. Youn H., Bettencourt L.M.A., Lobo J., et al. (2016). Scaling and universality in urban economic diversification. *J. R. Soc. Interface* **13**:20150937. DOI:10.1098/rsif.2015.0937
41. Arvidsson M., Lovsjö N. and Keuschnigg M. (2023). Urban scaling laws arise from within-city inequalities. *Nat. Hum. Behav.* **7**:365–374. DOI:10.1038/s41562-022-01509-1
42. Barthelemy M. (2016). Mobility patterns. The structure and dynamics of cities: Urban Data Analysis and Theoretical Modeling (Cambridge University Press), pp: 129-160. DOI:10.1017/9781316271377
43. Popović M., Štefančić H. and Zlatić V. (2012). Geometric origin of scaling in large traffic networks. *Phys. Rev. Lett.* **109**:208701. DOI:10.1103/PhysRevLett.109.208701
44. Song C., Koren T., Wang P., et al. (2010). Modelling the scaling properties of human mobility. *Nat. Phys.* **6**:818–823. DOI:10.1038/nphys1760
45. Huang J., Levinson D., Wang J., et al. (2018). Tracking job and housing dynamics with smartcard data. *Proc. Natl. Acad. Sci. U. S. A.* **115**:201815928. DOI:10.1073/pnas.1815928115
46. Palm M., Gregor B., Wang H., et al. (2014). The trade-offs between population density and households' transportation-housing costs. *Transp. Policy* **36**:160–172. DOI:10.

1016/j.tranpol.2014.07.004
47. McLafferty S. and Preston V. (2019). Who has long commutes to low-wage jobs. *Gender, race, and access to work in the New York region. Urban Geogr.* 40:1270–1290. DOI:10.1080/02723638.2019.1577091
48. Klove R.C. (1952). The definition of standard metropolitan areas. *Econ. Geogr.* 28:95–104. DOI:10.2307/141019
49. Anderson G. and Ge Y. (2005). The size distribution of Chinese cities. *Reg. Sci. Urban Econ.* 35:756–776. DOI:10.1016/j.regsciurbeco.2005.01.003
50. Qi W., Liu S. and Jin H. (2016). Applicability of the new standard of city-size classification in China. *Prog. Geogr.* 35:47–56. DOI:10.18306/dlkxjz.2016.01.006
51. Loo B.P.Y. and du Verle F. (2016). Transit-oriented development in future cities: towards a two-level sustainable mobility strategy. *Int. J. Urban Sci.* 21:54–67. DOI:10.1080/12265934.2016.1235488
52. Vincent-Geslin S. and Ravalet E. (2016). Determinants of extreme commuting. *Evidence from Brussels, Geneva and Lyon. J. Transp. Geogr.* 54:240–237. DOI:10.1016/j.jtrangeo.2016.06.013
53. Brueckner J.K. (2000). Urban sprawl: Diagnosis and remedies. *Int. Reg. Sci. Rev.* 23:160–171. DOI:10.1177/016001700761012710
54. Glaeser E.L and Kahn ME. (2004). Sprawl and urban growth. Handbook of regional and urban economics (Elsevier), pp: 2481–2527. DOI:10.3386/w9733
55. Duranton G. and Turner M.A. (2011). The fundamental law of road congestion: Evidence from US cities. *Am. Econ. Rev.* 101:2616–2652. DOI:10.1257/aer.101.6.2616
56. Levinson D. and Wu H. (2020). Towards a general theory of access. *J. Transp. Land Use* 13:129–158. DOI:10.5198/jtlu.2020.1660
57. Li X. and Gong P. (2016). Urban growth models: progress and perspective. *Sci. Bull.* 61:1637–1650. DOI:10.1007/s11434-016-1111-1
58. Andersson F., Haltiwanger J.C., Kutzbach M.J., et al. (2018). Job displacement and the duration of joblessness: The role of spatial mismatch. *Rev. Econ. Stat.* 100:203–218. DOI:10.1162/REST a 00707. DOI:10.1162/RESTa00707
59. Feng Z. and Boyle P. (2014). Do long journeys to work have adverse effects on mental health. *Environ. Behav.* 46:609–625. DOI:10.1177/0013916512472053
60. Loo B.P.Y and Axhausen KW. Getting out of energy-intensive and "dirty" transport. *Innovation* 3:100339. DOI:10.1016/j.xinn.2022.100339
61. Kuang W. (2020). 70 years of urban expansion across China: trajectory, pattern, and national policies. *Sci. Bull.* 65:1970–1974. DOI:10.1016/j.scib.2020.07.005
62. Czamanski D. and Broitman D. (2018). The life cycle of cities. *Habitat Int.* 72:100–108. DOI:10.1016/j.habitatint.2016.09.002
63. Cervero R. (1996). Jobs-housing balance revisited: trends and impacts in the San Francisco Bay Area. *J. Am. Plann. Assoc.* 62:492–511. DOI:10.1080/01944369608975714
64. Ewing R. and Cervero R. (2010). Travel and the built environment: A meta-analysis. *J. Am. Plann. Assoc.* 76:265–294. DOI:10.1080/01944361003766766
65. Zhou S., Liu Y. and Kwan M.P. (2016). Spatial mismatch in post-reform urban China: A case study of a relocated state-owned enterprise in Guangzhou. *Habitat Int.* 58:1–11. DOI:10.1016/j.habitatint.2016.08.003
66. Tang J., Zhao P., Gong Z., et al. (2023). Resilience patterns of human mobility in response to extreme urban floods. *Natl. Sci. Rev.* 10:nwad097. DOI:10.1093/nsr/nwad097

FUNDING AND ACKNOWLEDGMENTS

This work is financially supported by the National Natural Science Foundation of China (Grant No.42225106, and 42422103). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

AUTHOR CONTRIBUTIONS

J.H. and J.W. designed research; J.H., J.W. and W.F. performed research; J.H., J.W. and W.Q. contributed data and analytic tools; W.F. analyzed data; J.H., W.F., and J. W. writing-original draft, J.H., W.F., J. W., and B.L. writing-review & editing. All authors contributed to the manuscript and approved the final version.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DATA AND CODE AVAILABILITY

No new data were created or analyzed in this study. Commuting time and demographic information are obtained from a sample of 1‰ of China's population taken from the National 1% Sample Population Survey in 2015, covering almost 99% cities (288/293) in China (the distribution of participants can be seen in Figure S2). It is a census dataset of 811,452 participants and the distribution of participants can be seen in S3. Urban population and most of the data on urban attributes come from city statistical yearbooks, including the China Urban Construction Statistical Yearbook (2015), and the China City Statistical Yearbook (2016). All these statistical-year books provide dataset of cities in 2015. Air Quality Index and CO_2 emissions data come from the China Air Quality Online Monitoring and Analysis Platform. Topographic data from General Bathymetric Chart of the Oceans (GEBCO), an international organization of surveying and mapping experts.

LEAD CONTACT WEBSITE

Jiaoe Wang: https://people.ucas.ac.cn/~wangjiaoe
Jie Huang: https://people.ucas.ac.cn/~huangjie