**Applied Energy Symposium 2021: Low carbon cities and urban energy systems**
**September 4-8, 2021, Matsue, Japan**
**Paper ID: 95**

# Are compact cities lower carbon? Empirical evidence from 49 high-tier Chinese cities

Mengqi Hu[1], Ying Kong [2*]

1 Tsinghua-Berkeley Shenzhen Institute

2 Tsinghua-Berkeley Shenzhen Institute (Corresponding Author)

**ABSTRACT**

This study analyzes the impact of urban compactness on carbon emissions. The essay proposes three broad dimensions to evaluate compactness: urban form, spatial structure and infrastructure efficiency. The impact of compactness on carbon emissions is then analyzed by a panel model using data from 2002 to 2018 on 49 high-tier Chinese cities. The results suggest that of all compact variables, only mixed land use tends to be associated with less carbon emissions. In addition, higher ranking cities emit more carbon than lower ranking cities.

**Keywords:** compact city, carbon emissions, high-tier Chinese cities, panel model

## 1. INTRODUCTION

Is compact city a more sustainable and efficient urban development paradigm? This paper attempts to provide some insight by not only establishing linkages between compactness and sustainability in a cross section of 49 high-tier Chinese cities, but also a forward looking approach to "what can be done" given the complexity of different city backgrounds.

Since China's rapid urbanization in 1990s and the encroachment on the surrounding agricultural land, the rising urban built-up area has been leading to the increase of urban traffic congestion (Li, Xiong & Wang, 2019), domestic energy consumption (Ma & Jin, 2011), environmental challenges, public service costs and wealth inequities (Stoel, 1999). As one of the various approaches in response to these problems, the concept of "compact city" initially proposed within European and American contexts in order to save urban energy and resource consumption, has been increasingly become one of the reference strategies of Chinese city development (Ma & Jin, 2011). The construction of Shenzhen Guangming new district is just one of the paradigms of compact city concept in mainland China(Lv & lei, 2008). The Yujiapu Financial District, Xiangluowan Business District and TEDA MSD (Morden Service District) in Tianjin city also employed compact city theory for reference in its urban planning and design (Wang et al., 2013).

With the rising application of compact city in China, there is a burgeoning literature, in which scholars, academics and government professionals have discussed the significance of compact city development (Lv & lei, 2008). But the results vary from each other. This paper gives the evaluation indicators of urban compactness in China. A panel model is built using data from 2002 to 2018 to examine the influential determinants for reducing carbon emissions. On this basis, the feasibility of compact city development in China and research limitations are discussed at the end, providing scientific thinking for promoting sustainable development in high-tier Chinese cities.

## 2. DATA AND METHODS

### *2.1 Data sets and variables*

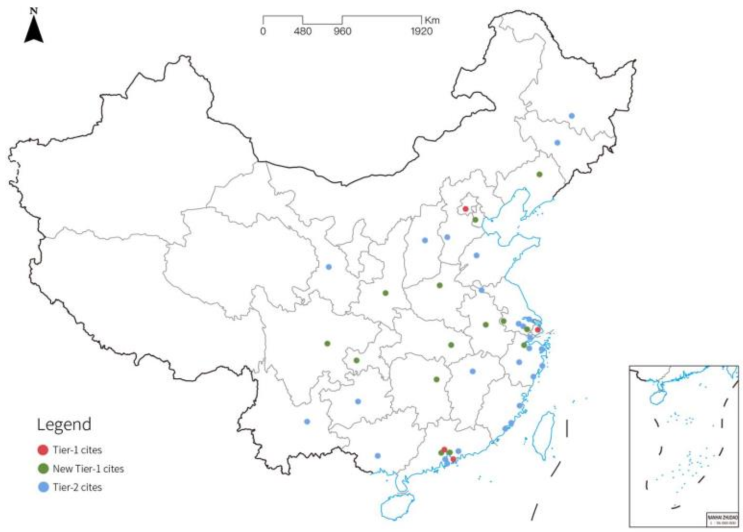


Fig 1 Geographical distribution of high-tier cities.

Dummy variables: China is enormous and diverse, and may be segmented geographically, culturally, and socio-economically. The heterogeneity that could potentially exist in the impacts needs to be explored. Unlike previous research dividing China into western, eastern, central regions (eg., Liu et al., 2020; Yi et al., 2017; Li et al., 2019b), this paper has chosen to segment China according to administrative units: tiers of cities published by Yicai Global. Tier-1, new tier-1 and tier-2 cities contain 4, 15, and 30 cities respectively. Figure 1 shows a detailed geographical distribution of these cities across China. As is presented, geographical distribution becomes less significant- clusters of cities in coastal or southeast region, with less cities in the west.

Traditionally, Tier-1 cities are often considered the megapolises of China. As the tiers progress, cities decrease in size, affluence, and move further away from prime locations. While city rankings may vary annually, there are very few changes in its tier. For example, Tier-1 class has remained the same (i.e., Beijing, Shanghai, Guangzhou, and Shenzhen) since 2013. Furthermore, from 2017 to 2020, only two cities Hefei and Foshan displays a change in tier by upgrading themselves to a higher tier. Therefore, it is reasonable to assume the tier classification of 2020, in a certain degree, represents cities' inherent and time-invariant characteristics in terms of geography, culture, history, and socio-economy. Specifically, this paper adds two dummy variables. T1 is assigned to one if a city is in the first tier and zero otherwise. T2 is assigned to one if a city is in Tier-2 class and zero otherwise.

Carbon emissions: Yi et al. (2017) estimate $CO_2$ emissions by fossil energy consumption such as raw coal, fuel coal, fuel oil and liquefied petroleum Gas (LPG). Since more than 90% of carbon emissions come from fossil-fuels, this paper adopts Yi et al. (2017)'s methodology and adapts it to suit the Chinese context. Due to the absence of data, LPG, man-made coal gas and natural gas are the main energy consumption sources being considered here.

Compact city indicators: This paper proposes compactness evaluation indicators from three dimensions: (1)urban form, (2)spatial structure, and (3) infrastructure efficiency. Urban form reflects the population distribution within the built-up area and is calculated by dividing the urban district population by built-up area. Spatial structure which involves cities' mixed-land use and spatial employment distribution follows the tradition in the urban economics and land use literature. Mixed use of land is measured by "Balance degree" as Chen & Liu (2001) have suggested. Employment distribution is represented by the share of employed population of a city's urban districts (Shiqu) to its total employment (EMP). It reflects how disproportionately jobs are clustered in the urban core instead of non-center areas such as counties and remote suburbs. Infrastructure efficiency is reflected in the efficiency of the use of public service facilities. This paper uses road surface area per capita (PROAD) and motor vehicle for public transport per 10,000 people (PMV) as variables.

Other control variables: These variables include 1) GDP per capita, measuring level of urban economic

Table 1 Variables' definitions

| Variables | Definition |
|---|---|
| $CO_2$ | Carbon emissions (t) |
| POP | The population density in built-up area (net density) (10,000 people/km$^2$) |
| J | Balance degree |
| EMP | Share of employment in urban central district to total employment |
| PROAD | Road surface area per capita (m$^2$) |
| PMV | Motor vehicle for public transport per ten thousand people (Standard Units) |
| PGDP | GDP per capita (RMB) |
| SGDP | Percentage of secondary industry contribution to total GDP (%) |
| T1 | Dummy variable. Equals ones if a city is in Tier-1 class and zero otherwise |
| T2 | Dummy variable. Equals ones if a city is in Tier-2 class and zero otherwise |

| Variables | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| $CO_2$ | 833 | 2198500 | 4712626 | 109.45 | 42200000 |
| PGDP | 833 | 55389.36 | 39477.29 | 5654.45 | 467749 |
| SGDP | 833 | 48.97 | 7.84 | 19.01 | 80.63 |
| POP | 833 | 0.84 | 0.34 | 0.10 | 2.43 |
| J | 833 | 0.84 | 0.06 | 0.55 | 0.95 |
| EMP | 833 | 0.71 | 0.24 | 0.11 | 1 |
| PROAD | 833 | 14.63 | 6.36 | 3.17 | 54.57 |
| PMV | 833 | 13.88 | 9.62 | 0.36 | 110.52 |
| T1 | 833 | 0.08 | 0.27 | 0 | 1 |
| T2 | 833 | 0.61 | 0.49 | 0 | 1 |

Fig 2 Descriptive statistics of variables.

development, economic growth and affluence, and 2) percentage of secondary industry to GDP, representing economic structure.

Urban construction land information is from China Urban Construction Statistical Yearbook. Information about gas consumption, public transport and the rest of data are collected from China City Statistical Yearbooks from 2002 - 2018. The definitions of variables are shown in Table 1. The descriptive statistics are shown in Figure 2.

### *2.2 Methods*

#### 2.2.1 Estimation of $CO_2$ emissions

$CO_2$ emissions are estimated according to The Calculation Method of $CO_2$ Emissions in Petrochemical Production published by Ministry of Industry and Information Technology of China in 2011, with reference to the Intergovernmental Panel on Climate Change (IPCC). The formula is as follows:

$$\sum CE_i = \sum FQ_i \times NCV_i \times EF_i$$

where $CE_i$ is $CO_2$ emissions from combustion of certain fuels (LPG, man-made coal gas and natural gas are considered here); $FQ_i$ denotes the consumption data of this certain type of fuel; $NCV_i$ represents net calorific value also known as lower heating value; $EF_i$ is the carbon emission coefficient. Net calorific values of different fuels and corresponding emission factors are shown in Table 2.

Table 2 $CO_2$ emission estimation coefficients

| Types of fuel | Net calorific values (MJ/ m$^3$) | $CO_2$ emission factors (kg/MJ) |
|---|---|---|
| Man-made coal gas | 18.003 | 0.0373 |
| Natural gas | 38.931 | 0.0543 |
| Liquefied petroleum gas | 50.179MJ/kg | 0.0616 |

#### 2.2.2 Estimation of mixed-land use

Entropy is a state function based on the second law of thermodynamics to describe the irreversibility of spontaneous processes. Shannon introduced the concept of entropy into information theory in 1948 to describe uncertainty, stability, and amount of information (Yan et al., 2006). In Chen & Liu (2001)'s research, the entropy of information (H) of land structure is given by the following:

$$H=-\sum_{i}^{N}(A_i/\sum_{i}^{N}A_i)\log(A_i/\sum_{i}^{N}(A_i)$$

where $A_i$ is the area of land in a certain use (eg., residential area, area for industrial operation, area for public utilities, area for storage, area for municipal utilities and greenland area, etc.); N is the total number of different land categories.

While Chen & Liu (2001) have proven the use of H in measuring urban land use structure, they point out that one existing problem is the variance in the number of land types (N) across cities and in different time period. The H values calculated by different N is therefore no longer comparable. To solve this problem, balance degree (J) is introduced:

$$J=H/H_m\,;\quad H_m=\log N$$

where $H_m$ is the maximum information entropy of land structure, representing the most diverse land system. Therefore, J can only take values between 0 and 1. By definition, A higher J indicates a more complex, mixed, balanced land use and therefore a more compact city. Table A3 lists the top ten cities in terms of POP, J, RES, PROAD and PMV in 2020.

2.2.3 random effects model

The paper employs a panel model to investigate the relationship between compact city and carbon emissions.

$$\ln(CO_2)_{it}=\beta_0 z_i+\beta_1(COMP)_{it}+\beta_2(CONTR)_{it}+\varepsilon_{it}$$

where $CO_2$ represents $CO_2$ emissions; COMP is a vector representing compactness variables, including net density (POP), balance degree (J), share of employment in urban district to total employment (EMP), road surface area per capita (PROAD) and motor vehicle for public transport per 10,000 people (PMV); CONTR denotes the vector for other control variables, including GDP per capita (PGDP) and percentage of secondary industry to GDP (SGDP); $z_i$ are time-invariant variables, including two dummy variables T1 and T2 to indicate whether the city belongs to Tier-1, new Tier-1 or Tier-2 class; $\varepsilon_{it}$ is the error term.

Before the regression analysis, unit-root test is performed to avoid spurious regression. The paper uses LLC, IPS, Fisher-ADF and Fisher-PP tests on all variables. The results show first order stationarity. Then panel cointegration test is performed using Pedron test and Kao test, both of which indicate constant co-variance over time. The VIF results suggest the variables do not suffer a high degree of multicollinearity. Therefore, long-run relation can be modeled. Random effects models are selected over pooled OLS as a result of Breusch-Pagan LM test.

## 3. RESULTS AND DISCUSSIONS

Figure 3 reports the regression results of all 6 models. Model 1, considering only control variables (LnPGDP and LnSGDP), is used to test the prevalence of Environmental Kuznets Curve (EKC) hypothesis, which undertakes upturned-U shape bond amid economic growth and environment pollutants (Yasin et al., 2020). The significantly positive impact of PGDP in all 6 models is consistent with existing literature (eg., Yi et al., 2017; Liu et al., 2020), suggesting that China has not reached the inflection point of EKC and that urban development level is still on the left side of the curve. The negative impact of SGDP is somewhat unexpected. One justification could be that, according to Li, Zhang & Jiang (2019a), China's green industry policies can be distinguished into three stages: development without green industrial policy (1978—1999); awakening to the significance of green industrial policy (2000—2011); developing stage of green industry policy (2012-today). We are, therefore, currently in a period during which green policies have been initiated and implemented, which accords with our results since the data taken is from 2002 to 2018.

Model 2-6 extend model 1 by adding different indicators for measuring compactness. Model 3 includes J, indicator of mixed land use. The coefficient is negative and significant at 10% confidence level, implying that a more diverse and balanced land structure might lead to less carbon emission. This is consistent with the research of P´erez-Soba et al. (2008), in which they suggest that multifunctional land use can be seen as a way towards sustainability. Moreover, mixed-land use pattern may reduce commuting distance and therefore related emissions. Model 4 considers EMP, measuring population distribution across the city. A positive effect has been found amid employment centralization and carbon emissions. This may be explained by the assumption that as central urban district develops to welcome more employment, cost of living has also grown higher especially housing expense. Consequently, living in satellite communities instead of urban center has become a popular choice among people. The assumption has been justified by Shanghai's example. While the city has remained its monocentric spatial

| | model1 | model2 | model3 | model4 | model5 | model6 |
|---|---|---|---|---|---|---|
| lnPGDP | 0.668*** | 0.677*** | 0.698*** | 0.686*** | 0.637*** | 0.615*** |
| | (0.0352) | (0.0398) | (0.0410) | (0.0412) | (0.0470) | (0.0476) |
| lnSGDP | -0.972*** | -0.983*** | -1.043*** | -1.058*** | -1.071*** | -1.020*** |
| | (0.198) | (0.199) | (0.201) | (0.200) | (0.200) | (0.200) |
| T1 | 1.031** | 1.009** | 0.980** | 0.907** | 1.011** | 0.967** |
| | (0.351) | (0.327) | (0.331) | (0.311) | (0.318) | (0.321) |
| T2 | -1.102*** | -1.096*** | -1.092*** | -1.006*** | -1.011*** | -1.003*** |
| | (0.195) | (0.181) | (0.183) | (0.175) | (0.177) | (0.178) |
| lnPOP | | 0.0535 | 0.0600 | 0.0514 | 0.111 | 0.0808 |
| | | (0.0914) | (0.0913) | (0.0913) | (0.0955) | (0.0958) |
| J | | | -1.014* | -1.052* | -0.994* | -0.938* |
| | | | (0.473) | (0.473) | (0.473) | (0.472) |
| EMP | | | | 0.522* | 0.534* | 0.522* |
| | | | | (0.208) | (0.208) | (0.208) |
| lnPROAD | | | | | 0.199* | 0.155 |
| | | | | | (0.0928) | (0.0941) |
| lnPMV | | | | | | 0.159** |
| | | | | | | (0.0614) |
| Constant | 10.86*** | 10.81*** | 11.67*** | 11.48*** | 11.49*** | 11.20*** |
| | (0.962) | (0.991) | (1.070) | (1.070) | (1.068) | (1.070) |
| Observations | 833 | 833 | 833 | 833 | 833 | 833 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Fig 3 Panel regression results with carbon emissions as the dependent variable.

structure from 2000 to 2010, a polycentric spatial pattern is emerging as a result of decreasing difference in housing population density between urban center and the suburbs (Wang & Yang, 2015). Housing suburbanization therefore comes as a result of employment centralization, causing the "increase in household driving, home fuel consumption, and land consumption brought about by population dispersion" (Kahn, 2000).

Model 5 and 6 investigate PROAD and PMV in terms of infrastructure efficiency. In line with Liu et al. (2020) and Yi et al. (2017), the coefficient of PROAD is positive and significant at 10% confidence level, suggesting that higher per capita road area leads to more $CO_2$ emissions. One reason could be that a relatively developed urban road network indicates a high level of suburbanization as road construction encroaches on the surrounding countryside. Model 6 contains all independent variables. While public transport service is supposed to replace and reduce private car travel, thus reducing oil consumption and carbon emissions (Yi et al., 2017), the significant positive effects of PMV on carbon emissions is unexpected. According to Li, Xiong & Wang (2019b), a higher number of buses per capita may increase urban congestion, which could be one of the reasons leading to more $CO_2$ emissions. Another possible explanation is that a high PMV does not necessarily lead to a lower share of private car travel. In fact, according to a recent market research by Ipsos, more Chinese people prefer to travel by private vehicles instead of public transportation especially during the COVID-19 period. In all 6 models, the two dummy variables T1 and T2 indicating city ranking remain significantly positive and negative respectively. Other things being equal, this suggests higher carbon emissions in more developed cities.

## 4. CONCLUSIONS

Among all compact variables for measuring urban form, spatial structure and infrastructure efficiency, only mixed land use is found to be negatively associated with carbon emissions. In other words, multifunctional land use has generally resulted in less carbon production. Infrastructure efficiency, however, does not necessarily contribute to carbon emissions reduction. In addition, employment centralization creates housing suburbanization and therefore increases carbon emissions. Analysis on the two control variables suggests that China has not reached the inflection point of the Environmental Kuznets Curve and that green industry policies in China has been highly effective in industry transformation. Moreover, Highly ranking cities is related with more carbon emissions.

The paper's findings contribute additional evidence to current literature and also provide theoretical support for future related policy making. On the one hand, for example, instead of focusing on increasing motor vehicles for public transport, encouraging increased participation in replacing and reducing private car travel may be more effective in alleviating traffic carbon emissions. For cities with centralized employment, a reasonable allocation of housing may reduce the imbalance of settlement distribution between urban center and suburbs, thus contributing to emissions reduction. On the other hand, cities may pay attention to the financial allocation to medical resources as well as economic development.

## REFERENCE

[1] Li, Y., Xiong, W., & Wang, X. Does polycentric and compact development alleviate urban traffic congestion? A case study of 98 Chinese cities. Cities 2019; 88 , 100–111.

[2] Ma, L., & Jin, F. Evaluation of Chinese urban compactness. Progress in Geography 2011; 30 , 500 1014. doi:10.11820/dlkxjz.2011.08.008.

[3] Stoel, J., Thomas B. Reining in urban sprawl. Environment: Science and Policy for Sustainable Development 1999; 41: 6–11.

[4] Lv, B., & lei, Q. Compact city: A sustainable way of urbanization. Urban Planning Forum 2008; 4: 61–63.

[5] Wang, T., Chen, T., & Zang, X. Theories and practices of eco city planning with master plan of sinosingapore eco city in Tianjin as an example. City Planning Review 2011.

[6]Liu, X., Mingshu, W., Wei, Q., Kangwu, & Xiaomi, W. Urban form, shrinking cities, and residential carbon emissions: Evidence from Chinese city-regions. Applied Energy 2020; 261: 114-409. doi:https://doi.org/10.1016/j.apenergy.2019.114409.

[7]Yi, Y., Ma, S., Guan, W., & Li, K. An empirical study on the relationship between urban spatial form and $CO_2$ in Chinese cities. Sustainability 2017; 9.

[9]Chen, Y., & Liu, M.-h. The basic laws of the shannon entropy values of urban land-use composition. Human Geography 2001; 16 , 20. doi:10.13959/j.issn.1003-2398.2001.04.005.

[10]Yan, L., Anyan, H., & Yazhi, D. Study on the evolution of water resource structure based on information entropy. Journal of Northwest Science Technological University of Agricultural and Forest 2006; 34 .

[11]Yasin, I., Ahmad, N., & Chaudhary, M. A. The impact of financial development, political institutions, and urbanization on environmental degradation: evidence from 59 less-developed economies. Environment, Development and Sustainability 2020. doi:10.1007/s10668-020-00885-w.

[12]Li, X., Zhang, Y., & Jiang, F. Green industrial policy: theory evolution and Chinese practicey. Journal of Finance and Economicst 2019; 45 , 4–27.

[13]P´erez-Soba, M., Petit, S., & Jones, L. Land use functions - a multifunctionality approach to assess the impact of land use changes on land use sustainability. Sustainability Impact Assessment of Land Use Changes 2008; (pp. 375–404). doi:https://doi.org/10.1007/978-3-540-78648-119.

[14]Wang, C., & Yang, S. Dynamic analysis on population suburbanization and new town development of shanghai city. City Planning Review 2015; (pp. 66–71).

[15]Kahn, M. E. The environmental impact of suburbanization. Journal of Policy Analysis and Management 2000; 19: 569–586.