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Compactness of Urban Growth, the Environment, and the Quality of Life: Evidence from China, 2000-2010



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Compactness of Urban Growth, the Environment, and the Quality of Life:

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by

Quan Yuan

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ABSTRACT OF THE THESIS

Compactness of Urban Growth, the Environment, and the Quality of Life:
Evidence from China, 2000-2010

by

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University of California, Los Angeles, 2013
Professor Rui Wang, Chair

Using panel data of Chinese cities during 2000-2010, this study measures the association between urban compactness and the indicators of the environment and quality of life, while controlling for population size and per-capita Gross Domestic Product. The results fail to support the hypothesis that compact development can significantly reduce energy consumption and carbon emission and improve air quality. Higher urban density is associated with not just lower level of car ownership, but lower level of transit usage as well. Dense urban development is found to be closely linked to low amount of road space and green area. The fact that urban compactness does not affect the environment and quality of life in a simple fashion suggests that the government should rather rely on multi-objective policy measures and technological improvement.

The thesis of Quan Yuan is approved.

Donald Shoup

Martin Wachs

Rui Wang, Committee Chair

University of California, Los Angeles

2013

# CONTENT

# 1 Introduction

Whether a city grows into a more or less compact one may have both negative and positive implications on its own evolution and the happiness of its citizens. Urban sprawl is even ranked among the top ten problems that influence the quality of life in a study in Australia (Marans and Stimson, 2011). Several government-sponsored reports evaluate the costs of urban sprawl and support compact development, with regard to the incidence of sprawl in the United States (Real Estate Research Corporation., 1974; Burchell, R. et al., 1998, 2000). However, among others, Gordon and Richardson (1989, 1994, 1996, and 1997) challenge the belief by providing evidence in Los Angeles and elsewhere. The enduring debate over the role of compactness in urban development particularly emphasizes its connections with environmental quality, resource efficiency, as well as quality of life. Evidence from different data samples in different time series against different cultural backgrounds presents various outcomes and explanations. Nonetheless, most of the studies are from developed countries, in particular the United States, while relevant research is limited in developing countries. So what is the evidence from China, where the grandest wave of urbanization in human history is happening?

This paper focuses mainly on transportation, energy consumption, carbon emission, air quality, and green space resources, and tests the relationship between urban compactness and these factors, against the background of China. Prefecture cities in China with populations of more than 500,000 people are included and the changes of the indicators between 2000 and 2010 are observed in the analysis. There is a reliable set of information measuring the rapid population and spatial growth across hundreds of cities in China during this period. The year 2000 marked the first time when temporary urban residents were included in urban population in China's national census. Urban population grew from 458.4 million in 2000 to 656.6 million in 2010, a 45% increase in just ten years. Such dramatic growth in population, however, is dwarfed by the growth in the land occupied by cities. Official statistics show that the total built-up area (BUA) of cities increased by 78.5% over the ten years, while new evidence based on satellite images (Wang et al. 2012) shows even greater growth of 85.5%, with average population density decreasing from 9,900 persons/km$^2$ in 2000 to 8,900 persons/km$^2$ in 2010. In terms of population, the proportion of mega cities, i.e. cities with more than three million people, in all the selected cities increased from 5% to 11% during 2000-2010; while the proportion of large cities, whose built-up area exceed 200 square kilometers, rose more notably from 3% to 14% in the period (Tan & Lu, 2003; China Society of Urban Economy et al., 2012)[1,2]. (See Figure 1 and 2) The significant inter-regional heterogeneity in the compactness of urban growth (the population growth/spatial growth ratio ranges from 0.18 to 2.89 among the 242 cities during 2000-2010) is instructive in explaining the change of the above factors during the process of urban development.

[1] In the report "*Green book of small-and-medium-sized cities: Annual report on development of small-and-medium-sized cities in China*" by China Society of Urban Economy et al., the authors categorize cities in China into three levels according to population size: Medium city (less than 1 million people); large city (1 million people to 3 million people); mega city (more than 3 million people) (China Society of Urban Economy et al., 2012).

[2] In the paper "*Distribution of China City Size Expressed by Urban Built-up Area*", the authors categorized cities in China into three levels according to size of built-up area: small city (smaller than 50 square kilometers); medium city (50 square kilometers to 200 square kilometers); large city (larger than 200 square kilometers) (Tan & Lu, 2003).

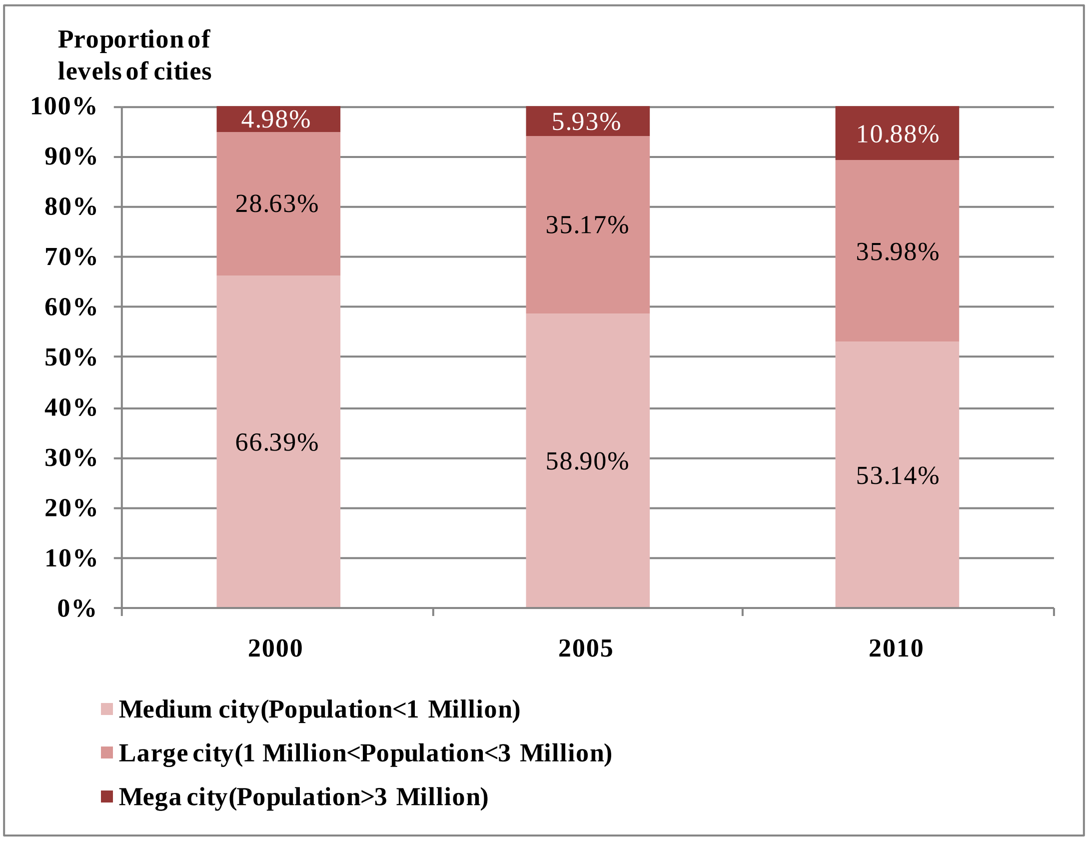


**Figure 1** Proportions of cities categorized according to population size in 2000, 2005 and 2010

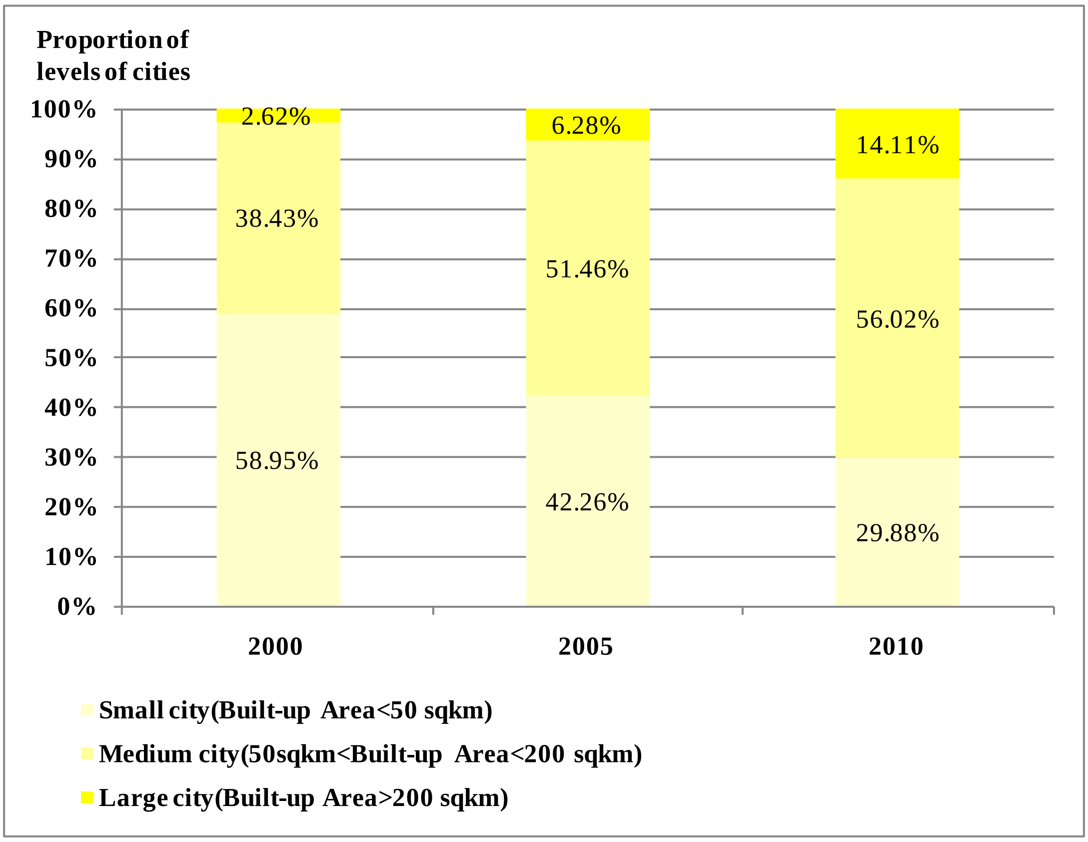


**Figure 2** Proportions of cities categorized according to size of built-up area in 2000, 2005 and 2010

## 2 Literature Review

Numerous theoretical and empirical studies as well as literature review on the relationship between urban compactness and travel behavior have been conducted over the past decades. Scholars evaluate and compare different research approaches to the question including interview and description, (cross-sectional) multivariate statistical models, and longitudinal simulation and models (Crane, 2000; Mokhtarian and Cao, 2008). Urban density and automobile ownership are crucial factors influencing travel behavior, while both of them are directly or indirectly associated with the level of compact development (Badoe and Miller, 2000; Ewing and Cervero, 2001; Bento et al., 2005; Bhat and Guo, 2007; Fang, 2008; Brownstone and Golob, 2009). By reducing the tendency to travel in private cars, higher urban density is also found to positively influence the usage of public transit, according to a number of studies in the United States (Smith, 1984; Dunphy and Fisher, 1996; Cevero, 1996).

Energy consumption is one of the most prominent factors in the discussion due to its close relationship between travel behavior, carbon emissions and air quality. A broad range of literature looks into the impact of urban compactness on energy consumption, mainly in the transportation sector. Many articles use land use density to measure compactness or choose not to distinguish low-density development from urban sprawl (Badoe and Miller 2001; Kim and Brownstone, 2010). It is generally assumed that as vehicle usage is reduced in more compact areas, per capita fuel consumption would be correspondingly lower (Newman and Kenworthy, 1988; Ewing, 1997; Burchell, R., et al., 1998). But this expectation is challenged because “density” is too complicated and vague to explain the relationship and other factors that may contribute more to determining differences in energy use (Gomez-Ibañez, 1991; Crane, 1996; Dunphy and Fisher, 1996; Boarnet and Crane, 2001). Incorporating new variables such as income and gasoline price, Newman and Kenworthy test the hypothesis on a global scale and reconfirm the importance of land use density in influencing fuel consumption (Newman and Kenworthy, 1989). Golob and Brownstone use statistics of 2079 households in the 2001 National Household Travel Survey (NHTS) and find out that a lower density of 1,000 housing units per square mile implies a positive difference of almost 1,200 miles per year and about 65 more gallons of fuel per household (Golob and Brownstone, 2009). Another similar study by Brownstone reveals an even more remarkable influence of residential density on the indicators using the US' national level data from the 2001 NHTS (Kim and Brownstone, 2010). Yin and Mizokami set up a Constant Elasticity of Substitution (CES) typed model to investigate the issue in Japan and the results show that higher energy consumption efficiency is found in cities that have more compact urban structure and mass transit usage (Yin and Mizokami, 2011). In 2009, the report "*Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and $CO_2$ Emissions*" by Transportation Research Board (TRB) concludes that more compact development patterns are likely to reduce VMT, and produce reductions in energy consumption and carbon emissions (TRB, 2009). Apart from transport energy use, residential energy consumption also draws attentions from academia. Ewing and Rong show that multifamily housing consumes much less energy for both heating and cooling than single family housing, and that the tendency of citizens in sprawling counties to live in big single family houses rather than compact multifamily houses lead to higher residential energy use (Ewing and Rong, 2008).

According to the literature, Carbon emissions are tightly connected with energy consumption, especially in the transportation sector, and thus it is also associated with the level of compactness. In the report "*Growing Cooler: the Evidence on Urban Development and Climate Change*", the authors argue that significant compact development will lead to the reduction of VMT and carbon emissions at the same time. Under a series of assumptions including market share of compact development(6/10 to 9/10), increment of new development or redevelopment relative to base(2/3), etc., there will be a 7 to 10 percent reduction in total transportation $CO_2$ emissions in the United States (Ewing et al., 2008). The authors of "*Driving and the Built Environment*" develop another estimate of potential savings in carbon emission from more compact development. They find that in assumed scenarios, only modest short-term reduction of carbon emissions would take place when significantly increasing compactness, but such reductions will grow over time For instance, in the upper-bound scenario which assumes the increment of new development or redevelopment relative to base as 75%, $CO_2$ emissions would be reduced by 7 to 8 percent to base condition by 2030, with the reduction widening to between 8 and 11 percent by 2050 (TRB, 2009). However, based on theoretical models, Gaigné et al casts doubts on the idea that more compact cities are always ecologically desirable, and argues that polycentric cities are more likely to reduce carbon emissions than compact and monocentric cities (Gaigné et al, 2012). Petsch et al. present a new approach for measuring and monitoring urban sprawl and carbon footprints: the visualization of carbon emission concentration and urban density through GIS tools (Petsch et al., 2011).

The impact of urban compactness on vehicle emission (usually referring to vehicle pollutant emitted, normally including carbon monoxide, volatile organic compounds, nitrogen oxides, ozone and particulates) and air quality has been carefully studied by scholars during the past decades. The fact that vehicle emissions increase with VMT "*gives compact development an edge over sprawl*", "*although the edge is diminished by the fixed hydrocarbon emissions associated with 'cold starts' and 'hot soaks*'" (Ewing, 2008). Relevant evidence is abundant. Frank et al. reveal an inverse relationship between the land use measures of household density, work tract employment density, and, in the case of nitrogen oxides, street connectivity (census block density) and vehicle emissions based on studies in Seattle, Atlanta and New Jersey (Frank et al., 1999, 2000). In another study led by Frank, an index of walkability is created based on residential density, street connectivity, land use mix and retail floor area ratio, all of which are also highly related to urban compactness. And the study discovers that a 5 percent increase in the index of walkability is associated with 5.6 percent fewer grams of oxides of nitrogen (NOx) emitted, and 5.5 percent fewer grams of volatile organic compounds (VOC) emitted (Frank et al., 2006). The model in a study of the Chicago MSA produces similar results and further shows the densification of urban zones to be more than twice as effective in reducing vehicle emission as the densification of suburban zones (Stone et al., 2007). During the discussion, a major controversy centers on the discrepancy between the amount of vehicle emissions and inhalation of the emissions: although more compactness can lead to less vehicle emissions, the higher population density might offset the influence when estimating the amount of intake (Schweitzer and Zhou, 2010). Frank and Engelke find increased compactness would promote physical activity and reduce regional air pollution levels, but meanwhile exacerbate traffic congestion and increase exposure to harmful emissions within central areas (Frank and Engelke, 2005). A group of scholars from UC Berkeley provide a good yet not perfect answer: "*depending on the density–emissions elasticity, infill development has the potential to reduce motor vehicle emissions yet increase per capita inhalation of these emissions, while sprawl has the potential to increase vehicle emissions but reduce inhalation of these emissions*" (Marshall et al., 2004). Finally a recent study of Schweitzer and Zhou finds that Ozone concentrations are significantly lower in compact regions, but ozone exposures in neighborhoods are higher in compact regions. Conversely, fine particulate concentrations do not correlate significantly with regional compactness, but fine particulate exposures in neighborhoods are also higher in compact regions (Schweitzer and Zhou, 2010).

As an important indicator of urban environment and quality of life, green space is also associated with urban compactness by researchers, especially those in Europe. *"Compact development and sprawl, which have obvious consequences for green and open space", have frequently led to deadlocks in planning"* (Ståhle, 2008). In spite of this, Jim emphasizes the significance of green space in compact development and raises a series of measures dealing with the preservation and allocation of green space (Jim, 2004). Ståhle evaluates green space accessibility through calculating green space within 500m bird's/walking/3 axial step distance, and finds that citizens in some dense inner city districts experience higher green space accessibility than citizens in some low-density "green" suburbs in

Stockholm based on two similar questionnaires in 2001 and 2004 (Ståhle, 2008).

The level of urban sprawl influences another crucial indicator of urban environment and quality of life, noise, especially that of transportation (Johnson, 2001). To reduce the vehicle usage and mitigate the transportation noise pollution, mixed-use development, compact development and public transit oriented development are recommended by scholars (Vreeker et al. 2004; McCallum-Clark et al., 2006; Frost and Ison, 2007). The strategy of compact development to deal with the issue of noise has been promoted and adopted in regional plans and urban design protocols in New Zealand (McCallum-Clark et al., 2006).

In summary, most of the literature dealing with the relationship between urban compactness and energy consumption, carbon emission and air quality are linked together by the following logical chain: Compactness=>travel behavior/VMT/vehicle usage->energy/fuel consumption->carbon/vehicle emission->air quality->intake of citizens. The association and causality between the factors within the chain have been raised, tested and argued during the debate on compactness and sprawl. There has been no consensus on how compactness influences on energy consumption or air quality, though the majority agrees that such influence does exist in urban life. Meanwhile, the relationship between compactness and green space as well as noise has not been studied thoroughly. Few articles delve into the association through empirical data analysis or model construction.

Based on the existing literature review, more efforts can be made in future work on this topic. First, few relevant studies use panel data to test the hypotheses. Panel data would be more informative for studying the relationship between compactness and the environment and quality of life indicators than cross-sectional data, which is commonly used in previous research. Longitudinal models using panel data can avoid the temporal mismatch which might occur in cross-sectional models, and be more reliable in terms of nonspuriousness (Mokhtarian and Cao, 2008). Second, the current literature is overwhelmingly from and about developed countries. Developing countries, especially those currently in a rapid urbanization process, such as China, call for immediate attention in terms of urban form and land use. Only a few recent articles discuss how carbon emissions are associated with urban compact development in China, (Anas and Timilsina, 2009; Zheng, Wang, Glaeser and Kahn, 2011) and research about other factors is even more limited. Third, as is mentioned above, taking more relevant variables into consideration would be helpful to figure out the relationship between density and life-of-quality indicators (Gomez-Ibañez, 1991; Dunphy and Fisher, 1996; Boarnet and Crane, 2001). These factors may include climate indicators (such as annual mean temperature, annual total precipitation, and annual mean wind speed), economic development factors (such as industrial structure measured by the ratio of industrial output to total economic output) and geographical factors (such as the amount of developable land around cities) (Saiz, 2010). Future work may take them into consideration when looking into the topic discussed here.

# 3 Research Approach

## 3.1 Data framework

Taking a panel of more than 200 cities in China during the period of 2000-2010, this paper aims to make up for part of the deficiency of the existing literature. A total of 242 cities in the data set were selected from all 286 prefecture cities in China which had population in excess of 500,000 in 2010. (See Figure 3~8) The condition is well accepted in China as a major criterion for mid-size cities. (China Society of Urban Economy et al., 2012) In addition, the four municipalities directly under the Central Government, Beijing, Shanghai, Tianjin and Chongqing, are also excluded from the list, since they are distinctly different from prefecture cities in terms of spatial scale, administrative powers, disposable resources and other advantages. On the other hand, the period of year 2000-2010 witnessed an impressive growth of cities in China, in almost all aspects. Meanwhile, a series of problems about environment and quality of life had arisen because of the explosion of urban population and the expansion of built-up area. The official statistics have been more systematic and reliable since 2000, the year when China conducted the 5$^{th}$ National Census. In this paper, within the period, the year 2000, 2005 and 2010 are chosen as the specific time points for observation. The data of the selected cities by the end of each of the three years is gathered and serve as the input of the following analysis.

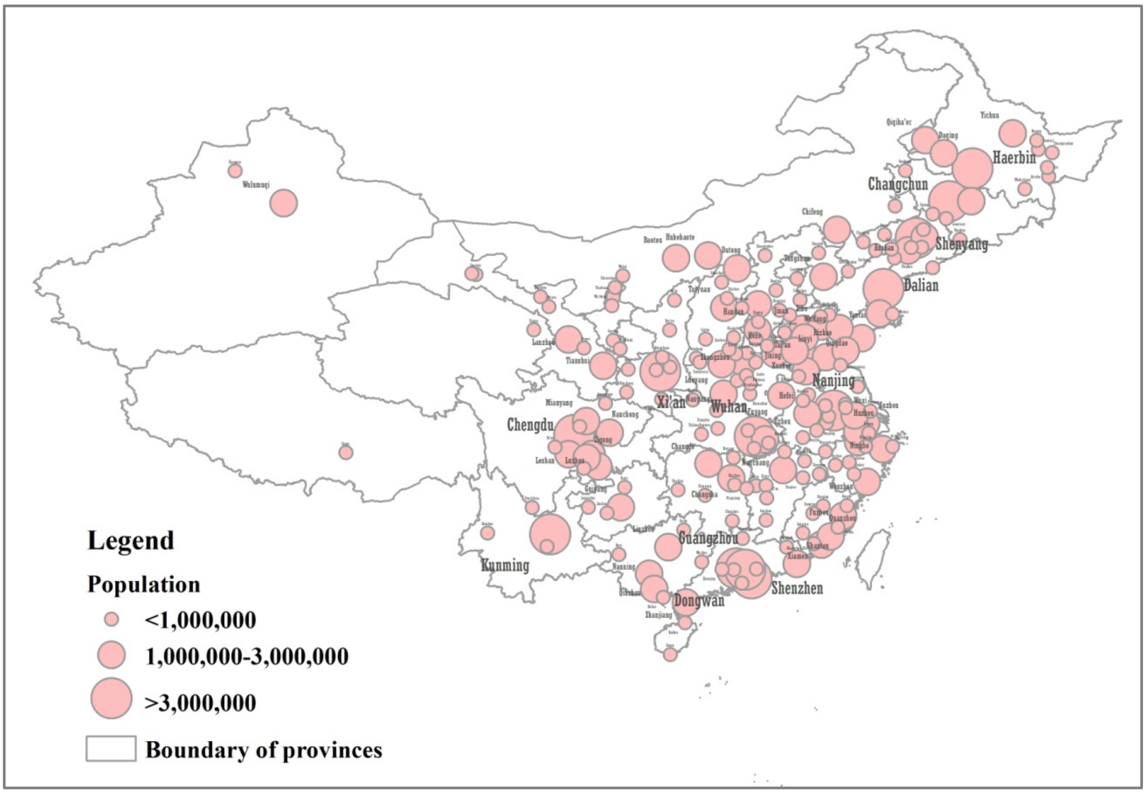


**Figure 3** Population sizes of selected cities in 2000

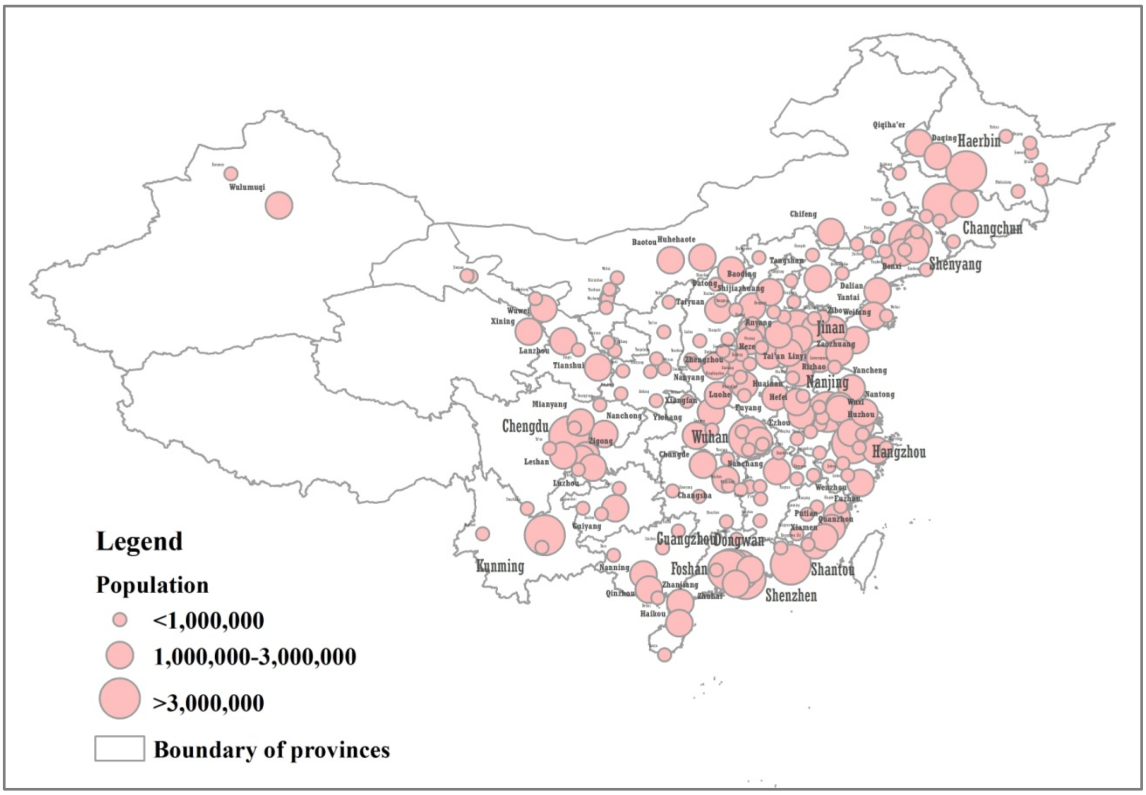


**Figure 4** Population sizes of selected cities in 2005

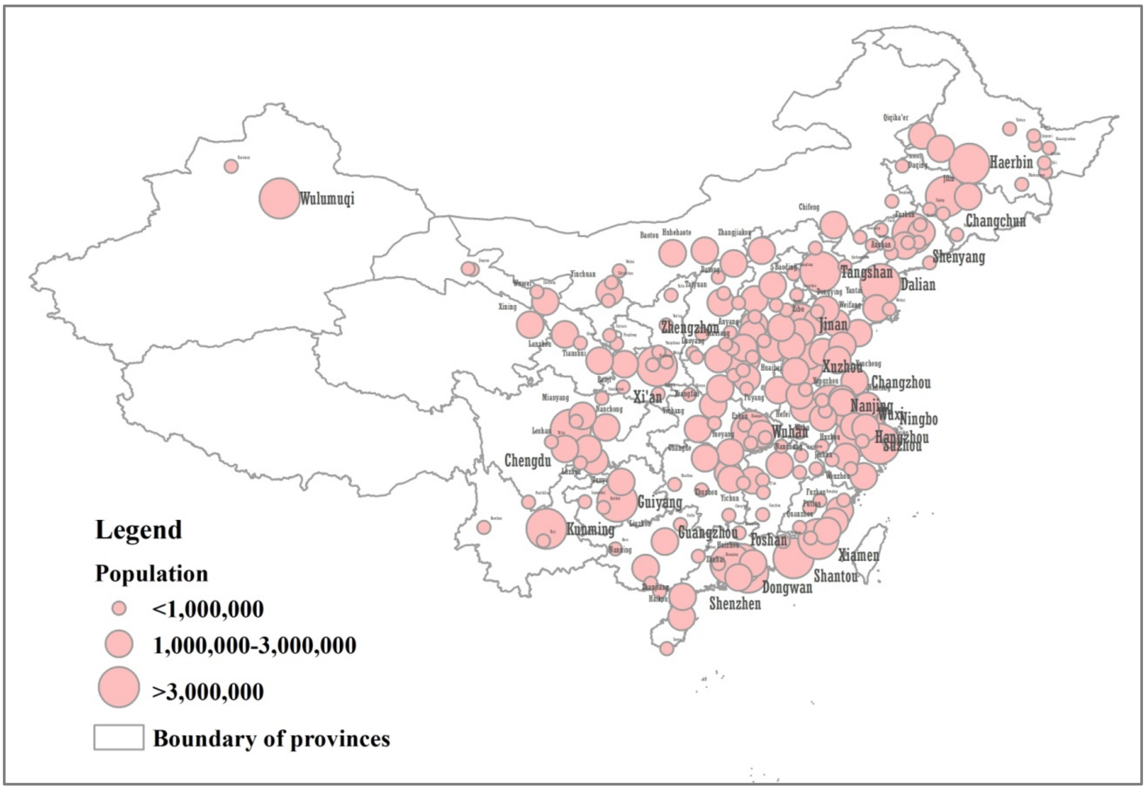


**Figure 5** Population sizes of selected cities in 2010

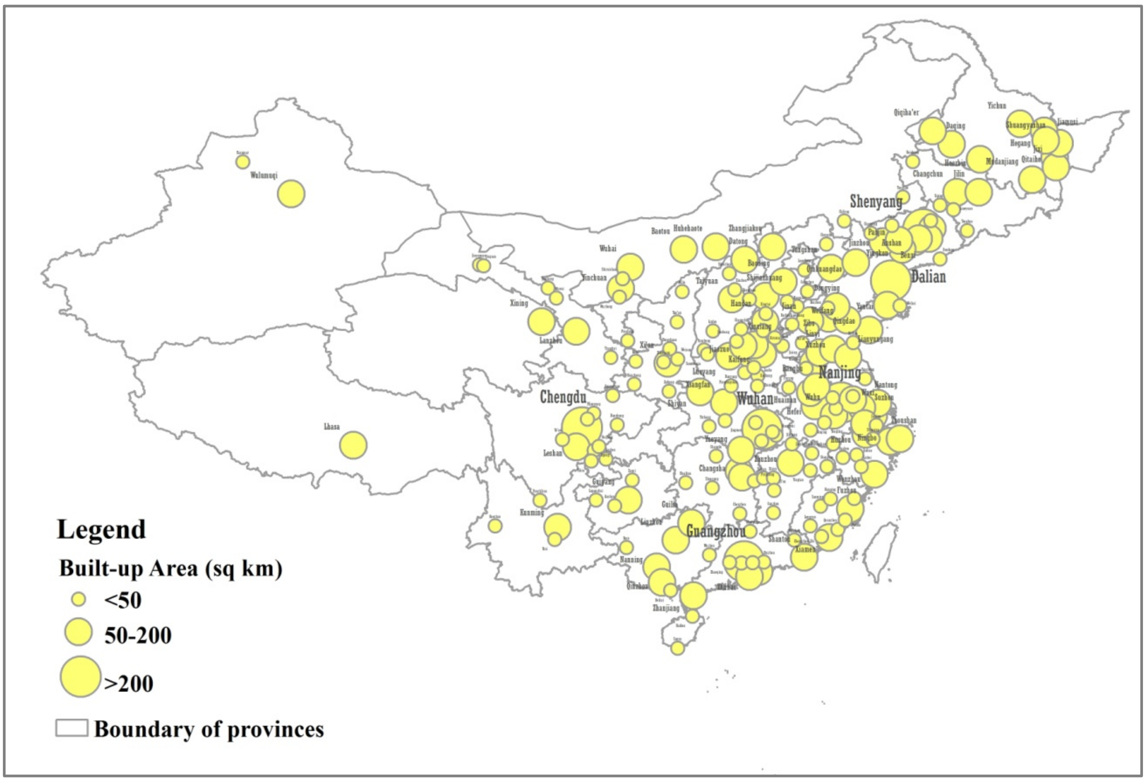


**Figure 6** Built-up areas of selected cities in 2000

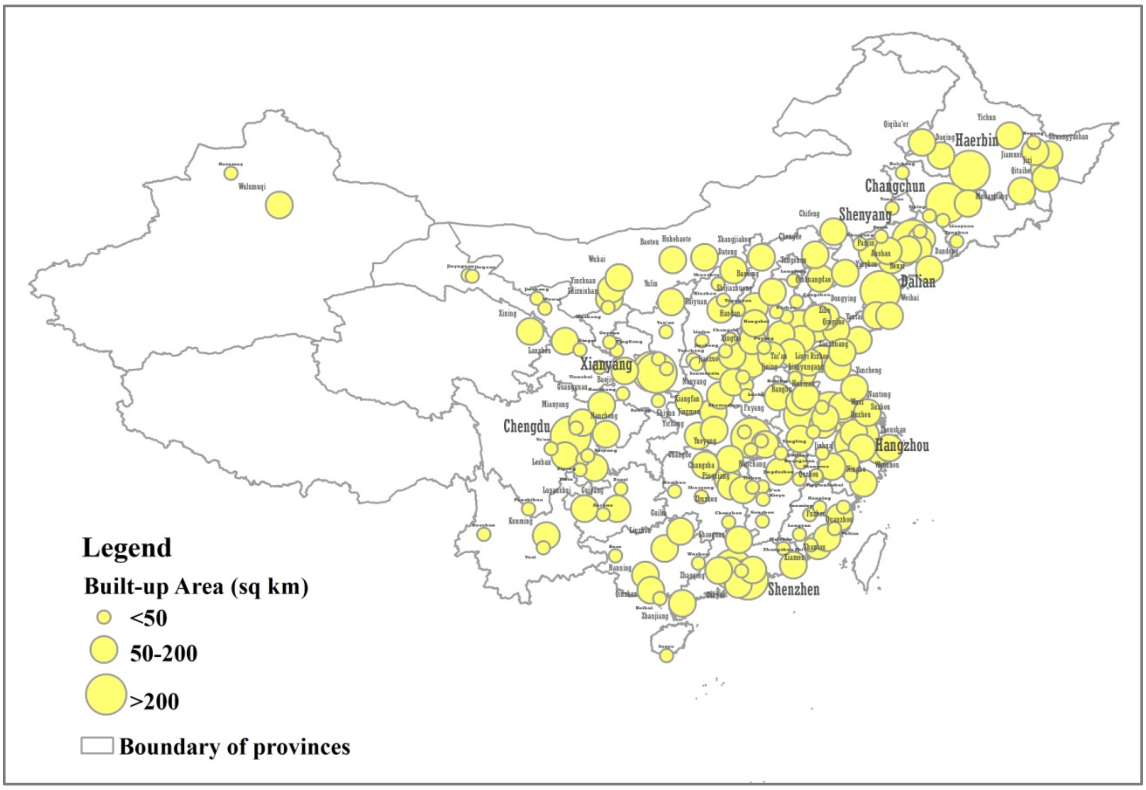


**Figure 7** Built-up areas of selected cities in 2005

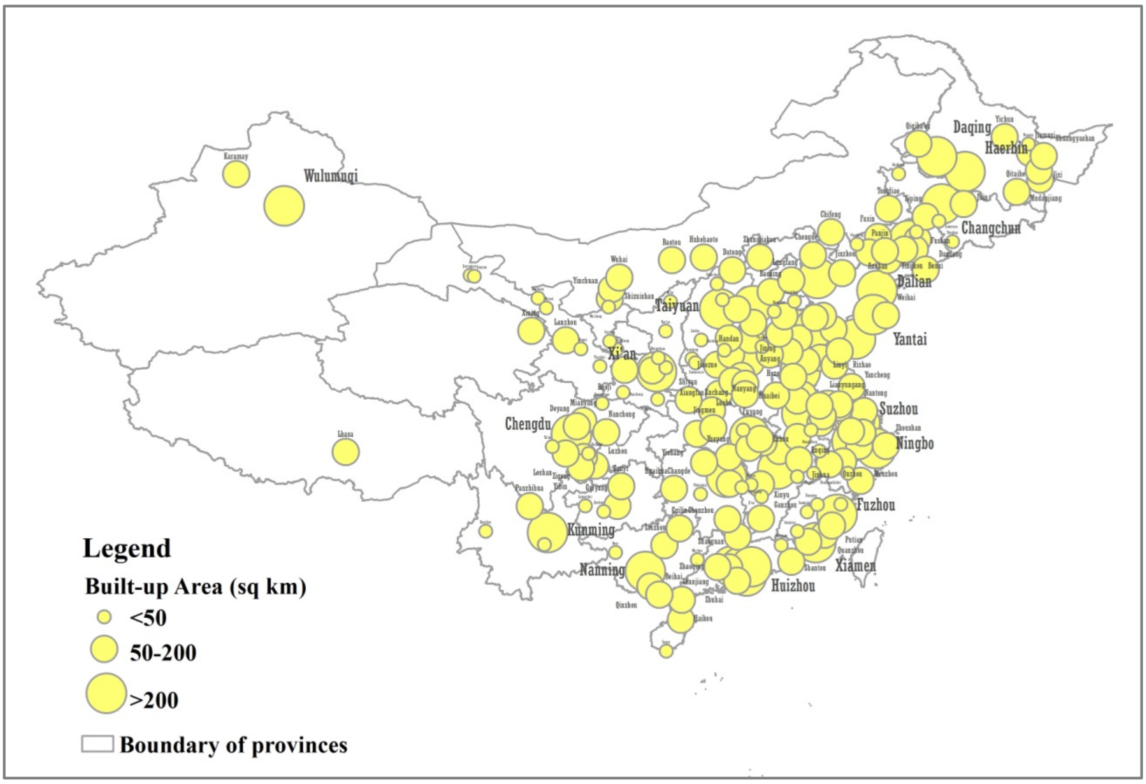


**Figure 8** Built-up areas of selected cities in 2010

### 3.2 Variables and data source

The concept model below is estimated to test the relationship between environmental and quality-of-life indicators and the population and spatial sizes of cities, controlling for economic development and other variables.

$$y_{i,t} = \beta_1 \cdot POP_{i,t} + \beta_2 \cdot DENSITY_{i,t} + \beta_3 \cdot GDP_{pc\ i,t} + B_4 \cdot X_{i,t} + v_i + \eta_t + \varepsilon_{i,t}$$

In the equation the dependent variable $y_{it}$ includes four groups of environmental and quality-of-life variables: transportation group, energy-carbon group, air-quality group and green-space group. The transportation group mainly contains per-capita urban road space, number of civil motor vehicles per capita, number of private motor vehicles per capita, annual ridership of public transit (bus) per capita, and number of buses per 10000 people. The data is collected from the China Urban Construction Statistical Yearbooks (2000-2010). There are two other variables relevant to transportation, mode share of transit, and mode share of transit/mode share of non-motorized modes (walk and bike), which will be used in regressions using the 2010 China Urban Survey (Commute Part) data. The energy-carbon group includes annual per-capita energy consumption, energy consumption per Gross Domestic Product (GDP) unit, per-capita $CO_2$ emissions and $CO_2$ emissions per GDP unit. These variables indicate the intensity and economic efficiency of energy usage as well as the level of carbon emission. Data is collected from the China Energy Statistical Yearbooks (2000-2010), the China Urban Construction Statistical Yearbooks (2000-2010), the Statistical Yearbooks and Energy Consumption Index Bulletins of all provinces (2000-2010). The air-quality variable group contains the median value of Air Pollution Index, and number of days with API larger than

50/100/150 in one year. The Ministry of Environmental Protection of the P.R.China regularly collects concentrations of selected major air pollutants including nitrogen oxides, sulfur dioxide and particulates from monitors in cities and converted them into pollution indexes. After that the highest index among the pollutants is defined as the Air Pollution Index. (MEP, 2006) The data comes from the China Statistical Yearbook of Environment (2000-2010). The green-space group is made up of per-capita green space and area of parks, percentages of built-up area used as green space and parks. The data comes from China Urban Construction Statistical Yearbook (2000-2010) and China City Statistical Yearbook (2000-2010). The author converted variables into per-capita based ones when necessary, in order to rule out the influence of population size on the variables. For instance, per-capita energy consumption is converted from the amount of total energy consumption divided by the number of population.

On the other side of the equation, the major independent variables of interest are population, built-up area, and level of economic growth. $POP_{it}$ is the population within urban municipal districts, $DENSITY_{i,t}$ is calculated based on built-up area and population of cities, while $GDP_{pc\ it}$ refers to the per-capita annual GDP. As a robustness check on the official statistics, the statistics of built-up area are measured alternatively using aforementioned satellite image-based data in years 2000 and 2010 for 147 largest cities by population. $X_{it}$ is a vector of control variables. (Gong, 2012) Depending on the choice of $y_{it}$, $X_{it}$ may include climate factors (such as annual mean temperature, annual total precipitation, and annual mean wind speed), and economic development factors (such as industrial structure measured by the ratio of industrial output to total economic output).

Data of all predictors except land developability can be found in the China Urban Construction Statistical Yearbook (2000-2010) and China City Statistical Yearbook (2000-2010). The summary of variables and their definitions are shown in Table 1.

**Table 1** Summary of variables and definitions

| Variables | Definition | Unit | Mean (SD) |
|---|---|---|---|
| *POP* | Permanent Population in municipal districts | 10,000 persons | 85.46 (98.02) |
| $GDP_{pc}$ | GDP per capita for municipal districts | 10,000 yuan | 446.89 (867.82) |
| *DENSITY* | Population density in built-up area (Source of built-up area: Official Yearbooks) | person/km$^2$ | 14930 (5566) |
| | Population density in built-up area (Source of built-up area: Satellite Image) | | 16290 (5776) |
| $SECONDARY_{\%}$ | Proportion of the Secondary Industry in the GDP for municipal districts | % | 51.13 (12.65) |
| *TEMP* | Average temperature in January | ℃ | 1.02 (8.79) |
| *RAIN* | Average annual precipitation | mm | 930.90 (495.29) |
| *WIND* | Average annual wind speed | m/s | 2.17 (0.56) |
| $ROAD_{pc}$ | Urban Road space per capita in municipal districts | m$^2$ | 7.62 (4.65) |
| $VEHICLE_{pc}$ | Number of Motor vehicles per capita | | 0.174 (0.164) |
| $PRIVATE\_VEH_{pc}$ | Number of Private Motor Vehicles per capita | | 0.125 (0.132) |
| $RIDERSHIP_{pc}$ | Annual Ridership of Public Transit per capita in municipal districts | | 88.94 (86.89) |
| $BUS_{pc}$ | Number of Buses per 10000 people in municipal districts | | 5.93 (3.97) |
| *TRANSIT* | Mode share of transit | % | 19.94 (11.66) |
| $TRANSIT_{\%}\ NONMOTOR$ | Mode share of transit/mode share of nonmotorized modes (walk and bike) | | 0.403 (0.313) |
| $ENERGY_{gdp}$ | Energy Consumption per GDP unit | ton standard coal/10,000 yuan | 1.63 (1.07) |
| $ENERGY_{pc}$ | Energy Consumption per capita | ton standard coal/person | 3.45 (3.41) |
| $CARBON_{gdp}$ | Carbon Emission per GDP unit | ton carbon/10,000 yuan | 3.42 (2.22) |
| $CARBON_{pc}$ | Carbon Emission per capita | ton carbon/person | 7.24 (8.40) |
| $PARK_{pc}$ | Area of Parks per capita in municipal districts | m$^2$ | 3.41 (4.21) |
| $GREEN_{\%}$ | Parks & Green Land as % of Complete Area in built-up area | % | 30.27 (9.01) |
| $GREEN_{pc}$ | Parks & Green Land per capita in municipal | m$^2$ | 30.69 (50.73) |
| $GREEN\_COVER_{\%}$ | Green Cover Area as % of Complete Area in municipal districts | % | 30.43 (9.39) |
| $AIR_{med}$ | Median value of Air Pollution Index | | 60.26 (10.22) |
| *AIR_50* | Number of days with API larger than 50 | day | 287.39 (56.30) |
| *AIR_100* | Number of days with API larger than 100 | day | 34.76 (28.70) |
| *AIR_150* | Number of days with API larger than 150 | day | 5.79 (10.10) |

### 3.3 Regression models

The research is intended to investigate the relationship between urban compactness and environmental as well as quality-of-life indicators in two approaches: cross-sectional structural equations models and longitudinal structural equations models. In general, cross-sectional data in each year (2000, 2005 and 2010) is tested in OLS structural equations models. The regression uses robust variance estimates to work out the coefficients. In addition, to diminish the total variance of the regression, some of the variables are presented in the form of the natural logarithm or the common logarithm. In all OLS regression models, year dummies are controlled and not reported; data in each year is put into regression with different year dummies, and the regression coefficients of variables other than year dummies are all reported finally. longitudinal structural equations models test panel data over years (normally 2000-2010), with standard errors clustered according to city codes (cities in the same provinces have the same initial digits of the city codes). The regression creates a city dummy for each city, and in this way the differences between cities except those in the other predictors are controlled in the regression. All in all, longitudinal structural equations models using panel data can more accurately test the relationship between dependent variables and the major predictors than Cross-sectional structural equations models. (Mokhtarian & Cao, 2008) However, there are limitations of the data sets including some loss of observations in certain years, which makes OLS structural equations models necessary to serve as an important reference for explaining the regression results.

# 4 Results

## 4.1 Transportation

The following equations are used to estimate the relationship between dependent variables in the transportation group and predictors including population, per-capita GDP and urban density:

$Ln\ (ROAD_{pc})_i = \beta_0 + \beta_1 \cdot Log\ (POP) + \beta_2 \cdot Ln\ (DENSITY)_i + \beta_3 \cdot Log\ (GDP_{pc}) + B_4 \cdot year\_dummies;$

$Ln\ (VEHICLE_{pc})_i = \beta_0 + \beta_1 \cdot Log\ (POP) + \beta_2 \cdot Ln\ (DENSITY)_i + \beta_3 \cdot Log\ (GDP_{pc}) + B_4 \cdot year\_dummies;$

$Ln\ (PRIVATE\_VEH_{pc})_i = \beta_0 + \beta_1 \cdot Log\ (POP) + \beta_2 \cdot Ln\ (DENSITY)_i + \beta_3 \cdot Log\ (GDP_{pc}) + B_4 \cdot year\_dummies;$

$Ln\ (RIDERSHIP_{pc})_i = \beta_0 + \beta_1 \cdot Log\ (POP) + \beta_2 \cdot Ln\ (DENSITY)_i + \beta_3 \cdot Log\ (GDP_{pc}) + B_4 \cdot year\_dummies;$

$Ln\ (BUS_{pc})_i = \beta_0 + \beta_1 \cdot Log\ (POP) + \beta_2 \cdot Ln\ (DENSITY)_i + \beta_3 \cdot Log\ (GDP_{pc}) + B_4 \cdot year\_dummies;$

in which, *i* stands for alternative choices of source of built-up area: official yearbooks or satellite-image data (the same for all equations below). Table 2 highlights the results of the regressions. Generally, the choice of source of built-up area does not matter much in the regression. Density apparently is negatively associated to all the dependent variables. As the density of land use and population concentration increases in a city, the density of road space would diminish therewith. The result concerning automobile ownership is consistent with the literature, which suggests high density tends to reduce the necessity and convenience of vehicle usage (Badoe and Miller, 2000; Ewing and Cervero, 2001). However, the finding that high density in Chinese cities fails to encourage people to use public transit, for instance buses in this case, is somehow against evidence in developed countries (Smith, 1984; Dunphy and Fisher, 1996; Cevero, 1996; Badoe and Miller, 2000). A possible explanation is that higher density creates more incentives for bicycling and walking instead of public transit in the cities, some of which have not developed a mature transit system. The hypothesis is further justified by the China Urban Survey data in 2010. (See Table 3) The results show that controlling for population size and per-capita GDP, higher densities are associated with lower shares of transit use (absolute shares and relative to non-motorized modal shares) for commuters in 2010.

The result of transportation regressions furthermore indicates that population size is negatively related to per-capita road space and vehicle ownership, but positive related to transit variables. A large size of population would potentially reduce the per-capita resource of road space, which is especially limited for rapidly growing mid-size cities. (Stares & Liu, 1995) Moreover, for the issue of public transit, large cities have more resources to strengthen their transit system and promote the usage of public transit. On the other hand, it is not surprising to see how per-capita GDP is related to the dependent variables. The level of economic development, i.e. per-capita GDP, is associated to per-capita road space and automobile ownership in the way that richer cities would spend more on transportation infrastructure including urban road system and public transit system. And it seems safe to conclude that in a more economically prosperous city, there are more citizens with enough purchasing power to buy motor vehicles.

**Table 2** Transportation regressions using cross-sectional data in 2000, 2005 and 2010

| Dependent variable | ln($ROAD_{pc}$) | ln($ROAD_{pc}$) | ln($VEHICLE_{pc}$) | ln($VEHICLE_{pc}$) | ln($PRIVATE\_VEH_{pc}$) | ln($PRIVATE\_VEH_{pc}$) | ln($RIDERSHIP_{pc}$) | ln($RIDERSHIP_{pc}$) | ln($BUS_{pc}$) | ln($BUS_{pc}$) |
|---|---|---|---|---|---|---|---|---|---|---|
| Source of Built-up Area | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image | Official Yearbook | Satellite Image |
| log(POP) | -0.0380 | -0.180*** | -0.169** | -0.0494 | -0.160* | 0.00440 | 0.363*** | 0.167* | 0.164*** | 0.0329 |
| | (0.0263) | (0.0394) | (0.0726) | (0.0824) | (0.0860) | (0.0873) | (0.0725) | (0.0979) | (0.0501) | (0.0833) |
| ln(DENSITY) | -0.355*** | -0.180*** | -0.252* | -0.470*** | -0.259 | -0.570*** | -0.641*** | -0.193 | -0.554*** | -0.209** |
| | (0.0693) | (0.0624) | (0.129) | (0.109) | (0.165) | (0.119) | (0.127) | (0.151) | (0.0833) | (0.0989) |
| log($GDP_{pc}$) | 0.453*** | 0.423*** | 0.429*** | 0.201 | 0.448*** | 0.130 | 0.654*** | 0.630*** | 0.498*** | 0.449*** |
| | (0.0513) | (0.0731) | (0.0993) | (0.131) | (0.125) | (0.139) | (0.0989) | (0.163) | (0.0707) | (0.102) |
| constant | -2.271*** | -1.153 | -5.684*** | -3.358** | -5.912*** | -3.212** | -3.479*** | -2.682* | -3.622*** | -2.757*** |
| | (0.487) | (0.733) | (0.831) | (1.321) | (1.079) | (1.394) | (0.865) | (1.579) | (0.594) | (0.892) |
| Obs | 693 | 265 | 455 | 131 | 439 | 130 | 688 | 265 | 696 | 266 |
| Adj. R-square | 0.520 | 0.527 | 0.285 | 0.236 | 0.268 | 0.246 | 0.380 | 0.229 | 0.508 | 0.340 |

Year dummies are controlled and not reported
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

**Table 3** Transportation mode split regressions using 2010 China Urban Survey data (cross-sectional data)

| Dependent variable | TRANSIT | TRANSIT | $TRANSIT_{\%}NONMOTOR$ | $TRANSIT_{\%}NONMOTOR$ |
|---|---|---|---|---|
| Type of regression | OLS | OLS ROBUST | OLS | OLS ROBUST |
| log(POP) | 0.0372*** | 0.0392*** | 0.107*** | 0.0768*** |
| | (0.0112) | (0.0112) | (0.0328) | (0.0216) |
| ln(DENSITY) | -0.0494** | -0.0545** | -0.0932* | -0.0925** |
| | (0.0210) | (0.0230) | (0.0513) | (0.0446) |
| log($GDP_{pc}$) | 0.0223 | 0.0158 | 0.120*** | 0.0736** |
| | (0.0157) | (0.0174) | (0.0385) | (0.0338) |
| constant | -0.189 | -0.140 | -1.295*** | -0.742** |
| | (0.145) | (0.164) | (0.372) | (0.317) |
| Obs | 239 | 239 | 239 | 239 |
| Adj. R-square | 0.1223 | | 0.1808 | |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Fixed effect regressions provide results showing how cities would evolve in terms of transportation variables when the values of the predictors change. (See the equations and Table 4 below) More compact development is linked to less road space per capita while higher level of economic development works in a reverse way. There is a positive connection between population size and vehicle ownership. As a city grows in population, some favorable changes of the city, such as more connectivity with nearby cities, would encourage citizens to purchase more cars.

$$\mathrm{Ln}\ (\mathrm{ROAD}_{pc})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\ (\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\ (\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\ (\mathrm{GDP}_{pc}) + \mathrm{B}_4 \cdot city\_dummies$$

$$\mathrm{Ln}\ (\mathrm{VEHICLE}_{pc})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\ (\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\ (\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\ (\mathrm{GDP}_{pc}) + \mathrm{B}_4 \cdot city\_dummies$$

$$\mathrm{Ln}\ (\mathrm{PRIVATE\_VEH}_{pc})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\ (\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\ (\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\ (\mathrm{GDP}_{pc}) + \mathrm{B}_4 \cdot city\_dummies$$

$$\mathrm{Ln}\ (\mathrm{RIDERSHIP}_{pc})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\ (\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\ (\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\ (\mathrm{GDP}_{pc}) + \mathrm{B}_4 \cdot city\_dummies$$

$$\mathrm{Ln}\ (\mathrm{BUS}_{pc})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\ (\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\ (\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\ (\mathrm{GDP}_{pc}) + \mathrm{B}_4 \cdot city\_dummies$$

**Table 4** Transportation regressions using panel data in 2000-2010

| Dependent variable | $\ln(\mathrm{ROAD}_{pc})$ | $\ln(\mathrm{ROAD}_{pc})$ | $\ln(\mathrm{VEHICLE}_{pc})$ | $\ln(\mathrm{PRIVATE\_VEH}_{pc})$ | $\ln(\mathrm{RIDERSHIP}_{pc})$ | $\ln(\mathrm{RIDERSHIP}_{pc})$ | $\ln(\mathrm{BUS}_{pc})$ | $\ln(\mathrm{BUS}_{pc})$ |
|---|---|---|---|---|---|---|---|---|
| Source of Built-up Area | Official Yearbooks | Satellite Image | Official Yearbooks | Official Yearbooks | Official Yearbooks | Satellite Image | Official Yearbook | Satellite Image |
| log(POP) | -0.113 | 0.226 | 0.955*** | 1.219*** | 0.0198 | 0.180 | -0.0741 | 0.146 |
| | (0.306) | (0.300) | (0.283) | (0.395) | (0.320) | (0.545) | (0.177) | (0.267) |
| ln(DENSITY) | -0.466*** | -0.479* | -0.0574 | -0.283 | -0.304*** | -0.444 | -0.323*** | 0.0273 |
| | (0.0795) | (0.243) | (0.257) | (0.254) | (0.114) | (0.508) | (0.0667) | (0.273) |
| $\log(\mathrm{GDP}_{pc})$ | 0.480*** | 0.465*** | 0.899*** | 1.050*** | 0.523*** | 0.302 | 0.366*** | 0.476*** |
| | (0.0827) | (0.114) | (0.134) | (0.196) | (0.118) | (0.312) | (0.0505) | (0.122) |
| constant | -2.105* | -3.468* | -15.39*** | -18.49*** | -1.076 | 0.742 | -1.567* | -3.680* |
| | (1.220) | (1.766) | (1.406) | (1.994) | (1.224) | (2.996) | (0.800) | (1.892) |
| Obs | 591 | 209 | 447 | 431 | 586 | 209 | 594 | 210 |
| Adj. R-square | 0.717 | 0.696 | 0.834 | 0.792 | 0.756 | 0.656 | 0.835 | 0.747 |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

### 4.2 Energy consumption & Carbon Emission

The regression equations for the energy-carbon group are more complicated. (See the equations below) Considering that the secondary sector (or industrial sector, which creates a finished, tangible product: production and construction.) of the economy generates much more energy consumption and carbon emission, the proportion of secondary sector in the GDP ($SECONDARY_{\%}$) is included in the equation. Meanwhile, some seasonal energy consumption activities such as heating in the winter can also be influential, so the average temperature in January (TEMP) is put into the regression as well.

$$\text{Ln}\,(\text{ENERGY}_{pc})_i = \beta_0 + \beta_1 \cdot \text{Log}\,(\text{POP}) + \beta_2 \cdot \text{Ln}\,(\text{DENSITY})_i + \beta_3 \cdot \text{Log}\,(\text{GDP}_{pc}) + \beta_4 \cdot \text{SECONDARY}_{\%} + \beta_5 \cdot \text{TEMP} + \text{B}_6 \cdot \textit{year\_dummies};$$

$$\text{Ln}\,(\text{ENERGY}_{gdp})_i = \beta_0 + \beta_1 \cdot \text{Log}\,(\text{POP}) + \beta_2 \cdot \text{Ln}\,(\text{DENSITY})_i + \beta_3 \cdot \text{Log}\,(\text{GDP}_{pc}) + \beta_4 \cdot \text{SECONDARY}_{\%} + \beta_5 \cdot \text{TEMP} + \text{B}_6 \cdot \textit{year\_dummies};$$

$$\text{Ln}\,(\text{CARBON}_{pc})_i = \beta_0 + \beta_1 \cdot \text{Log}\,(\text{POP}) + \beta_2 \cdot \text{Ln}\,(\text{DENSITY})_i + \beta_3 \cdot \text{Log}\,(\text{GDP}_{pc}) + \beta_4 \cdot \text{SECONDARY}_{\%} + \beta_5 \cdot \text{TEMP} + \text{B}_6 \cdot \textit{year\_dummies};$$

$$\text{Ln}\,(\text{CARBON}_{gdp})_i = \beta_0 + \beta_1 \cdot \text{Log}\,(\text{POP}) + \beta_2 \cdot \text{Ln}\,(\text{DENSITY})_i + \beta_3 \cdot \text{Log}\,(\text{GDP}_{pc}) + \beta_4 \cdot \text{SECONDARY}_{\%} + \beta_5 \cdot \text{TEMP} + \text{B}_6 \cdot \textit{year\_dummies};$$

Table 5 indicates several interesting findings. First, density appears hardly relevant to any one of the dependent variables. It is necessary to clarify that the data on energy consumption and carbon emission used in the regression covers all sectors including industrial, agriculture, etc., among which transportation serves as an indispensable but not dominant part. The paper fails to test the argument in previous literature about density and transportation energy consumption and carbon emission, due to the unavailability of data on the transportation sector. What we can conclude here is that density does not significantly influence the all-sector energy consumption or carbon emissions. Second, both population size and per-capita GDP of a city are positively associated to per-capita energy consumption and carbon emissions, but negatively related to per-GDP-unit variables. A feasible explanation is that as the city grows in either population or economic power, the agglomeration of people creates additional (personal and social) activities, which subsequently generate more per-capita energy consumption and carbon emission. Meanwhile, prosperity can attract more investment on local economy and create the agglomeration effect, which further facilitates the improvement of productivity and energy efficiency. For instance, when industries or firms in the same production chain locate near each other, there will more cooperation and lower total transportation costs, bringing about the declining of per-GDP-unit energy consumption and carbon emission. Additionally, the significantly positive coefficients of $SECONDARY_{\%}$ suggest in the selected mid-size Chinese cities, the weight of the secondary sector greatly influences energy consumption and carbon emission in the positive direction. Finally, the coldness of winter is also remarkably connected with all the dependent variables, as we assumed. Particularly in the north of China, where low wintertime temperature leads to frequent usage of, or even heavy reliance upon heating, and thus increases energy consumption and carbon emissions. The fact that many mid-size cities strongly depend on coal and other fossil fuels for winter heating further lowers the efficiency of energy usage and raises the intensity of carbon emissions.

**Table 5** Energy consumption and carbon emission regressions using cross-sectional data in 2000, 2005 and 2010

| Dependent variable | $\ln(ENERGY_{pc})$ | $\ln(ENERGY_{pc})$ | $\ln(ENERGY_{gdp})$ | $\ln(ENERGY_{gdp})$ | $\ln(CARBON_{pc})$ | $\ln(CARBON_{pc})$ | $\ln(CARBON_{gdp})$ | $\ln(CARBON_{gdp})$ |
|---|---|---|---|---|---|---|---|---|
| Source of Built-up Area statistics | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image |
| log(POP) | 0.0361 | 0.0329 | -0.107** | -0.141** | 0.111* | 0.287*** | -0.109*** | -0.0996* |
| | (0.0522) | (0.103) | (0.0417) | (0.0644) | (0.0591) | (0.100) | (0.0391) | (0.0550) |
| ln(DENSITY) | -0.0207 | -0.0932 | -0.140* | -0.0147 | -0.0993 | -0.223 | -0.121 | -0.0394 |
| | (0.101) | (0.185) | (0.0828) | (0.0797) | (0.104) | (0.136) | (0.0793) | (0.0774) |
| $\log(GDP_{pc})$ | 0.594*** | 0.561*** | -0.274*** | -0.190** | 0.715*** | 0.684*** | -0.213*** | -0.181** |
| | (0.0737) | (0.166) | (0.0605) | (0.0865) | (0.0791) | (0.154) | (0.0599) | (0.0899) |
| $SECONDARY_{\%}$ | 0.00734** | 0.00521 | 0.00883*** | 0.00460 | 0.00563* | 0.00942* | 0.00782*** | 0.00751** |
| | (0.00332) | (0.00609) | (0.00259) | (0.00365) | (0.00332) | (0.00567) | (0.00237) | (0.00363) |
| TEMP | -0.0231*** | -0.0203*** | -0.0158*** | -0.0149*** | -0.0307*** | -0.0259*** | -0.0256*** | -0.0283*** |
| | (0.00480) | (0.00692) | (0.00381) | (0.00537) | (0.00466) | (0.00698) | (0.00323) | (0.00389) |
| constant | -5.481*** | -5.045*** | 3.105*** | 2.587*** | -6.188*** | -6.999*** | 3.436*** | 2.945*** |
| | (0.635) | (1.400) | (0.513) | (0.817) | (0.652) | (1.345) | (0.495) | (0.823) |
| Obs | 397 | 119 | 442 | 120 | 441 | 121 | 441 | 121 |
| Adj. R-square | 0.410 | 0.263 | 0.279 | 0.246 | 0.550 | 0.516 | 0.367 | 0.449 |

Year dummies are controlled and not reported
Standard errors in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Fixed effect regression shows similar relationships except for $SECONDARY_{\%}$. (See equations and the Table 6 below) After controlling other attributes of the selected cities, the proportion of the secondary sector in GDP can hardly be associated with energy-carbon variables. It is possible that the association between the weight of secondary sector and energy consumption as well as carbon emission in cross-sectional regression is magnified because of other differences of the cities. With the evolution and upgrading of many secondary industries during recent decades, their impacts on the overall intensity and efficiency of energy usage in cities become less influential, compared with other industries.

$$\mathrm{Ln}\ (ENERGY_{pc})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\ (POP) + \beta_2 \cdot \mathrm{Ln}\ (DENSITY)_i + \beta_3 \cdot \mathrm{Log}\ (GDP_{pc}) + \beta_4 \cdot SECONDARY_{\%} + B_5 \cdot city\_dummies;$$

$\mathrm{Ln}\ (\mathrm{ENERGY}_{\mathrm{gdp}})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\ (\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\ (\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\ (\mathrm{GDP}_{\mathrm{pc}}) + \beta_4 \cdot \mathrm{SECONDARY}_{\%} + \mathrm{B}_5 \cdot city\_dummies;$

$\mathrm{Ln}\ (\mathrm{CARBON}_{\mathrm{pc}})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\ (\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\ (\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\ (\mathrm{GDP}_{\mathrm{pc}}) + \beta_4 \cdot \mathrm{SECONDARY}_{\%} + \mathrm{B}_5 \cdot city\_dummies;$

$\mathrm{Ln}\ (\mathrm{CARBON}_{\mathrm{gdp}})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\ (\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\ (\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\ (\mathrm{GDP}_{\mathrm{pc}}) + \beta_4 \cdot \mathrm{SECONDARY}_{\%} + \mathrm{B}_5 \cdot city\_dummies.$

**Table 6** Energy consumption and carbon emission regressions using panel data in 2000-2010

| Dependent variable | ln($ENERGY_{pc}$) | ln($ENERGY_{gdp}$) | ln($CARBON_{pc}$) | ln($CARBON_{gdp}$) |
|---|---|---|---|---|
| log(POP) | 0.430* | -0.511*** | 0.633*** | -0.409*** |
| | (0.235) | (0.104) | (0.103) | (0.0742) |
| ln(DENSITY) | -0.0338 | 0.0188 | -0.173 | 0.0655* |
| | (0.0824) | (0.0602) | (0.147) | (0.0393) |
| log($GDP_{pc}$) | 0.582*** | -0.338*** | 0.470*** | -0.218*** |
| | (0.0947) | (0.0458) | (0.0643) | (0.0373) |
| $SECONDARY_{\%}$ | 0.00532 | 0.00386 | -0.00167 | 0.00260 |
| | (0.00706) | (0.00261) | (0.00349) | (0.00233) |
| constant | -7.109*** | 5.843*** | -5.813*** | 4.979*** |
| | (1.200) | (0.625) | (0.567) | (0.413) |
| Obs | 389 | 433 | 433 | 433 |
| Adj. R-square | 0.875 | 0.908 | 0.970 | 0.947 |

Source of Built-up Area statistics: Official Yearbooks
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

### 4.3 Air quality

As the following equations indicate, the group of indicators to predict air quality variables contains population, per-capita GDP, density, the proportion of secondary sector in the GDP ($SECONDARY_{\%}$), average temperature in January (TEMP), average annual precipitation (RAIN) and average wind speed (WIND). (See equations below) Given the intimate connection between energy consumption and air quality, the author maintains all the predictors in the "energy-carbon" regressions, and additionally puts another two factors, precipitation and wind speed, into the "air-quality" regressions. As is known, precipitation and wind speed have considerable influence on the formation and diffusion of pollutants, and then on air quality.

$AIR_{med\ i} = \beta_0 + \beta_1 \cdot Log\ (POP) + \beta_2 \cdot Ln\ (DENSITY)_i + \beta_3 \cdot Log\ (GDP_{pc}) + \beta_4 \cdot SECONDARY_{\%} + \beta_5 \cdot TEMP + \beta_6 \cdot Ln\ (RAIN) + \beta_7 \cdot WIND + B_8 \cdot year\_dummies;$

$AIR\_50_i = \beta_0 + \beta_1 \cdot Log\ (POP) + \beta_2 \cdot Ln\ (DENSITY)_i + \beta_3 \cdot Log\ (GDP_{pc}) + \beta_4 \cdot SECONDARY_{\%} + \beta_5 \cdot TEMP + \beta_6 \cdot Ln\ (RAIN) + \beta_7 \cdot WIND + B_8 \cdot year\_dummies;$

$AIR\_100_i = \beta_0 + \beta_1 \cdot Log\ (POP) + \beta_2 \cdot Ln\ (DENSITY)_i + \beta_3 \cdot Log\ (GDP_{pc}) + \beta_4 \cdot SECONDARY_{\%} + \beta_5 \cdot TEMP + \beta_6 \cdot Ln\ (RAIN) + \beta_7 \cdot WIND + B_8 \cdot year\_dummies;$

$AIR\_150_i = \beta_0 + \beta_1 \cdot Log\ (POP) + \beta_2 \cdot Ln\ (DENSITY)_i + \beta_3 \cdot Log\ (GDP_{pc}) + \beta_4 \cdot SECONDARY_{\%} + \beta_5 \cdot TEMP + \beta_6 \cdot Ln\ (RAIN) + \beta_7 \cdot WIND + B_8 \cdot year\_dummies;$

A negative connection between population density and air quality variables is found in the regression, especially when the regression uses the satellite-image data as the source of built-up area. Higher density is associated with lower API and less air pollution. Although the above "energy-carbon" regressions provide no significant evidence on the impact of compactness on energy consumption and carbon emission, the result here justifies its positive link to air quality. The regression also shows a positive relationship between air quality variables and population size, and it means the agglomeration of people would adversely influence the air quality of a city. Economic development seems almost irrelevant to air quality, since no significant correlations between air quality indicators and per-capita GDP or $SECONDARY_{\%}$ are reveled in the regressions. Finally the coefficients of climate predictors indicate that they do influence the level of air pollution, although in different ways. As mentioned above, low winter temperature probably leads to high energy usage for heating and aggravates air pollution. High level of precipitation and wind speed both expedite the diffusion of air pollutants and help mitigate urban air pollution, as the regression results suggest.

**Table 7** Air quality regressions using cross-sectional data in 2000, 2005 and 2010

| Dependent variable | $AIR_{med}$ | $AIR_{med}$ | AIR_50 | AIR_50 | AIR_100 | AIR_100 | AIR_150 | AIR_150 |
|---|---|---|---|---|---|---|---|---|
| Source of Built-up Area statistics | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image |
| log(POP) | 4.073** | 2.915** | 22.75** | 14.55* | 8.745** | 8.998*** | 2.166* | 1.878* |
| | (1.656) | (1.462) | (9.241) | (8.391) | (4.343) | (3.285) | (1.248) | (0.973) |
| ln(DENSITY) | -1.617 | -3.811* | -15.14 | -22.87* | -4.341 | -10.84** | -1.511 | -2.559** |
| | (3.025) | (2.160) | (18.24) | (13.05) | (7.520) | (4.551) | (2.189) | (1.195) |
| log($GDP_{pc}$) | -3.370 | -4.116 | -19.10 | -25.71 | -7.679 | -9.945* | -1.541 | -1.695 |
| | (2.908) | (2.634) | (15.22) | (17.06) | (7.584) | (5.581) | (1.936) | (1.479) |
| $SECONDARY_{\%}$ | 0.0919 | 0.119 | 0.683 | 0.653 | 0.0250 | 0.250 | -0.0733 | 0.0260 |
| | (0.0885) | (0.0782) | (0.509) | (0.568) | (0.247) | (0.196) | (0.0743) | (0.0528) |
| TEMP | -0.350** | -0.124 | -2.413*** | -1.386 | -0.941*** | -0.518 | -0.239 | -0.102 |
| | (0.144) | (0.125) | (0.839) | (0.870) | (0.350) | (0.364) | (0.159) | (0.112) |
| ln(RAIN) | -2.444 | -1.852 | -8.439 | -7.211 | -10.33* | -6.698 | -4.199* | -2.778 |
| | (1.954) | (1.992) | (9.764) | (10.17) | (5.864) | (7.168) | (2.500) | (2.121) |
| WIND | -4.559*** | -3.507* | -26.22*** | -22.48* | -13.07*** | -9.977*** | -2.769** | -1.217 |
| | (1.358) | (1.894) | (8.758) | (12.78) | (3.739) | (3.719) | (1.262) | (1.088) |
| constant | 100.9*** | 108.1*** | 445.5*** | 550.2*** | 161.4** | 144.2** | 47.32** | 33.03** |
| | (22.98) | (22.68) | (128.1) | (147.4) | (64.89) | (58.65) | (22.58) | (16.53) |
| Obs | 173 | 92 | 173 | 92 | 173 | 92 | 173 | 92 |
| Adj. R-square | 0.249 | 0.103 | 0.255 | 0.123 | 0.323 | 0.218 | 0.225 | 0.171 |

Year dummies are controlled and not reported
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

What we see in the fixed effect regression results is a totally different story. (See equations and Table 8 below) None of the four predictors, population, per-capita GDP, density and $SECONDARY_{\%}$, is significantly related to API variables. The reason might be that after controlling all other factors included in the city dummies, the connections of the four independent variables with air quality are not as statistically notable as we assumed.

$$AIR_{med\ i} = \beta_0 + \beta_1 \cdot Log(POP) + \beta_2 \cdot Ln(DENSITY)_i + \beta_3 \cdot Log(GDP_{pc}) + \beta_4 \cdot SECONDARY_{\%} + B_5 \cdot city\_dummies;$$

$$AIR\_50_i = \beta_0 + \beta_1 \cdot Log(POP) + \beta_2 \cdot Ln(DENSITY)_i + \beta_3 \cdot Log(GDP_{pc}) + \beta_4 \cdot SECONDARY_{\%} + B_5 \cdot city\_dummies;$$

$$AIR\_100_i = \beta_0 + \beta_1 \cdot Log(POP) + \beta_2 \cdot Ln(DENSITY)_i + \beta_3 \cdot Log(GDP_{pc}) + \beta_4 \cdot SECONDARY_{\%} + B_5 \cdot city\_dummies;$$

$$AIR\_150_i = \beta_0 + \beta_1 \cdot Log(POP) + \beta_2 \cdot Ln(DENSITY)_i + \beta_3 \cdot Log(GDP_{pc}) + \beta_4 \cdot SECONDARY_{\%} + B_5 \cdot city\_dummies.$$

**Table 8** Air quality regressions using panel data in 2000-2010

| Dependent variable | $AIR_{med}$ | AIR_50 | AIR_100 | AIR_150 |
|---|---|---|---|---|
| log(POP) | -2.231 | 0.634 | -23.37 | -3.964 |
| | (6.363) | (34.26) | (17.37) | (7.961) |
| ln(DENSITY) | 1.239 | 34.13 | 7.303 | -1.625 |
| | (9.215) | (45.34) | (21.80) | (6.412) |
| $log(GDP_{pc})$ | -9.916 | -17.97 | -23.45 | -7.583 |
| | (7.091) | (26.08) | (19.28) | (6.023) |
| $SECONDARY_{\%}$ | 0.164 | 1.032 | -0.147 | 0.0408 |
| | (0.288) | (1.448) | (0.845) | (0.305) |
| constant | 171.1** | 406.5 | 400.8** | 102.0* |
| | (67.94) | (298.4) | (173.2) | (52.28) |
| Obs | 166 | 166 | 166 | 166 |
| Adj. R-square | 0.478 | 0.664 | 0.500 | 0.333 |

Source of Built-up Area statistics: Official Yearbooks
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

### 4.4 Green space

In terms of the green-space group, the OLS regression equations are as follows. Besides the major three predictors, TEMP (average temperature in January) and RAIN (average annual precipitation) are also included. Climate conditions such as winter temperature and precipitation remarkably influence the growth of plants, and may directly affect the density of green space system in cities.

$$\mathrm{Ln}\,(\mathrm{PARK}_{pc})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\,(\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\,(\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\,(\mathrm{GDP}_{pc}) + \beta_4 \cdot \mathrm{TEMP} + \beta_5 \cdot \mathrm{Ln}\,(\mathrm{RAIN}) + \mathrm{B}_6 \cdot \mathit{year\_dummies};$$

$$\mathrm{Ln}\,(\mathrm{GREEN}_{pc})_i = \beta_0 + \beta_1 \cdot \mathrm{Log}\,(\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\,(\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\,(\mathrm{GDP}_{pc}) + \beta_4 \cdot \mathrm{TEMP} + \beta_5 \cdot \mathrm{Ln}\,(\mathrm{RAIN}) + \mathrm{B}_6 \cdot \mathit{year\_dummies};$$

$$\mathrm{GREEN}_{\%\,i} = \beta_0 + \beta_1 \cdot \mathrm{Log}\,(\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\,(\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\,(\mathrm{GDP}_{pc}) + \beta_4 \cdot \mathrm{TEMP} + \beta_5 \cdot \mathrm{Ln}\,(\mathrm{RAIN}) + \mathrm{B}_6 \cdot \mathit{year\_dummies};$$

$$\mathrm{GREEN\_COVER}_{\%\,i} = \beta_0 + \beta_1 \cdot \mathrm{Log}\,(\mathrm{POP}) + \beta_2 \cdot \mathrm{Ln}\,(\mathrm{DENSITY})_i + \beta_3 \cdot \mathrm{Log}\,(\mathrm{GDP}_{pc}) + \beta_4 \cdot \mathrm{TEMP} + \beta_5 \cdot \mathrm{Ln}\,(\mathrm{RAIN}) + \mathrm{B}_6 \cdot \mathit{year\_dummies};$$

Density is found negatively related to the dependent variables, although the associations with $\mathrm{GREEN}_{\%}$ and $\mathrm{GREEN\_COVER}_{\%}$ are not statistically significant. Given a fixed amount of built-up area, the denser a city is, the lower per-capita area of land developed as parks or green space there would be. The inference is partly supported by the regression results. No significant relationship is found between green-space dependent variables and population size. But the impacts of $\mathrm{GDP}_{pc}$ are highlighted in the table. As we assumed, economic development does effectively facilitate the improvement of an open space system. The regression also discovers that the connection of temperature with green space is not notable enough but precipitation is related to the proportion of green land or green cover area positively. Consequently, precipitation rather than temperature would be a key restriction for the density of green space in Chinese cities. It might explain why many cities in the south of China have better green space systems than the northern ones. (See Table 9)

**Table 9** Green space regressions using cross-sectional data in 2000, 2005 and 2010

| Dependent variable | ln($PARK_{pc}$) | ln($PARK_{pc}$) | ln($GREEN_{pc}$) | ln($GREEN_{pc}$) | $GREEN_{\%}$ | $GREEN_{\%}$ | GREEN_ $COVER_{\%}$ | GREEN_ $COVER_{\%}$ |
|---|---|---|---|---|---|---|---|---|
| Source of Built-up Area statistics | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image | Official Yearboo | Satellite Image | Official Yearbook | Satellite Image |
| log(POP) | 0.0587 | -0.128 | 0.0499 | -0.0571 | 0.420 | -0.811 | 0.708 | -0.781 |
| | (0.0642) | (0.0875) | (0.0608) | (0.0866) | (0.475) | (0.643) | (0.496) | (0.727) |
| ln(DENSITY) | -0.763*** | -0.290** | -1.012*** | -0.296*** | -0.0482 | -0.416 | -1.031 | -0.365 |
| | (0.138) | (0.132) | (0.111) | (0.0936) | (1.070) | (0.889) | (1.407) | (1.033) |
| log($GDP_{pc}$) | 0.379*** | 0.122 | 0.498*** | 0.408*** | 5.091*** | 3.059*** | 4.944*** | 3.157** |
| | (0.111) | (0.149) | (0.0766) | (0.108) | (0.734) | (1.124) | (0.914) | (1.271) |
| TEMP | 0.00134 | -0.00918 | 0.00325 | 0.000170 | 0.0779 | 0.0337 | 0.0860 | 0.0790 |
| | (0.00779) | (0.0125) | (0.00604) | (0.0110) | (0.0585) | (0.0625) | (0.0679) | (0.0728) |
| ln(RAIN) | 0.133 | 0.285 | 0.104 | -0.0936 | 1.447* | 1.910* | 2.175** | 1.365 |
| | (0.0999) | (0.214) | (0.0910) | (0.192) | (0.800) | (1.106) | (0.855) | (1.197) |
| constant | -3.743*** | -0.985 | -2.268** | 0.406 | -32.55*** | -4.036 | -29.19*** | 2.101 |
| | (1.123) | (1.585) | (0.988) | (1.612) | (7.668) | (10.96) | (9.998) | (13.44) |
| Obs | 687 | 266 | 691 | 266 | 690 | 262 | 688 | 262 |
| Adj. R-square | 0.356 | 0.293 | 0.542 | 0.442 | 0.303 | 0.388 | 0.356 | 0.365 |

Year dummies are controlled and not reported
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Different from the above results, the fixed effect regression results show a strong positive relationship between population size and $GREEN_{\%}$ as well as GREEN_$COVER_{\%}$. (See Table 10) As a city grows into a larger one in terms of population, it can benefit from such growth in many ways, including obtaining more land resources as well as other public and natural resources from central government. On the other hand it may be required to meet higher standards for urban open space system. All these changes can lead to a higher proportion of green land or green cover space.

$$\text{Ln}(PARK_{pc})_i = \beta_0 + \beta_1 \cdot \text{Log}(POP) + \beta_2 \cdot \text{Ln}(DENSITY)_i + \beta_3 \cdot \text{Log}(GDP_{pc}) + B_4 \cdot city\_dummies;$$

$$\text{Ln}(GREEN_{pc})_i = \beta_0 + \beta_1 \cdot \text{Log}(POP) + \beta_2 \cdot \text{Ln}(DENSITY)_i + \beta_3 \cdot \text{Log}(GDP_{pc}) + B_4 \cdot city\_dummies;$$

$$\text{GREEN}_{\%\ i} = \beta_0 + \beta_1 \cdot \text{Log (POP)} + \beta_2 \cdot \text{Ln (DENSITY)}_{i} + \beta_3 \cdot \text{Log (GDP}_{pc}) + B_4 \cdot \textit{city\_dummies};$$

$$\text{GREEN\_COVER}_{\%\ i} = \beta_0 + \beta_1 \cdot \text{Log (POP)} + \beta_2 \cdot \text{Ln (DENSITY)}_{i} + \beta_3 \cdot \text{Log (GDP}_{pc}) + B_4 \cdot \textit{city\_dummies}.$$

**Table 10** Green space regressions using panel data in 2000-2010

| Dependent variable | ln(PARK$_{pc}$) | ln(PARK$_{pc}$) | ln(GREEN$_{pc}$) | ln(GREEN$_{pc}$) | GREEN$_{\%}$ | GREEN$_{\%}$ | GREEN_COVER | GREEN_COVER |
|---|---|---|---|---|---|---|---|---|
| Source of Built-up Area statistics | Official Yearbooks | Satellite Image | Official Yearbooks | Satellite Image | Official Yearboo | Satellite Image | Official Yearboo | Satellite Image |
| log(POP) | 0.102 | -0.188 | 0.323 | 0.689 | 9.213*** | 7.775* | 6.814** | 5.527 |
| | (0.239) | (0.501) | (0.292) | (0.537) | (2.499) | (4.655) | (2.683) | (4.308) |
| ln(DENSITY) | -0.467** | -0.971* | -0.626*** | -1.512*** | -0.173 | -2.703 | 0.250 | -4.725 |
| | (0.211) | (0.570) | (0.229) | (0.424) | (1.819) | (4.779) | (2.483) | (4.722) |
| log(GDP$_{pc}$) | 0.685*** | 0.577** | 0.591*** | 0.233 | 7.611*** | 6.303*** | 9.828*** | 6.348** |
| | (0.0979) | (0.289) | (0.134) | (0.235) | (0.865) | (2.261) | (1.269) | (2.701) |
| constant | -6.104*** | -3.189 | -3.968*** | -1.621 | -84.84*** | -66.75*** | -92.93*** | -51.78** |
| | (1.230) | (2.895) | (1.493) | (2.368) | (12.24) | (24.00) | (13.96) | (23.15) |
| Obs | 585 | 210 | 589 | 210 | 588 | 206 | 586 | 206 |
| Adj. R-square | 0.722 | 0.570 | 0.634 | 0.618 | 0.545 | 0.500 | 0.588 | 0.520 |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

## 5 Conclusion and Discussion

The explosion of population and expansion of built-up area in the recent decade have jointly changed the environment of Chinese cities. Whether a city develops into a more compact one or a more sprawling one might affect many aspects of urban life, ranging from energy consumption to personal health. The existing literature emphasizes the research on the relationship between urban compactness and travel behavior, in tandem with energy consumption, carbon emissions and air pollution in the transportation sector. Other issues related to urban environment and quality of life such as green space and noise are also associated with compact development by researchers. In spite of numerous evidence raised, no consensus has been achieved so far. Similar studies are scarce in developing countries and fewer data-based conclusions are available.

In this paper, the author uses panel data of Chinese mid-size cities during 2000-2010 to test the connections between compactness and selected indicators of environment and quality of life. Some of the outcomes provide support to previous findings from developed countries, but other results indicate new ways to interpret the relationships.

The research begins with transportation indicators and focuses on transportation infrastructure (per-capita road space), motor vehicle (including private vehicle) and public transit (mainly bus service). In line with our expectations, higher density is associated with lower per-capita road space and vehicle ownership. Nonetheless, it is also connected to lower usage of public bus service, which is inconsistent with what happens in the United States and Europe. Additional analysis on data in the 2010 China Urban Survey shows similar results. The inconsistency most likely results from the fact that most Chinese mid-size cities are still in the early stage of motorization and development of public transit, and bicycling and walking are still playing an indispensable role in citizens' daily life. Hypothetically, compact development can effectively reduce the demand for private motor vehicles and public transit, while increasing the frequency of non-motorized modes.

The regression results about energy consumption and carbon emission indicate that urban density is not significantly relevant to any of the dependent variables. It is not comparable with previous conclusions on the topic, since the data in this study is from all sectors rather than the transport sector alone. However, based on both of the cross-sectional and panel regressions, the relationship between urban compactness and all-sector energy consumption or carbon emissions is not evident enough.

In terms of air quality, cross-sectional regression results are partly different from panel regression. Cross sectional data provides evidence that differences in density among cities are relevant to the gap in air pollution index, especially when satellite-image is chosen as the data source of built-up area. However, panel data results reject the significance of such a relationship, although the statistically insignificant coefficients also suggest a negative connection between them.

As earlier studies have shown, compact development does not promote green space creation. Per-capita park area and green space are both significantly negatively associated with density; proportion of green space and green cover area are also negatively related to density, though the relationship is not statistically significant.

Besides urban density, the research simultaneously studies the connections between dependent variables (related to transportation, energy consumption, air quality and green space) and population size, per-capita GDP and other factors such as the weight of secondary sector and climate indicators. In general, higher per-capita GDP is strongly associated with better environment conditions such as higher density of green space. But in many cases, the relationships between population size and the variables are mixed.

Based on the findings above, there are several possible policy implications for the future development of Chinese cities. First, compact development may reduce the accessibility to public resources for the citizens. As the regression results suggest, higher density is significantly associated with lower per-capita road space and green area. In fact, the levels of these public resources in Chinese cities are found much lower than the average level of cities in developed countries. For instance, both New York and London had more than 25 $m^2$ per capita of road space in 2000 (Ng et al., 2010), while the average per-capita road space of mid-sized cities in China was only 5.49 $m^2$ at that time. Although it had increased remarkably to 9.46 $m^2$ by the end of 2010, such a gap was still too large to ignore. Given that the scarcity of road space could lead to the decrease of average travel speed and aggravate congestion (Ng et al., 2010), the government should exert more efforts on the development of urban infrastructure and public service in the coming decades. In addition, to optimize the structure of transportation systems will be an important target for Chinese cities. Based on the data in the 2000-2010, higher density is related to lower usage of both private vehicles and public transit. To deal with the recent explosive growth of private vehicles, governments may set compact development as one of their major strategies. But according to the experience in the developed countries, the promotion of public transit could be equally effective and even more sustainable in the near future. Moreover, the relationship between urban compactness and energy consumption, carbon emission and air quality is not as significant as assumed in Chinese cities. Governments might pay more attentions to other policy measures and technology improvement, including raising the environmental standards of fuels and expediting the elimination of inefficient vehicles, to name a few.

Finally, certain constraints on data availability mentioned above make additional research and analysis in the future necessary. New data on energy consumption and carbon emission in the transportation sector can be used to further reveal its direct connection with compactness, and compare it with previous findings in the developed countries. Also, more detailed data sets on travel behavior (such as VMT and VHT), air quality (for instance, concentrations of each air pollutants), household income and other indicators will be helpful to study the topic more directly.

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